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# Oil price volatility in the context of Covid-19

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## ABSTRACT

The recent coronavirus pandemic (COVID-19) has negatively impacted the whole economy, especially the oil industry, in at least two ways. First, it created a demand shock as COVID-19 reduced global demand for crude oil, increased uncertainty, and triggered a serious economic recession in most developed and emerging countries. Second, it led to a supply shock as the pandemic resulted in an oil trade war between the major oil-producing nations (Saudi Arabia and Russia). Both shocks led to very high levels of oil price volatility. Our paper explores the dynamics of this volatility and explains the effects of these two shocks (induced by an adjustment of oil demand and supply) on West Texas Intermediate (WTI) crude oil price volatility. Accordingly, we show that oil price volatility reacted substantially to the pandemic-induced oil shocks. In particular, we document the impact of uncertainty caused by these shocks and investor anxiety on oil price volatility. We show that greater uncertainty leads to more oil price volatility. Our findings remained unchanged even after controlling for modeling robustness.

## 1. Introduction

Oil price volatility that tracks changes in oil price has continuously been considered a major but complex issue. Indeed, oil is not only a major component in production but is also a key driver in consumer purchasing power. Oil price volatility basically results from changes in oil price toward its mean value. These changes in oil price depend on the interaction between oil demand and oil supply, which are as well directly or indirectly impacted by economic conjecture and geopolitical tension (Hamilton, 1983). For instance, while oil price volatility in the 1970s was due to a supply shock, the oil price changes observed in the aftermath of the global financial crisis of 2008–2009 were caused by a demand shock (Hamilton, 2009). However, since 2014–2015, the oil industry has undergone a profound change prompted by the US shale revolution. Indeed, since 2014, the US shale oil has led to a boom in domestic crude oil production. Shale oil currently comprises more than a third of onshore crude oil production.

Indeed, in addition to Russia and the Organization of Petroleum Exporting Countries (OPEC), known as OPEC+, the US is now the world's top oil producer with a significant impact on the oil trade and pricing. Indeed, even with the design of OPEC+ and the alliance between Saudi Arabia and Russia to coordinate oil production, the impact of a supply shock has become more limited, largely due to the production of shale oil in Canada<sup>1</sup> and the US<sup>2</sup>. This structural change in the oil industry has introduced more complexity into both the oil industry and oil pricing policies (Aghababa and Barnett, 2016) and has led to a considerable oil price volatility since 2014. Indeed, in

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<sup>1</sup> Shale oil production is handled by private companies and it has a deregulated oil pricing system.

<sup>2</sup> Saudi Arabia, Russia and the USA have become the three largest oil producers with more than 30% of global oil production, while OPEC + accounts for over 50% of all oil production. In particular, since 2018, the US has switched from a major oil importer to the world's largest producer of crude oil, overtaking Saudi Arabia and Russia.

addition to the turbulence and complex geopolitical environment surrounding OPEC and its divergence with countries in crisis (Libya, Nigeria, Venezuela), other factors (uncertainty about Iran and its conflict with the US, doubt about oil reserves, oil extraction costs and exploration of new sources, the impact of the US joining the oil producers' cartel, COVID-19, etc.) have changed oil pricing strategies significantly.

While, in the past, Saudi Arabia, for instance, considered as the OPEC leader, might cut oil production to increase oil price levels, this option is now less effective, and oil producing countries are experiencing considerable difficulty in reaching a common agreement on oil supply<sup>3</sup>

Interestingly, the intrinsic complexity of the oil industry has been exacerbated by COVID-19 as the ongoing coronavirus crisis generated a dual shock for the oil market. First, it resulted in a supply shock. Indeed, given the failure of Saudi Arabia and Russia to reach a deal in March 2020 on cuts to oil output, Saudi Arabia significantly boosted its oil production above its present capacity of 12.5 million barrels a day. In particular, it announced massive discounts and began trading its production below the official selling prices, resulting in a fall of around 30% in oil prices in March 2020. This in turn led to the largest drop in oil price since January 1991, the last worst day being January 17, 1991 when the WTI lost 33% during the Persian Gulf War<sup>4</sup>. Clearly, the oil trade war and low oil prices are not in the interest of any of the three major oil producers (Saudi Arabia, Russia and the US). The former US president, Donald Trump, thus pushed Saudi Arabia and Russia to cut their oil production, which they agreed to on 11<sup>th</sup> April 2020. Accordingly, oil prices rose, showing volatility of around 20% and more thereafter<sup>5</sup>.

Second, COVID-19 also triggered a demand shock in the oil industry caused by the lockdown in different countries. The coronavirus crisis affected a wide range of energy markets and its impact on oil markets was particularly severe as it reduced the circulation of people and goods, sparking a major downturn in demand for fuel. In particular, uncertainty surged due to the risk of propagation across the globe. This uncertainty heightened anxiety, with governments urged to shut down major industries in the largest oil-importing developed and emerging countries.

Consequently, COVID-19 led to a sharp decline in oil demand,<sup>6</sup> which was already marked by a high level of uncertainty, especially in the US, Japan and the EU. Indeed, the oil market remains extremely volatile. The recent good news about COVID-19 vaccines, for instance, prompted a new upswing in oil prices.

