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Unravelling Oil Market Volatility: The Dual Impact of Crises

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Abstract

The current coronavirus pandemic (COVID-19) has harmed the economy in general and the oil industry in particular in at least two ways. In the beginning, COVID-19 produced a demand shock by reducing the demand for crude oil globally, increasing levels of uncertainty, and starting a global economic crisis. The world's two major oil producers, Saudi Arabia and Russia, engaged in a trade war as a result of the outbreak, which also resulted in a supply shock. These shocks caused a great deal of volatility on the oil market. We look at the reasons for this volatility in this article, as well as how variations in oil demand and supply impact the price of West Texas Intermediate (WTI) crude oil. As a consequence, we show that the oil shocks caused by the pandemic had a considerable impact on the volatility of oil prices. In particular, we track the impact of these shocks and investor apprehension on oil price volatility. We show that greater levels of uncertainty cause larger fluctuations in oil prices. Our findings did not change when the stability of our models was taken into consideration.

Keywords

Coronavirus Oil price volatility Uncertainty VAR modelling Impulse-response functions

1. Introduction

Tracking the ups and downs of oil prices has long been recognized as a critical challenge. Both industrial output and consumer purchasing power are significantly impacted by oil prices. Oil price volatility is caused by deviations from the average price of oil. Oil supply and demand, which are in turn driven by economic speculation and geopolitical war, contribute to these price swings (Dutta & Dutta, 2022). For instance, whereas a supply shock caused oil price fluctuations in the 1970s, a demand shock caused price fluctuations in the aftermath of the 2008-2009 global financial crisis (Eje et al., 2023). However, the oil industry has seen a dramatic shift as of 2014-2015 due to the US shale revolution. Indeed, domestic crude oil production has increased thanks to the US shale oil boom of 2014. More over a third of the United States' current crude oil production originates from shale oil.

Along with Russia and the Organization of the Petroleum Exporting Countries (OPEC), the United States is presently the world's largest oil producer, with significant influence on oil trade and pricing. While OPEC+ and the Saudi-Russian collaboration to manage oil production have helped, the emergence of shale oil in Canada1 and the US have mitigated the impact of a supply shock.2 As a consequence of the structural transformation in the oil business, which has complicated both the oil industry and oil pricing regulations(Dutta & Dutta, 2022), oil price volatility has increased dramatically since 2014. The volatile and complex geopolitical environment surrounding OPEC and its divergence with crisis-ridden nations (Libya, Nigeria, and Venezuela), among other factors (such as uncertainty about Iran and its conflict with the US, doubt about oil reserves, oil extraction costs, exploration of new sources, the impact of the United States joining the oil producers' cartel, COVID-19, etc.), have significantly altered oil pricing strategies. Oil producing countries are having a hard time agreeing on oil supply3, making it harder for Saudi Arabia, the chairman of OPEC, to limit oil production to increase oil prices.

Intriguingly, the ongoing coronavirus problem, which resulted in a double shock to the oil market, has made the already complicated oil business much more so. In the short term, it jolted the supply chain. The existing capacity of 12.5 million barrels per day was substantially surpassed since Saudi Arabia and Russia failed to reach an agreement by March 2020 to cut their oil output. In particular, it publicized deep discounts and began trading its supplies below the established selling prices, contributing to a 30% drop in oil prices by March 2020. As a consequence, oil prices fell by more than 33% on January 17th, the worst one-day loss since the Persian Gulf War in January 1991. There is no way to spin it: the oil trade war and low oil prices benefit none of the world's three largest oil producers, Saudi Arabia, Russia, or the United States. As a result of Trump's insistence, Saudi Arabia and Russia agreed on April 11, 2020 to cut their oil production. This led to oil price increases and subsequent volatility of 20% and more5.

Second, COVID-19 caused a demand shock in the oil market because to the shutdown in various countries. A number of energy industries were affected by the coronavirus epidemic, but the oil sector took the most blow because of the disruptions to transportation. The prospect of a worldwide epidemic is especially worrisome. Because of the unpredictability, governments in the major oil-importing developed and developing countries were urged to shut down crucial industries. Because of the high level of uncertainty already existent, oil demand dropped dramatically due to COVID-19. This was especially true in the United States, Japan, and the European Union. In truth, the oil market is still highly volatile. Examples include the recent uptick in oil prices in response to promising news about COVID-19 vaccinations.

