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Pandemics and Oil Shocks

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Abstract

This paper investigates the role of the COVID-19 pandemic in oil markets, focusing on the great oil price crash in April 2020. Using a 5-variable structural vector autoregression (SVAR) model, the study identifies an oil price shock arising from the pandemic together with supply, demand, and financial market shocks to global oil markets. The results show that a pandemic shock causes a delayed decrease in oil prices. Moreover, financial market conditions that affect financial investment decisions play a significant role in oil price movements. The study also computes the forecast error variance decomposition and finds that the impact of a pandemic shock, financial speculation shock, and aggregate demand shock are crucial in the short run. The findings offer new opportunities for applications in energy research.

Keywords: pandemic, oil price shocks, structural VAR, uncertainty, great oil price crash, COVID-19

JEL Classification: I150, Q41, Q43, Q47

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1 Introduction

In January 2020, Chinese authorities identified the novel coronavirus SARS-CoV-2, now known as COVID-19. Less than three months later, the virus became a global pandemic. The United States recorded its first case on January 19, 2020, and since then, it has recorded more than 50 million cases. Globally, there are several million deaths. As containment efforts continue across the world, several countries are feeling the effects of lockdowns, and economic uncertainty brought about by the pandemic. In February 2020, the World Health Organization warned that it is impossible to predict which direction the novel coronavirus will take (WHO 2020). Today, the pandemic remains elusive due to the virus's mutations, and no one knows where the pinball will drop. The difficulty in predicting the virus's transmissibility has increased uncertainty in global commodity markets (Bakas and Triantafyllou 2020).

What do pandemics have to do with oil prices? Fluctuations in oil prices are driven by both demand and supply forces (Kilian 2008, 2009; Hamilton 2009; Bastianin et al. 2016; Herrera et al. 2019; among others). In a typical year, increasing global economic activity shifts the demand for oil, which by itself leads to an increase in the price. Increases in oil discoveries and technological innovations in oil production also shift supply leading to lower prices. The trend in oil production has been upward for some time due to the US shale revolution (Kilian 2016). Baumeister and Kilian (2016) find that the sharp decline in the Brent price after June 2014 may be explained by the cumulative effects of positive supply shock attributed in part to the shale

oil revolution. However, the outbreak of the coronavirus and the uncertainty about its causes and possible repercussions have led to the resurgence of the demand side (Kwon 2020). Unlike the traditional aggregate demand shock, this demand shock is different because it is inextricably tied to the COVID-19 pandemic and primarily triggers fear and anxiety, significantly reducing consumer and business confidence (Byrne et al. 2019; Eichenbaum et al. 2020; Sharif et al. 2020).

The objective of this paper is to investigate the role of the COVID-19 pandemic in oil markets, focusing on the great oil price crash in April 2020. The study uses a 5-variable structural vector autoregression (SVAR) model to identify an oil price shock arising from the pandemic together with the supply, demand, and financial market shocks to global oil markets. Several alternative model specifications prove the robustness of the analysis.

The rest of the paper is structured as follows. Section 2 provides a brief review of the literature. Section 3 presents the methodology to distinguish between a pandemic shock and other shocks that underlie oil price movements. Section 4 presents and discusses the results. Section 5 reports the robustness checks. Section 6 discusses the forecast error variance decomposition results. Section 7 offers some concluding remarks.

2 A brief review of the literature

Since the 2008 financial crisis, the focus of the oil literature has been on examining whether financial market conditions predict oil prices (Zhang and Cao 2013; Kilain 2014; Mohammed 2020; Natoli 2021). However, recently, the focus has shifted on the impact of pandemics on oil prices (Albulescu 2021; Mugaloglu et al. 2021; Salisu et al. 2020, Bakas and Triantafyllou 2020; Salisu and Adediran 2020; Lyocsa and Molnar 2020; Sharif et al. 2020; Yang et al. 2021; Zhang et al. 2020).

The motivation for linking pandemic uncertainty to oil price is drawn from Van Robays (2016) where the evidence suggests that movements in energy prices can be explained by macroeconomic uncertainty. Recent literature in this regard has extended this analysis and shown that pandemic uncertainty negatively impacts oil prices. For example, Salisu et al. (2020) examined the oil-stock market relationship during the pandemic relative to the evidence before it. The study finds that both oil and stock markets may experience greater initial and prolonged impacts of own and cross shocks during the pandemic than the period before it. Furthermore, the probability of having negative oil and stock returns during the pandemic may be due to uncertainty associated with the relevant markets.