Nevertheless, oil demand appears to have reached its peak, with the major economies already showing signs of a need to diversify (Elder and Serletis, 2010; Dai and Serletis, 2018; Aye et al., 2014; Van Eyden et al., 2019). Further, uncertainty regarding both the industry and recovery from COVID-19 remains high, a situation that could lead to increased inertia with respect to the demand shock. Indeed, developed and emerging countries are already showing signs of a major economic recession with a sharp rise in unemployment. Moreover, given the ongoing exceptional budgetary policies adopted by governments to try to support the national health care systems, public deficits and public debt are expected to exorbitant levels<sup>7</sup>.

Accordingly, the current situation is unprecedented for the oil industry. In addition to the usual context of the geopolitical environment and increased political tension, as well as the lingering vulnerability of commodity markets since the recent global financial crisis (Garcia et al., 2019), the coronavirus pandemic has led to a major new challenge for the oil industry, taken by surprise by the public health crisis that has affected both supply and demand.

In this paper, we examine the extent to which the current public health crisis has affected oil price and seek to measure its impact on oil price volatility. To this end, we investigate oil price volatility with regard to a shock that affected both supply and demand in the context of COVID-19. Further, examining information associated with these shocks, we also consider whether it is possible to improve forecasts of the future dynamics of oil price volatility. This is particularly important to help investors and policymakers gain a better understanding of oil price dynamics in the context of a similar health crisis.

To our knowledge, there has been little research to date in this area. Joo and Park (2017) recently showed that stock price uncertainty has a significant negative effect on crude oil returns. Jawadi and Ftiti, (2019) evinced the sharp rise in oil volatility due to uncertainty, while Yilmazkuday (2020), Ramelli and Wagner (2020) and Zhang et al. (2020) argued that coronavirus triggers price volatility on the stock markets based on emotional responses. Albulescu (2020) also showed that statements about the spread of coronavirus drove oil price volatility. Indeed, the rapid expansion of the coronavirus epidemic had a disparate impact on economies

<sup>3</sup> On 11th April 2020, Saudi Arabia, the United States and Russia agreed to the largest oil production cut ever negotiated in an unprecedented coordinated effort aimed at stabilizing oil prices and, incidentally, global financial markets.

<sup>4</sup> On March 27th, 2020, Brent reached its lowest level since 2003. Indeed, by falling below 54% in March, Brent recorded its worst-ever monthly performance.

<sup>5</sup> Saudi Arabia, Russia and the USA need a high oil price –around US\$60–US\$80 per barrel–to maintain their macro-financial equilibrium. However, their provisions and financial sustainability to deal with a weak oil price are very different. In Saudi Arabia, we estimate the extraction cost per barrel at US\$3, which is the cheapest. Its foreign reserves were estimated at around US\$500 billion in 2020 (against US\$740 billion in 2013) but the recent oil trade war led to a loss of US\$105 billion. In response to the massive drop in price, Saudi Aramco announced a disinvestment program and a cut in capital expenditure from a planned \$35–40 billion to \$25–30 billion. For various reasons, Russia is more sustainable than Saudi Arabia: its foreign reserves are around US\$550 billion, its fiscal deficit is lower than that of Saudi Arabia, and the economy is more diversified with other liabilities. The situation is more complex for the US. Indeed, while cheap oil is good for US consumers, especially during this presidential election year, US companies prefer a high oil price as it pushes up their expenses and gives them a higher level of debt. According to Moody's, debt for US and Canadian energy companies between 2020 and 2024 is evaluated at around US\$86 million.

<sup>6</sup> COVID-19 has led to a fall in oil demand of around 30 to 35 million barrels a day according to the International Energy Agency.

<sup>7</sup> In early April 2020, the US Labor Department announced that over 16 million people had lost their jobs in about three weeks. COVID-19 also led to major losses in the financial markets and, on 9 March 2020, the Dow Jones fell over 2,000 points, or 7.8%, the largest point drop in its history.

exposed to oil price volatility (Kingsly and Henri, 2020). Sharif, Aloui and Yarovaya (2020) examined the links between the spread of COVID-19, oil price volatility, the stock market and economic policy uncertainty. Using wavelets, the authors illustrated the differential impact of the COVID-19 risk over the short and the long term. They concluded that the flow of news and information continuously put out by the media played a key role in the dissemination of economic shocks across the market. In the COVID-19 context, Buckman et al. (2020) studied the influence of market sentiment. Based on sentiment scores for economics-related news articles, and adopting a lexical approach, they supported the idea of a strong linkage between news sentiment and a survey-based consumer sentiment measure that induced a strongly procyclical tendency (particularly useful in a context like the COVID-19 crisis).

In order to investigate the effect of COVID-19 on oil price volatility, we studied the relationship between oil price volatility and economic policy uncertainty. Indeed, COVID-19 appears to have generated shocks to both supply and demand, with both shocks increasing uncertainty. Thus, focusing on economic policy uncertainty allowed us to further capture the effects of COVID-19 via the uncertainty channel. Formally, we ran a VAR model to estimate the impulse-response functions, developing a suitable multivariate framework to assess the effects of COVID-19 on oil price volatility.

The remainder of this paper is organized in four sections. Section 2 briefly presents the econometric framework. The main empirical results are discussed in section 3. Section 4 concludes.

## 2. The econometric framework

Using the Vector Autoregressive (VAR) framework introduced by Sims (1980), we investigated the interdependence between time series while allowing a variable to depend on its lagged values and those of other explanatory variables. Interestingly, this framework also handles a vector of two or more variables without differentiating between endogenous and exogenous variables.