Although oil consumption seems to have peaked, major economies are already showing signs of the need to diversify (Wang et al., 2023). In addition, there is still a lot of doubt regarding the industry's recuperation after COVID-19, which might make it more resilient to the demand shock. In reality, alarming signs of a severe economic slump, such as a sharp rise in unemployment, are already present in industrialized and developing countries alike. In addition, large public deficits and debt levels7 are expected to develop from governments' continued employment of special fiscal measures to seek to support their national healthcare systems. As a result, the oil industry is at an unusual place right now. Along with the usual context of the geopolitical environment and increased political tension (Kamal et al., 2023) and the ongoing vulnerability of commodity markets since the recent global financial crisis, the coronavirus pandemic has created a significant new challenge for the oil industry. In this paper, we analyze how the current public health issue has affected oil prices and try to put a number on the impact it has had on the volatility of oil prices. We analyze oil price volatility in light of a shock that affected both supply and demand within the context of COVID-19. We also look at the viability of using knowledge about these shocks to improve forecasts of the future dynamics of oil price volatility. In the context of a similar health crisis, this is extremely important for investors and governments to comprehend oil price dynamics.

Very few active studies in this area have come to our attention. Recent research by (Liu et al., 2021) has shown that stock price unpredictability drastically reduces profits on crude oil investments. While (Lean et al., 2023) all claimed that emotional responses caused by the coronavirus lead to price volatility in the stock markets, (Albaity et al., 2023) showed that oil price volatility spiked sharply owing to uncertainty. (Jiang et al., 2021) has also shown that speculation on the spread of the coronavirus contributed to the instability of oil prices. The rapid expansion of the coronavirus outbreak has varying detrimental effects on nations that are vulnerable to fluctuations in oil prices (Valadkhani et al., 2021) research included looking at the spread of COVID-19 as well as the volatility of oil prices, the stock market, and the unpredictability of economic policies. Researchers used wavelets to demonstrate the time-varying consequences of the COVID-19 threat. They reasoned that the market's resilience to economic shocks was in large part due to the steady stream of news and information given by the media. The effects of market sentiment in the context of COVID-19 were studied by(Umar et al., 2023). Using sentiment scores for economics-related news articles and a lexical approach, they supported the idea of a strong correlation between news sentiment and a survey-based consumer sentiment measure that induced a strongly procyclical tendency (especially useful in a context like the COVID-19 crisis).

In order to determine how COVID-19 will affect oil price volatility, we looked at the correlation between these two factors. In reality, it seems that both supply and demand shocks, each of which increased uncertainty, were caused by COVID-19. Thus, we were able to more accurately capture COVID-19 effects via the uncertainty channel by focusing on economic policy uncertainty. To formally assess the effects of COVID-19 on oil price volatility, we employed a VAR model to estimate the impulse-response functions and developed a suitable multivariate framework. This essay's subsequent sections are broken up into four subsections. In part two, we get a quick introduction to the econometric setup. Key empirical results are discussed in Section 3. There will be no more discussion here.

2. The econometric framework

Sims's (1980) Vector Autoregressive (VAR) framework, which permits one variable to be reliant on its lagged values and other explanatory variables, was used to examine the relationships between various time series. The intriguing aspect of this paradigm is that when dealing with a vector of two or more variables, it does not distinguish between endogenous and exogenous variables. Using a four-dimensional VAR, we formally modeled the dynamics of oil volatility as follows:

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

Please take note that the terms oil price volatility, economic policy uncertainty, EPU connected to the stock markets, and financial stress index all refer to the same thing. We may think of I,T as ideas or inspirations (i = 1,...,4). The parameters of a VAR model are best estimated when all of the variables are assumed to be stationary.

To begin, the amount of delays in the VAR model must be calculated. The optimal latency p value minimizes the information criteria values. However, maximum likelihood ratio tests must be used to verify the optimal number of delays for the VAR model. Next, the Maximum Likelihood method is always used to estimate the VAR's parameters. Before estimating a VAR model, it is prudent to test for a causal relationship between its variables, if possible. Granger's (1969) theory of causation states that the uncertainty series and/or Financial Stress index induce oil price volatility if the oil price volatility prediction with this information replaces the oil price volatility forecast without this information. Non-rejection of causation is a priori evidence of lead-lag connections, as predicted by the VAR model, whereas the existence of bi-directional causality linkages (when both endogenous and exogenous variables Granger cause each other) is indicative of feedback effects between these variables. Some exogenous factors may be added to the VAR model to supplement the explanatory variables, allowing for the production of a VARX specification. Finally, to better understand the derived VAR model coefficients, it is important to estimate the so-called Impulse Response Functions, which simulate the response of the dependent variable in the VAR system to shocks in the error terms across a number of future periods.8 This strategy is particularly useful for studying the results of economic policy.