Albulescu (2021) investigated the effect of the official announcements regarding COVID-19 new cases of infection and fatality, on the volatility of the financial markets in the United States. The study considers both COVID-19 global and US figures and shows that the health crisis enhanced the S&P 500 realized volatility. Similarly, Yang et al. (2021) find that greater fluctuation in the global oil prices increases stock market volatility and economic policy uncertainty in both the US and China.

Bakas and Triantafyllou (2020) investigated the impact of economic uncertainty related to global pandemics on the volatility of the broad commodity price index and the sub-indexes of crude oil and gold. Their results show that pandemic uncertainty has a strong negative impact on the volatility of commodity markets, especially so on the oil market, while the effect on the gold market is positive but less significant.

Salisu and Adediran (2020) and Devpura and Narayan (2020) examined the role of uncertainty due to the COVID-19 pandemic in predicting energy market volatility. These studies show that energy market volatility increased during the COVID-19 sample period. Moreover, Zhang et al. (2020) conclude that global financial market risks have increased substantially in response to the pandemic, with financial markets becoming extremely volatile and unpredictable.

To summarize, recent studies in the literature show that the COVID-19 pandemic has introduced a different dimension to the structure and functioning of energy markets that warrant

further exploration. Thus, this paper aims to investigate whether pandemic uncertainty explains the great oil price crash in April 2020. Given the importance of crude oil price fluctuations, understanding its drivers, particularly at a time when it reached its lowest point in history is imperative.

3 Methodology and Data

Following Kilian and Park (2009) and Degiannakis et al. (2014), the study defines a 5-factor structural VAR model for the global crude oil market as:

$$\mathbf{A_0 z_t} = \boldsymbol{\alpha_0} + \sum_{\boldsymbol{i=1}}^{\mathbf{24}} \mathbf{A_i z_{t-i}} + \boldsymbol{\varepsilon_t} \qquad [1]$$

where $\mathbf{z}_t$ is a vector of monthly time series consisting of five endogenous variables, i.e., global crude oil production ($PROD_t$), global real economic activity index (REA_t), real oil price (ROP_t), OECD consumer confidence index (CCI_t), and real S&P returns (RSP_t). $\mathbf{A_0}$ represents the contemporaneous matrix. $\mathbf{A_i}$ is the autoregressive coefficient matrices. The error term ε_t is a vector of serially and mutually uncorrelated structural innovations.

The structural shocks are recovered from the reduced-form shocks:

$$v_t = \mathbf{A}_0^{-1} \boldsymbol{\varepsilon}_t \qquad [2]$$

where v_t represents the reduced-form errors.

The recursive identification as in Kilian and Park (2009) and Degiannakis et al. (2014), and allowing for pandemic uncertainty (anxiety) is defined as:

$$\begin{pmatrix} v_{1t}^{PRDO} \\ v_{2t}^{REA} \\ v_{3t}^{RSP} \\ v_{4t}^{CCI} \\ v_{5t}^{ROP} \end{pmatrix} = \begin{bmatrix} a_{11} & 0 & 0 & 0 & 0 \\ a_{21} & a_{22} & 0 & 0 & 0 \\ a_{31} & a_{32} & a_{33} & 0 & 0 \\ a_{41} & a_{42} & a_{43} & a_{44} & 0 \\ a_{51} & a_{52} & a_{53} & a_{54} & a_{55} \end{bmatrix} \begin{pmatrix} \varepsilon_{1t}^{OSS} \\ \varepsilon_{2t}^{ADS} \\ \varepsilon_{3t}^{FSS} \\ \varepsilon_{4t}^{ANXS} \\ \varepsilon_{5t}^{OSDS} \end{pmatrix} \qquad [3]$$

where OSS = oil supply shocks, ADS = aggregate demand shocks, FSS = financial speculation shocks, ANXS = anxiety shocks, and OSDS = oil-specific demand shocks.