Formally, we performed the following four-dimensional VAR to model the dynamics of oil volatility:

$$\begin{aligned}
 Y_t &= \Phi_0 + \Phi_1 Y_{t-1} + \dots + \Phi_p Y_{t-p} + \varepsilon_t \\
 \text{where : } Y_t &= \begin{pmatrix} OV \\ EPU \\ ERMEPU \\ FSI \end{pmatrix}, \varepsilon_t = \begin{pmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \\ \varepsilon_{3t} \\ \varepsilon_{4t} \end{pmatrix} \\
 \Phi_0 &= \begin{pmatrix} \alpha_1^0 \\ \alpha_2^0 \\ \alpha_3^0 \\ \alpha_4^0 \end{pmatrix}, \Phi_p = \begin{pmatrix} \alpha_{1p}^1 & \alpha_{1p}^2 & \alpha_{1p}^3 & \alpha_{1p}^4 \\ \alpha_{2p}^1 & \alpha_{2p}^2 & \alpha_{2p}^3 & \alpha_{2p}^4 \\ \alpha_{3p}^1 & \alpha_{3p}^2 & \alpha_{3p}^3 & \alpha_{3p}^4 \\ \alpha_{4p}^1 & \alpha_{4p}^2 & \alpha_{4p}^3 & \alpha_{4p}^4 \end{pmatrix} \\
 \varepsilon_t &\rightarrow i.i.d(0, \Sigma_\varepsilon).
 \end{aligned} \tag{1}$$

Note: OV, EPU, EMREEPU, FSI denote oil price volatility, Economic Policy Uncertainty, Equity Market-related EPU and Financial Stress Index respectively.  $\varepsilon_{it}$  ( $\forall i = 1, \dots, 4$ ) are impulses or innovations.

Variables included in a VAR model should be stationary in order to accurately estimate the parameters of the above model.

First, the number of lags needs to be specified for the VAR model using information criteria. In practice, the optimal value of the lag  $p$  should minimize the information criteria values. However, maximum likelihood ratio tests need to be applied to double-check the optimal number of lags for the VAR model. Next, to estimate these parameters, we always estimate the VAR using the Maximum Likelihood method. Otherwise, it is recommended to test for the presence of a causality relationship between the variables included in the VAR model before moving on to its estimation. With regard to the causality theory introduced by Granger (1969), the uncertainty series and/or Financial Stress index Granger cause oil price volatility if the oil price volatility forecast using the information provided by these variables supplants the oil price volatility forecast without this information. Non-rejection of causality is *a priori* an indication of the presence of lead-lag relationships as expected with the VAR model, while the presence of bi-directional causality relationships (when both endogenous and exogenous variables Granger cause each others) is a sign of feedback effects between these variables. It is also possible to augment the VAR model with some exogenous variables that supplement the explanatory variables, yielding thus a VARX specification. Finally, in order to enhance our analysis of the estimated VAR model coefficients, it is useful to estimate the so-called Impulse Response Functions, which reproduce the response of the dependent variable in the VAR system to shocks in the error terms for several periods in the future.<sup>8</sup> This analysis is particularly useful to examine the effects of economic policies.

<sup>8</sup> In practice, we always measure the size of a given shock as the value of one standard deviation. For more details, see Hamilton (1994) and Greene (2005).

### 3. Empirical results

#### 3.1. The data

Our aim is to clarify the dynamics of oil price volatility sparked by the changes that affected the oil industry during the present COVID-19 crisis. To this end, we examined daily data over the period 2<sup>nd</sup> January 2014 - 1<sup>st</sup> April 2020 that we collected from the Federal Reserve Bank of St Louis.<sup>9</sup> This sample is useful to analyze oil price volatility from the start of the US shale revolution in 2014 to the ongoing COVID-19 epidemic. The use of daily data (closing prices) is particularly useful to capture key information to chart oil price evolution. We used the well-known oil price benchmark, the West Texas Index, for the oil data. To investigate uncertainty through which we could indirectly capture the effects of oil supply and demand shocks induced by COVID-19, we used the daily Economic Policy Uncertainty (EPU) Index, based on US newspaper articles.<sup>10</sup> The EPU index captures information from 10 leading US newspapers (USA Today, Miami Herald, Chicago Tribune, Washington Post, Los Angeles Times, Boston Globe, San Francisco Chronicle, Dallas Morning News, New York Times and the Wall Street Journal), using the following keywords: “economic” or “economy”, “uncertain” or “uncertainty” and one or more of “congress”, “deficit”, “Federal Reserve”, “legislation”, “regulation” and “White House”.<sup>11</sup> The EPU index captures basically uncertainty related to economic policies. We also used a second proxy for uncertainty using the Equity Market Related EPU Index<sup>12</sup> (EMREPU). As for the EPU index, the EMREPU is built from an analysis of newspaper articles, including terms related to equity market uncertainty and published in newspapers from the Access World News NewsBank service, with a focus on newspapers in the United States. These papers range from large national papers such as USA Today to small local newspapers, which also contained the terms ‘uncertainty’ or ‘uncertain’, ‘economic’ or ‘economy’ and one or more of the following terms: ‘equity market’, ‘equity price’, ‘stock market’ or ‘stock price’. The EMREPU index measures uncertainty related to investor’s sentiment, confidence, etc. Finally, we also used the OFR FSI (Office of Financial Research Financial Stress Index<sup>13</sup>), which aggregates information related to stress from different market indicators and provides a measure of systemic financial stress. Accordingly, while the use of the EPU index captures uncertainty over economic policies related to a supply shock, the EMREPU and the OFR FSI indexes are particularly useful to explore the effects of investor behavior and confidence, information asymmetry and vulnerability that are more dependent on a demand shock.