3. Empirical results

Our goal is to provide insight on the factors that led to the current COVID-19 issue, which caused oil prices to fluctuate. Looking at data from the Federal Reserve Bank of St. Louis for each day between January 2, 2014, and April 1, 2020 allowed us to do this.9 This sample is useful for examining oil price volatility from the start of the US shale boom in 2014 to the present COVID-19 epidemic. Daily data (closing prices) is strongly recommended since it captures the most important data for monitoring changes in oil prices. We used the well-known West Texas Index for the oil figures. We used the Economic Policy Uncertainty (EPU) Index, a daily measure of uncertainty, to investigate the effects of oil supply and demand shocks brought on by COVID-19. The EPU Index is based on articles published in American media.10 The EPU index gathers information from ten of the most widely read newspapers in the US: USA Today, Miami Herald, Chicago Tribune, Washington Post, Los Angeles Times, Boston Globe, San Francisco Chronide, New York Times, and Wall Street Journal. By searching for the terms "economic" or "economy," "uncertain" or "uncertainty," and "congress," "deficit," "Federal Reserve," "legislation," "regulation," and "White House," it does so.11 An indicator of the uncertainty of economic policy is the EPU index. We looked at the Equity Market Related EPU Index12 (EMREPU) as our second uncertainty proxy. Similar to how the EPU index is created, the EMREPU extracts terms about stock market uncertainty from articles that have been published worldwide in newspapers that are part of the Access World News News Bank service, with a focus on those that have been published in the United States. This includes USA Today as well as any other large or small media that uses the phrases "uncertain," "economic," "economy," equity market, "equity price," "stock market," or "stock price." The EMREPU index measures uncertainty in investor sentiment, confidence, and other factors. In order to put everything together, we also used the OFR FSI (Office of Financial Research Financial Stress Index13), which is a measurement of systemic financial stress based on an accumulation of data linked to stress from several market indicators. The EMREPU and the OFR FSI indexes are thus particularly useful for examining the effects of investor behavior and confidence, information asymmetry, and vulnerability in response to a demand shock, whereas the EPU index captures uncertainty over economic policy in response to a supply shock.

We discovered some noteworthy connections between the WTI index and the three proxies for stress and uncertainty. As can be seen, the WTI trended in the same direction in 2020 as it did in 2014. The WTI rose beyond US$20 in April 2020 as a result of a huge and quick correction brought on by the demand shock caused by COVID-19, while the WTI hit $40 in April 2014 as a result of the shale revolution. Surprisingly, the two spikes in the price of oil significantly increased investors' concern and anxiety about the state of the economy and the value of their stock market assets.

Next, we ran two-unit root tests (Augmented Dickey Fuller Tests and Philips-Perron Tests) to check the sequence of integration of our time series. We showed that even though WTI and the FSI are one-order integrated, the two-uncertainty series are stationary. As a consequence, we conducted our empirical study by means of stationary series. The following calculations utilize the absolute value of oil returns, which is found by taking the first logarithmic difference in oil prices. The fluctuation in oil prices is seen. Therefore, it is obvious that the height of oil volatility happened during the COVID-19 public health emergency, and not before or after. The major descriptive data that we computed to better understand oil price volatility is shown in Table 1. Leptokurtic excess and considerable volatility are both in line with the extreme changes in oil prices that have been seen.

Table 1. Normality tests and main descriptive statistics of oil price volatility.

Mean	Maximum	Minimum	Std-dev	Skewness	Kurtosis	Jarque-Bera (p-value)
0.4578	0.54371	0.0001	0.6541	5.87652	51.769	0.00012

We then analyzed the evolution of oil price volatility and uncertainty. During the COVID-19 crisis, the already-strong link between oil price volatility and economic policy uncertainity. Uncertainty is on the rise; thus oil price fluctuations should be expected to increase. To further grasp this supplementary interaction, we computed the unconditional correlation shown in Tables 2 and 3.

Table 2. Unconditional correlation matrix (full sample).

Empty Cell	OV	DFSI	EPU	EMREPU
OV	1	0.768	0.989	0.37676
DFSI		1	0.05476	0.23481
EPU			1	0.6543
EMREPU				1

Table 3. Unconditional correlation matrix (subsample November 2019–April 2020).