The identification scheme presented in [3] implies the following contemporaneous restrictions. First, oil production does not respond contemporaneously to changes in oil demand caused by changes in global economic activity because of high adjustment costs in oil production and the uncertainty surrounding the state of the global crude oil market. However, oil supply disruption can influence global economic activity, oil price, financial market conditions, and consumer confidence within the same month. Second, global economic activity is not immediately influenced by oil prices as it takes time for global economic activity to react. In contrast, an aggregate demand shock will have a contemporaneous impact on oil prices, financial market conditions, and consumer confidence, considering the likelihood of immediate reaction time of prices, financial markets, and consumer sentiments. Third, in highly integrated globalized financial markets, oil production and aggregate demand react contemporaneously to shocks in the financial markets. Fourth, because consumer sentiments are sensitive to conditions in global energy and financial markets, the CCI reacts instantaneously to oil supply, aggregate demand, and financial market shocks. Finally, regarding the ROP innovation, any changes in the price of oil that are not explained by all the aforementioned shocks are captured by the oil-specific demand events. This identification scheme allows for the computation of the five structural shocks we consider the key drivers of oil price: oil supply shocks, aggregate demand shocks, financial speculation shocks, anxiety shocks, and oil-specific demand shocks. The hypotheses are that all five shocks affect the real price of oil, although without *a priori* hypotheses as to the nature of the effects.

The study utilized data for the sample period January 1974 to April 2020. $PROD$, REA, and ROP are series commonly used in the literature to capture oil price fundamentals, i.e., supply and demand. $PROD$ is the percentage change of total world crude oil production obtained from the U.S. Energy Information Administration (EIA) International Energy Statistics database. REA is measured by the index developed in Kilian (2009) and updated in Kilian (2019). This index is constructed using single-voyage freight rates for bulk dry commodity cargoes deflated by the U.S. CPI and detrended linearly to remove the impacts of technological advances in shipbuilding and long-term trends in sea transport demand. ROP is measured by the U.S. crude oil importer acquisition cost by refiners from EIA deflated by the U.S. consumer price index.

A unique feature of the COVID-19 pandemic is that it triggered fear and anxiety globally. Thus, the study includes the OECD CCI to capture consumer expectations and anxieties/sentiments about future developments. The data is obtained from the OECD Main Economic Indicators database. The indicator is set at 100, with values above 100 signifying a boost in consumer confidence (optimism), whereas values below 100 indicate a loss in consumer confidence (pessimism).[1] The study also includes the real S&P 500 returns (RSP) to capture the role of financial market conditions. The RSP returns is constructed by subtracting the consumer price index inflation rate from the log S&P 500 closing price obtained from yahoo finance.

The estimation results are based on 24 lags, which have become standard in the oil shocks literature due to the existence of long cycles in global commodity markets (see, for example, Kilian 2008; Kilian, 2009; Kilian and Park 2009; Chen et al. 2014; Bastianin et al. 2016; Kilian and Lutkepohl 2017; Kilian and Zhou 2020; among others). Although AIC indicates a lag length of 15, the estimation results based on 24 lags are similar to those based on the 15 lags.

4 Results

4.1 Impulse response to structural shocks

To illustrate the relative importance of the identified structural shocks as sources of oil price volatility, the impulse responses of ROP to a one-standard deviation shock are presented in Fig. 1. The vertical axis is the direction and magnitude of the response and the horizontal axis is the time elapsed, in monthly frequency, following the shock. The dotted and dashed lines represent one-standard and two-standard error bands.

From the bottom left (last row) of Fig. 1, an unexpected increase in oil supply causes a statistically significant decrease in ROP, which bottoms out after approximately six months. An unexpected increase in aggregate demand triggers a statistically significant increase in ROP, which peaks after four months. An unanticipated financial speculation shock causes a statistically significant decrease in ROP. An unexpected increase in oil market-specific demand has an immediate positive impact on ROP, which is also statistically significant. These results are consistent with the findings in the literature (Kilian 2009; Peersman and Van Robays 2012; Kilian and Murphy 2014; Chen et al. 2014; Degiannakis et al. 2014; Baumeister and Hamilton 2019; Zhou 2020, among others).