#### 3.2. Preliminary analysis

In Fig. 1, we plotted the WTI index and the three proxies of uncertainty and stress variables under consideration and noted some interesting findings. As we can see, the WTI showed the same profile in 2020 as in 2014. However, while in 2014, the oil price correction was associated with the shale revolution and the WTI was up to US\$40; in April 2020, there was a strong and abrupt correction due to the demand shock prompted by COVID-19, which pushed the WTI to exceed the level of US\$20. Interestingly, these dual oil price shocks exponentially increased the level of uncertainty with regard to economic policies, as well as stress and equity-related uncertainty for investors.

Next, we applied two unit root tests (Augmented Dickey Fuller Tests and Philips-Perron Tests) to check the order of integration of our time series<sup>14</sup> and showed that while WTI and the FSI are integrated of one order, the two series of uncertainty are stationary. Accordingly, we conducted our empirical analysis using stationary series. Hereafter, we compute oil price volatility as the absolute value of oil returns, which are computed as the first logarithmic difference of oil prices). We report oil price volatility in Fig. 2<sup>15</sup>. Consequently, we can see that while oil volatility was higher during the shale revolution, it reached the highest levels during the COVID-19 public health crisis.

In order to gain a clearer picture of the characteristics of oil price volatility, we compute its main descriptive statistics and report them in Table 1. We find evidence of leptokurtic excess and high volatility, suggesting further evidence of oil price volatility excess.

We then explored the evolution of uncertainty and oil price volatility. From Fig. 3, it is clear that oil price volatility and economic policy uncertainty show a positive correlation, which grew significantly stronger during the COVID-19 crisis. This suggests that at least an increase in uncertainty implies greater oil price volatility. In order to apprehend this further interaction, we computed the unconditional correlation that we report in Tables 2 and 3.

We can see positive correlations between oil price volatility and the stress and uncertainty indexes, suggesting that the COVID-19 shock generated more oil price volatility, mainly due to increased uncertainty and investor stress and anxiety. Further, when focusing on the sub-period of November 2019–April 2020, which corresponds to the discovery of the new coronavirus in China, the correlation between oil price volatility and Economic Policy Uncertainty rose by about 87% with regard to the bilateral correlation over the whole period (Table 3), reflecting the effect of COVID-19 on oil price volatility that occurred through the channel of uncertainty. This suggests that oil price volatility was driven by uncertainty from November 2019, given that the demand shock comes basically from

<sup>9</sup> For more details, see: <https://fred.stlouisfed.org/tags/series?t=epu>.

<sup>10</sup> For more details, see: <https://fred.stlouisfed.org/series/USEPUINDXD>.

<sup>11</sup> See Baker et Al (2020) for additional information.

<sup>12</sup> This data is available at: <https://fred.stlouisfed.org/series/WLEMUINDXD>.

<sup>13</sup> For more details, see: <https://www.financialresearch.gov/financial-stress-index/>.

<sup>14</sup> We do not report the results of the unit root tests to save space, but the results are available upon request.

<sup>15</sup> We also proxy oil price volatility (OV) by the root squared value of oil price returns and obtained similar findings. We do not report these results to save space, but they are available upon request.