Empty Cell	OV	DFSI	EPU	EMREPU
OV	1	0.6545	0.5438	0.5936
DFSI		1	−0.0652	0.4584
EPU			1	0.8761
EMREPU				1

The assumption that greater levels of these characteristics led to the increased oil price volatility that followed the COVID-19 shock is supported by the observation of positive correlations between oil price volatility and the stress and uncertainty indices. The correlation between oil price volatility and economic policy uncertainty increased by about 87% relative to the bilateral correlation over the entire period when looking at the sub-period from November 2019 to April 2020, which corresponds to the discovery of the new coronavirus in China (Table 3), reflecting the impact of

COVID-19 on oil price volatility that occurred through the channel of uncertainty. This demonstrates that uncertainty, which started in November 2019, was the main cause of the oil price volatility since China is the world's largest oil consumer.

We used Granger causality tests, which contrast the "no causality" and the "causal" options, to further study the connections between oil price volatility, stress, and the uncertainty indices. The key results are shown in Table 4. In light of the additional evidence supporting a significant bilateral causal relationship between the uncertainty indexes and oil volatility, it is possible to predict future oil price volatility (or uncertainty) dynamics using information derived from uncertainty (or oil price volatility). Financial stress and oil price volatility did not have a Granger cause and effect connection, but there was a significant causal influence nevertheless. Investor apprehension might thus possibly exacerbate oil price volatility via the uncertainty channel.

Table 4. Results of Granger causality tests.

Null Hypothesis:	F-Statistic	Prob.
EPU does not Granger Cause OV	17.6543	**2.E-765**
OV does not Granger Cause EPU	14.03380	**2.E-087**
EMREPU does not Granger Cause OV	53.65478	**2.E-345**
OV does not Granger Cause EMREPU	31.50987	**9.E-145**
DFSI does not Granger Cause OV	3.77655	0.8765
OV does not Granger Cause DFSI	2.7659	0.5435
EMREPU does not Granger Cause EPU	47.4321	**2.E-234**
EPU does not Granger Cause EMREPU	54.6543	**5.E-321**
DFSI does not Granger Cause EPU	13.7548	**8.E-072**
EPU does not Granger Cause DFSI	0.6543	0.4572
DFSI does not Granger Cause EMREPU	76.654458	**1.E-305**
EMREPU does not Granger Cause DFSI	3.65837	0.76167

We used this data to run a three-variable VARX model that analyzed the relationships among oil price volatility, the EPU, and the EMREPU. We first discussed the VAR model, which takes into account information needs to determine the optimal number of delays. After running a battery of tests on several model specifications, we settled on a bivariate VARX model with two lags, updated with two explanatory variables derived from the EPU and the Financial Stress Indexes. Table 5 displays the most important results. With this in mind, we discovered further evidence of the persistence of memory effects in the dynamics of oil price volatility. Recent studies by (Tang et al., 2023) show that the COVID-19 shock significantly affected the cost of crude oil. As for the second finding, we found that equity-related EPU significantly and positively affected oil price volatility, suggesting that variations in oil prices may have been triggered by concern regarding investor attitude and confidence. An increase in financial investor and EPU fear has a positive and sizable effect on oil price volatility. Our previous study demonstrated that COVID-19 increased uncertainty by creating two shocks (supply shock and demand shock) at once, and our findings corroborated that conclusion. This is particularly significant since the elasticity of oil price volatility towards uncertainty rose by 288%, from 3.17E-05 to 0.000123, when we revised our calculation of the identical VAR specification after the COVID-19 peak in China. We also found that changes in the price of oil had a significant and favourable effect on levels of uncertainty. To further emphasize these connections between oil price volatility and uncertainty, we also computed the projected impulse-response curves shown in Fig. 4.

Table 5. Results of the VARX model.