The impulse response of ROP to the anxiety shock is of particular interest in this study. The anxiety shock has been normalized to represent a negative one-standard deviation shock. The impulse response shows that unanticipated anxiety shock has a negative statistically significant effect on ROP (Fig. 1, last row, fourth column). Specifically, ROP reacts negatively to unanticipated anxiety shock approximately two months after the shock, and the adverse reaction accelerates after five months. This suggests that economic anxiety (uncertainty) related to

[1] We broadened the coverage of the study by using the OECD + 6 major economies consumer confidence index (OECD+6 CCI). The +6 major countries are non-OECD economies of Brazil, China, India, Indonesia, the Russian Federation, and South Africa. Moreover, we run different estimations using the OECD business confidence index (BCI) to measure of anxieties/sentiments about future developments. We did not use the business confidence index for OECD + 6 major economies (OECD+6 BCI) because available data began in July 1983.

global pandemics triggers a decline in ROP. Bakas and Triantafyllou (2020) and Elleby (2020) found similar results, although the authors examined a broad set of commodities, including oil.

The anxiety/pandemic uncertainty shock has implications beyond the ROP. As the impulse responses in Fig. 1 show, anxiety shock also lowers oil production and global real economic activity with a delay of approximately four months. In contrast, anxiety shock increases volatility in financial markets after a brief decline. The increased volatility in financial markets following a brief decline due to the pandemic anxiety shock is consistent with Bickley et al. (2020) finding that the variability of traded value in financial markets increased substantially due to the COVID-19 pandemic.

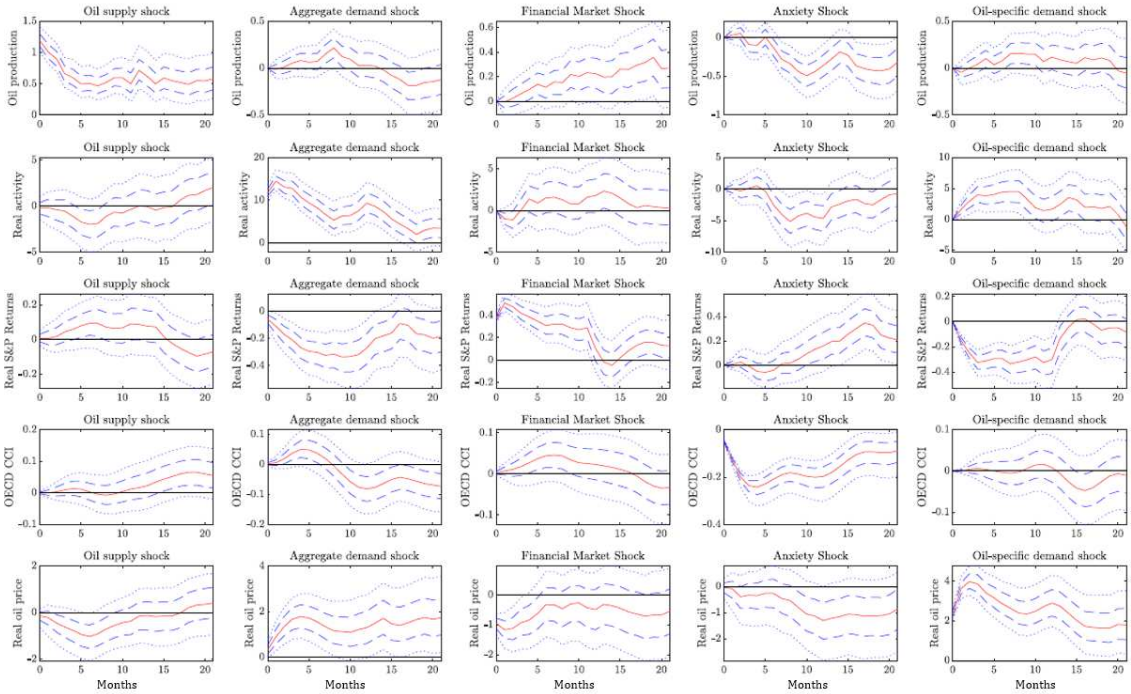

Fig. 1. Responses to one S.D. structural shocks using OECD CCI.
Note: dashed and dotted lines represent one- and two-standard error bands.