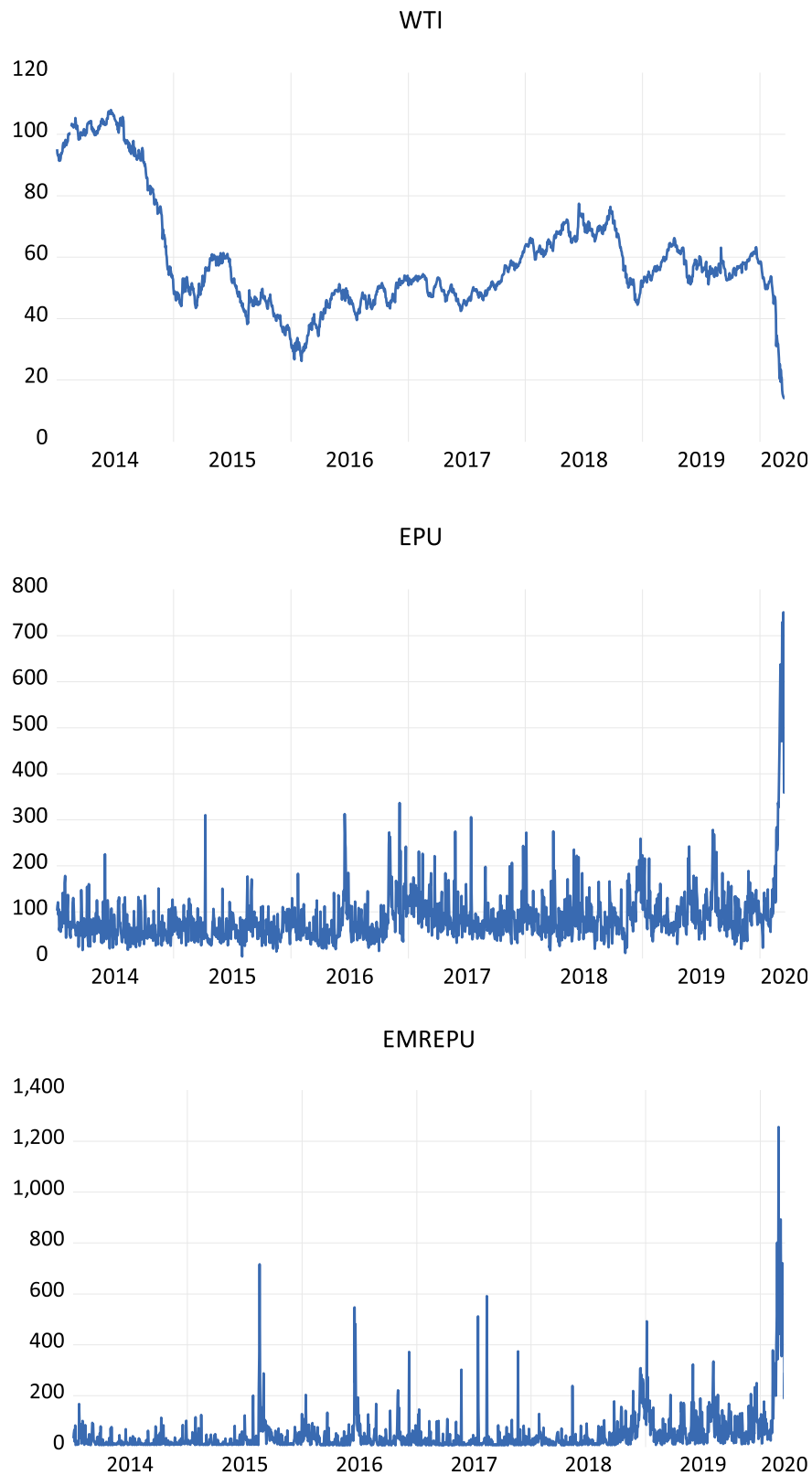
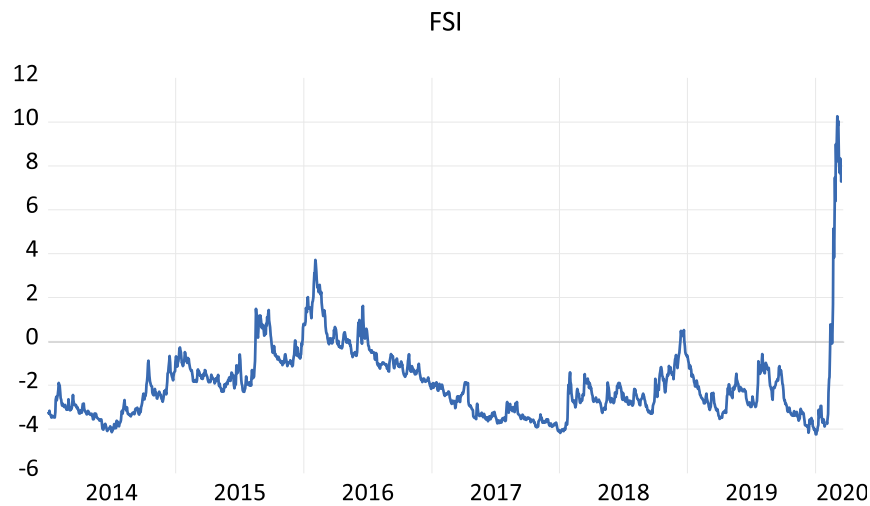
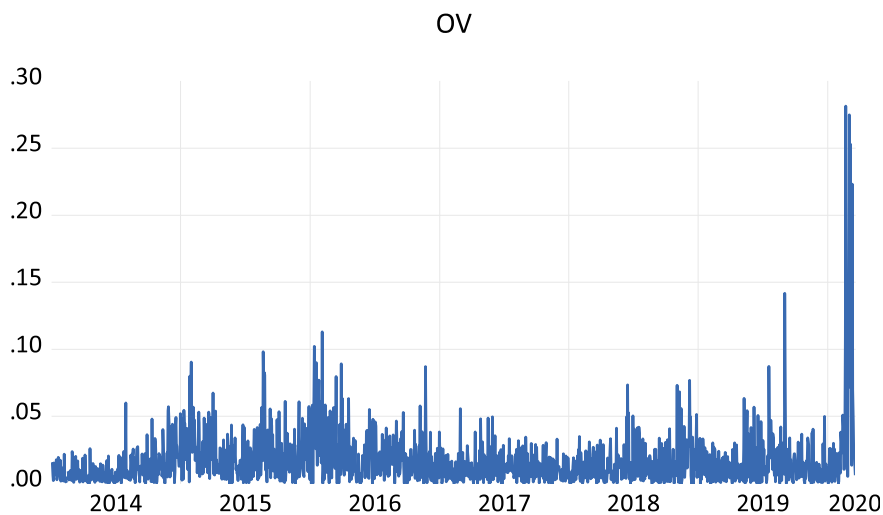


Fig. 1. Oil price, uncertainty and stress indexes.



**Note:** WTI, EPU, ERMEPU and SFI denote the WTI oil price index, the Economic Policy Uncertainty Index, the Equity Related EPU index and the Stress Financial Index respectively.