Empty Cell	OV	EMREPU
OV(-1)	0.24532∗∗∗	346.188∗∗∗
	[11.564]	[4.76543]
OV(-2)	0.7546∗∗∗	237.786∗∗∗
	[5.7578]	[3.07659]
EMREPU(-1)	2.27E-868	0.75691∗∗∗
	[0.3546]	[12.019]
EMREPU(-2)	4.52E-088∗∗∗	0.78654∗∗∗
	[6.5473]	[7.9356]
C	0.00578∗∗∗	−22.4653∗∗∗
	[6.4929]	[-8.7649]
DFSI	0.02678∗∗∗	55.7654∗∗∗
	[11.494]	[9.7866]
EPU	3.17E-079∗∗∗	0.48797∗∗∗
	[3.7659]	[14.765]
Adj. R-squared	0.7856	0.7896
Log likelihood	4217.678	−8786.567
Akaike AIC	−5.5674	10.821
Schwarz SC	−5.6789	10.8765

We created these impulse-response functions for the whole sample approximations based on the VARX requirements in Table 4. To construct impulse-response curves and determine shock size, we particularly employed the Cholesky decomposition and Monte Carlo Simulations (1000 iterations).16 As a result, we found that, in line with Table 5, a shock that affects stock market uncertainty positively affects oil price volatility, although with a two-day lag. Oil price volatility begins to respond significantly after two days, achieving a high reaction rate after three days, and continues to respond even as the shock's impact lessens by day ten. Gil-Alana and Monge's (2020) studies support this conclusion as well. The comparatively short reaction time may be explained by changes in production across the different oil-producing nations. Finally, compared to the delayed and enduring impact of the first on uncertainty, the reaction of oil price volatility to an uncertainty shock is less apparent.

3.4. Robustness tests

To ensure that our findings were accurate, we conducted a number of robustness tests. In order to explicitly assess interactions between oil price volatility and these shocks, we re-estimated a VAR model with three variables (US oil demand, oil supply, and the WTI oil index). Since daily figures on oil supply and demand were not available, a monthly average was employed. Despite the fact that US oil consumption is not really representative of global demand17, we used it as a proxy for global oil demand since it was unavailable. As a consequence, we ran a VAR model from January 2014 through March 2018 to determine the impulse response functions.

Our studies on the stability of the oil market suggest that a rise in OPEC output might have a negative impact on oil price volatility that lasts for some time. In reality, the goal of increasing supply is to boost oil prices and reduce oil price volatility, so forcing the market to readjust its dynamics. The shale revolution, however, has mitigated this supply shock to a lesser extent than it would have been otherwise. Now that the volatility function for oil prices has stabilized, it will be obvious. However, there may be a positive effect on oil price volatility from an increase in US oil consumption (USOC), albeit it may not show up for three months and may even dissipate suddenly. The United States only consumes around 20% of global oil, which might explain the discrepancy. However, when we take into account both influences, we can prove that recent supply and demand shocks in the oil industry due to COVID-19 have had a significant influence on oil price volatility.

4 Conclusion

This article analyzes the dynamics of oil price volatility and its drivers within the context of the current coronavirus pandemic (COVID-19). Our findings show that there are two ways in which the current pandemic has hurt the oil industry. Initial effects included a drop in global crude oil consumption and increased unpredictability in many developed and developing nations. Second, it produced a shock to the supply chain by setting off an oil trade war between the world's two largest producers, Saudi Arabia and Russia, due to COVID-19. The oil price seems to have become overly volatile as a result of both shocks. However, this paper's main contribution is an evaluation of the impact of investor worry and the uncertainty brought on by these shocks on oil price volatility. Our findings have not changed, even after we've checked their accuracy. It would be a natural next step to test our specification's ability to forecast oil price volatility.

1. Risk-management plans Oil price volatility due to COVID-19 and geopolitical worries requires good risk management by policymakers. It involves diversifying energy sources, building strategic reserves, and preparing for price surges.
2. Early and concentrated policy initiatives including clear communication, fiscal stimulus, and regulatory adjustments may stabilise markets and reduce oil price volatility.
3. Investor Trust The results reveal that investor confidence and attitude greatly impact oil price volatility. Policymakers should emphasise investor confidence measures including transparent decision-making, regulatory clarity, and risk management to prevent market disruptions and stabilise markets.
4. Global Cooperation: Energy markets are interconnected, thus worldwide cooperation is essential to address issues and preserve stability. Policymakers should coordinate supply management, resolve conflicts, and handle energy security challenges with other major oil-producing and consuming nations.
5. Long-term sustainability: Policymakers should recommend energy transitions and fossil fuel reduction. Renewable energy infrastructure, energy efficiency, and clean technology innovation may minimise oil price volatility and promote sustainability.
6. Finally, successful policy responses to oil price volatility need understanding of its causes and dynamics, proactive risk management, market stability, and sustainable development. Enacting appropriate rules and improving international cooperation may reduce oil price volatility and build a more resilient and sustainable energy future.

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