**Fig. 1.** . (continued).



**Note:** OV denotes the oil price volatility.

**Fig. 2.** Oil price volatility.

**Table 1**

Normality tests and main descriptive statistics of oil price volatility.

Mean	Maximum	Minimum	Std-dev	Skewness	Kurtosis	Jarque-Bera (p-value)
0.017	0.281	0.000	0.021	5.272	51.61	0.000

Note: Std-dev denotes standard deviation.

China, which is the world's largest oil consumer.

### 3.3. VAR modeling

In order to better analyze the interactions between oil price volatility, stress and the uncertainty indexes, we applied Granger

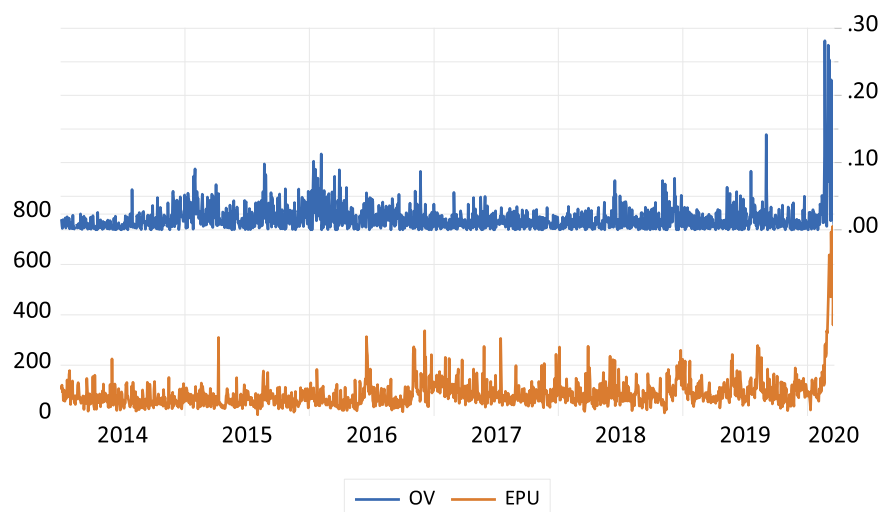


Fig. 3. Oil price volatility and uncertainty dynamics.

Table 2

Unconditional correlation matrix (full sample).

	OV	DFSI	EPU	EMREPU
OV	1	0.250	0.330	0.366
DFSI		1	0.0146	0.181
EPU			1	0.630
EMREPU				1

**Note:** WTI, EPU, EMREPU and SFI denote the WTI oil price index, the Economic Policy Uncertainty Index, the Equity Related EPU index and the Stress Financial Index respectively.

Table 3

Unconditional correlation matrix (subsample November 2019–April 2020).

	OV	DFSI	EPU	EMREPU
OV	1	0.355	0.617	0.586
DFSI		1	−0.042	0.274
EPU			1	0.721
EMREPU				1

**Note:** WTI, EPU, EMREPU and SFI denote the WTI oil price index, the Economic Policy Uncertainty Index, the Equity Related EPU index and the Stress Financial Index respectively.

Table 4

Results of Granger causality tests.

Null Hypothesis:	F-Statistic	Prob.
EPU does not Granger Cause OV	13.4232	<b>2.E-06</b>
OV does not Granger Cause EPU	13.0330	<b>2.E-06</b>
EMREPU does not Granger Cause OV	51.5847	<b>2.E-22</b>
OV does not Granger Cause EMREPU	28.2095	<b>9.E-13</b>
DFSI does not Granger Cause OV	1.41336	0.2436
OV does not Granger Cause DFSI	1.07201	0.3426
EMREPU does not Granger Cause EPU	44.0771	<b>2.E-19</b>
EPU does not Granger Cause EMREPU	48.1452	<b>5.E-21</b>
DFSI does not Granger Cause EPU	11.8144	<b>8.E-06</b>
EPU does not Granger Cause DFSI	0.84335	0.4305
DFSI does not Granger Cause EMREPU	69.6245	<b>1.E-29</b>
EMREPU does not Granger Cause DFSI	1.16683	0.3116

**Note:** Values in bold correspond to the rejection of the causality hypothesis.

causality tests, testing the null hypothesis of “no causality” against the alternative hypothesis of causality. The main results are presented



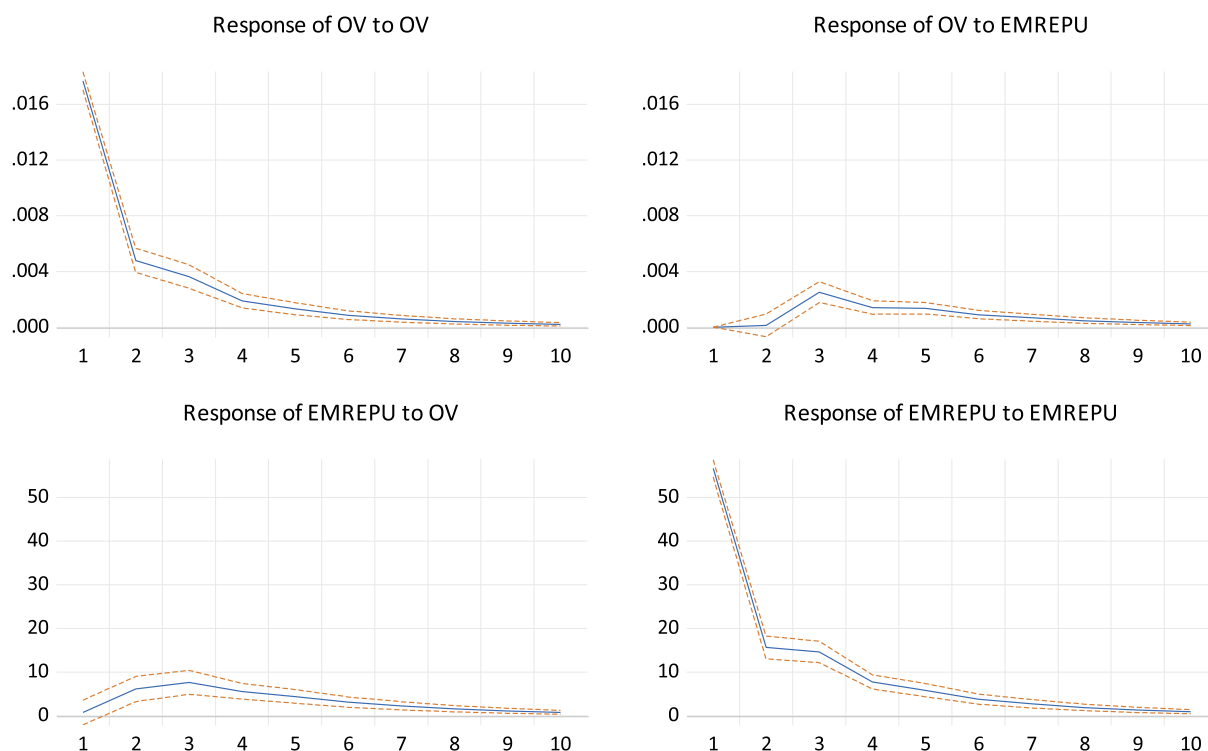
**Table 5**  
Results of the VARX model.

	OV	EMREPU
OV(-1)	0.2707*** [ 11.44]	336.18*** [ 4.433]
OV(-2)	0.1293*** [ 5.413]	237.30*** [ 3.099]
EMREPU(-1)	2.27E-06 [ 0.316]	0.2761*** [ 12.01]
EMREPU(-2)	4.32E-05*** [ 6.043]	0.1806*** [ 7.887]
C	0.0052*** [ 6.389]	-22.457*** [-8.591]
DFSI	0.0204*** [ 11.44]	55.875*** [ 9.766]
EPU	3.17E-05*** [ 3.446]	0.4397*** [ 14.90]
Adj. R-squared	0.3136	0.5633
Log likelihood	4217.6	-8786.9
Akaike AIC	-5.2273	10.917
Schwarz SC	-5.2039	10.940

**Note:** Values in [.] denote the t-ratios.

(\*\*\*) denote the statistical significance at 1% statistical level.

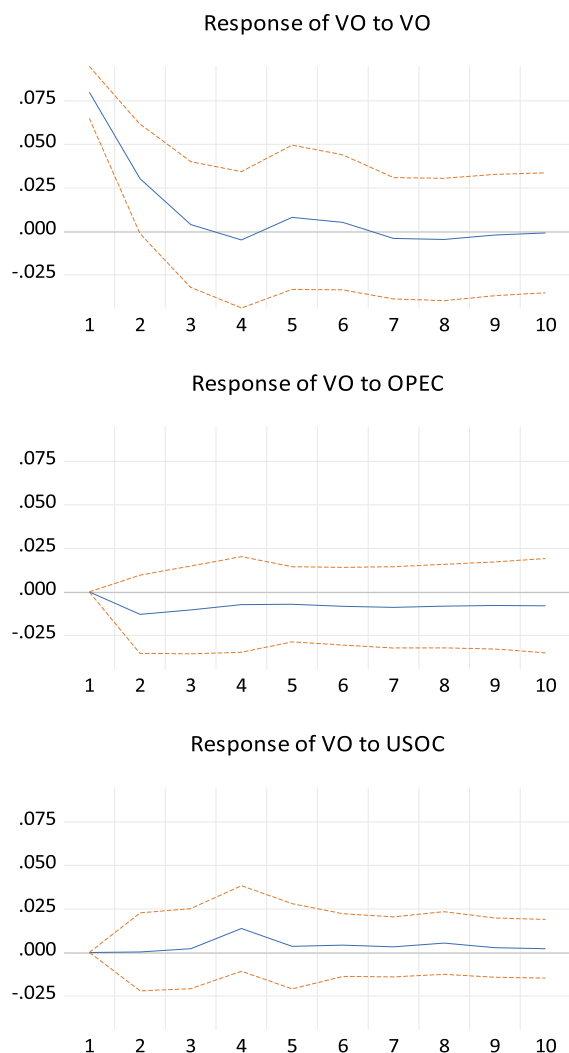
#### Response to Cholesky One S.D. (d.f. adjusted) Innovations $\pm 2$ S.E.



**Fig. 4.** Estimated response-impulse functions.

in Table 4. Accordingly, we find further evidence of a significant bilateral causality relationship between the uncertainty indexes and oil volatility, suggesting that information arising from uncertainty (resp. oil price volatility) might allow us to forecast the future dynamics of oil price volatility (resp. uncertainty). Further, while financial stress does not Granger cause oil price volatility, we found that it has a significant causality effect on uncertainty. Consequently, it is not unexpected that investor stress might impact oil price volatility as this proceeds through the uncertainty channel.

Taking this finding into account, in the next step we ran a three-variable VARX model in which we assessed the interaction between

Response to Cholesky One S.D. (d.f. adjusted) Innovations  $\pm 2$  S.E.

**Note:** VO denotes monthly oil price volatility, USOC measures the US consumption of oil, OPEC measures the oil supply by OPEC countries.

**Fig. 5.** Estimated response – Impulse functions for oil price volatility with oil demand and supply.

oil price volatility, EPU and EMREPU. In the first step, we specified the VAR model using the information criteria to determine the optimal number of lags. Following diverse specification tests, the best-fitting specification was found to be a bivariate VARX model with two lags, which we augmented with two explanatory variables derived from the EPU and the Financial Stress Indexes. We report the main results in Table 5. We, thus, noted further evidence of memory effects in the dynamics of oil price volatility, suggesting that the latter remains persistent. This is in line with a recent study of Gil-Alana and Monge (2020) who showed a significant and persistent effect of COVID-19 shock on Crude Oil prices. Second, we found that equity-related EPU has a positive and significant effect on oil price volatility, suggesting that uncertainty related to investor's sentiment and confidence has been a source for oil price changes. Moreover, an increase in financial investor stress and EPU also has a positive and significant effect on oil price volatility. This finding confirmed our previous analysis whereby COVID-19 increased uncertainty through two simultaneous shocks (supply shock and demand shock). This is particularly relevant because when we re-estimated the same VAR specification in the aftermath of the COVID-19 peak in China, the elasticity of oil price volatility towards uncertainty jumped from  $3.17\text{E-}05$  to  $0.000123$ , showing an increase of 288%. In turn, we also found that oil price volatility has a positive and significant effect on uncertainty. To illustrate these interactions between oil price

volatility and uncertainty, we also computed the estimated impulse-response functions that we report in Fig. 4.

We estimated these impulse-response functions on the basis of the VARX specification in Table 4 and for the whole sample under consideration. In particular, we computed the impulse-response functions using Monte Carlo Simulations (number of repetitions: 1000) and we defined the size of a shock using the Cholesky decomposition.<sup>16</sup> Accordingly, we found that, as in Table 5, a shock affecting equity-related uncertainty has a positive effect on oil price volatility, but with a two-day delay. Indeed, oil price volatility reacts aggressively after two days, reaching a high response rate after three days, and this reaction persists as the effect of the shock has still not disappeared after ten days. This result is also in line with the conclusion of Gil-Alana and Monge (2020). The short reaction delay can be explained by the fact that changes are required to adjust production between the different oil country producers. Finally, while a shock affecting oil price volatility has a delayed and persistent effect on uncertainty, its impact is less marked than the reaction of oil price volatility to an uncertainty shock.

### 3.4. Robustness tests

In order to double-check our findings, we conducted some robustness tests. In particular, to directly test the interactions between oil price volatility and these shocks, we re-estimated a VAR model using three variables: US oil demand, oil supply, and the WTI oil index. This estimation was made using monthly data, as daily data for oil supply and oil demand were not available. Further, while we referred to OPEC oil output for oil production, we used US oil demand as a proxy for oil demand (given that world oil demand is not available), even it is not really representative of worldwide global demand.<sup>17</sup> Accordingly, we ran a VAR model over the period January 2014–March 2020<sup>18</sup> and estimated the impulse response functions that we report in Fig. 5.

This analysis of robustness indicated that an increase in oil supply by OPEC could negatively impact oil price volatility and might be persistent. Indeed, a supply shock/cut is designed to increase oil prices, pushing the price to correct its dynamic through a reduction in oil price volatility. However, as mentioned earlier, the impact of this supply shock is no longer as strong as in the past due to the shale revolution. This is apparent henceforth through the stability of the oil price volatility function. Otherwise, an increase in US oil consumption (USOC) could positively impact oil price volatility (Ehouman, 2020), but with a three-month delay and an effect that could disappear very suddenly. This is explained by the fact that US oil consumption is only a percentage of global oil consumption (about 20%). However, taking the two effects altogether, we confirm that recent supply and demand shocks in the oil industry due to COVID-19 have had a significant impact on oil price volatility.

## 4. Conclusion

This study investigates the dynamics of oil price volatility and its drivers in the context of the recent coronavirus pandemic (COVID-19). Our findings confirm that the ongoing pandemic has had a negative impact on the oil industry in at least two ways. First, it led to a demand shock as it reduced global demand for crude oil while increasing uncertainty for most developed and emerging economies. Second, it led to a supply shock as COVID-19 triggered an oil trade war between the major oil-producing nations (Saudi Arabia and Russia). Both shocks appear to have led to excessive oil price volatility. The main contribution of this paper, however, is its assessment of the impact of uncertainty caused by these shocks and investor anxiety on oil price volatility. Our findings are unchanged even after checking their robustness. A natural future extension would be to test the capacity of our specification to forecast future oil price volatility.

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<sup>16</sup> See Hamilton (1994) for more details.

<sup>17</sup> The choice is also due to the non-availability of this data.

<sup>18</sup> We do not report the results of the VAR model to save space, but the results are available upon request.

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