4.2 Historical Evolution of the Structural Shocks During the Great Oil Price Crash

Fig. 2 shows the historical evolution of the structural shocks from January 2020 to April 2020. Clearly, since January 2020, the bulk of the drop in oil price has been driven by oil-specific demand (pink line), followed by aggregate demand (red line), financial market conditions (bright green line), and pandemic anxiety conditions (turquoise line), with pandemic anxiety becoming more evident from March 2020. The combined adverse impact of the demand-side shocks, i.e., aggregate demand, pandemic anxiety, and oil-market specific demand on oil price, could be attributed to an inverted Maslow's hierarchy of needs (Maslow, 1943). Specifically, as COVID-19 unfolded and lockdowns and economic uncertainty intensified during the early stage of the pandemic, demand for food and other necessities superseded the demand for crude oil and gasoline. In this way, crude oil and gasoline became non-essential goods during that period, which may have contributed to the great oil price crash in April 2020. This is in line with EIA's findings that US crude oil and petroleum products consumption declined across all sectors (transportation, commercial, industrial, and residential), contributing to a record 7% drop in US energy consumption in 2020, with much of the decrease attributed to the economic responses to the COVID-19 pandemic during the spring of 2020 (EIA 2021). Similarly, IEA (2021) finds that global energy demand in 2020 fell by 4%, the largest decline since World War II and the largest ever absolute decline.

The second objective of this paper is to examine whether the brief Russia-Saudi oil price war that began in March 2020 impacted oil prices in April 2020. As the historical decomposition shows in Fig. 2 (blue line), oil production does not exhibit much variation since January 2020, even with the increased oil supply from the Russia-Saudi price war following the collapse of the OPEC+ alliance in March 2020. This signifies that although supply played some role in oil price movements, its impact is inconsequential from January 2020 to April 2020.

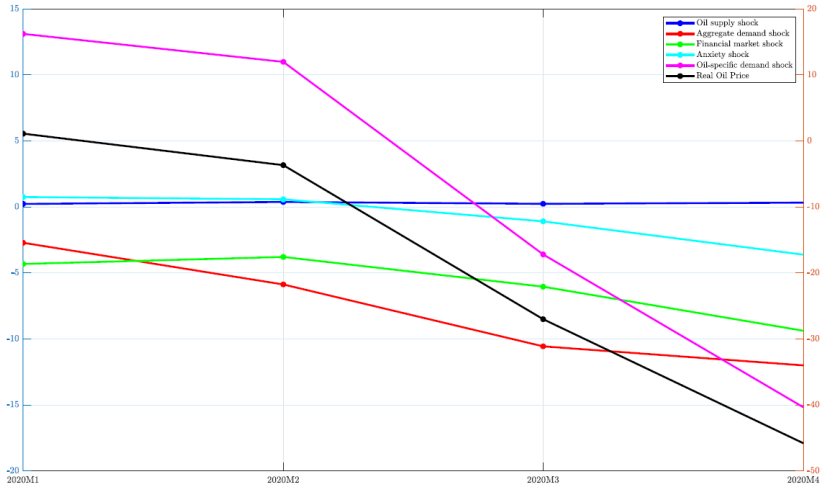

Fig. 2. Evolution of structural shocks from January 2020-April 2020
Note: Structural residuals implied by model [1], in monthly frequency, using the OECD CCI.

4.3 Other measures of anxiety

We broadened the study's coverage by extending the measure of confidence/anxiety beyond OECD countries. Specifically, we used the OECD+6 CCI to capture anxiety on a relatively larger global scale. The +6 major countries are non-OECD economies of Brazil, China, India, Indonesia, the Russian Federation, and South Africa. The OECD+6 account for 80.03% of global COVID-19 cases. The OECD+6 CCI data is available from January 1980 to March 2020. The impulse responses from using the OECD+6 CCI are reported in Fig. 3. As the figure shows, the results are broadly consistent with the OECD CCI's main findings. However, some difference is detectable in the response of ROP to anxiety shocks. In particular, unexpected anxiety shock triggers an immediate and persistent decrease in ROP, which is statistically significant. It could be that the extension of our coverage by using the OECD+6 CCI to measure anxiety on a relatively more extensive scale captured additional effects originating from the dynamics in consumer sentiments.

Furthermore, we run different estimations using the OECD BCI as another measure of anxiety, particularly from the producer side of the global economy. Results are reported in Fig. 4 and are similar to the main findings using the OECD CCI. The one difference is that unlike in the case of consumer anxiety shock, which caused a delayed decline in ROP, producer anxiety shock triggers an immediate and persistent fall in ROP. This finding suggests that when producers are anxious or uncertain about future market conditions, their anxiety immediately affects ROP.

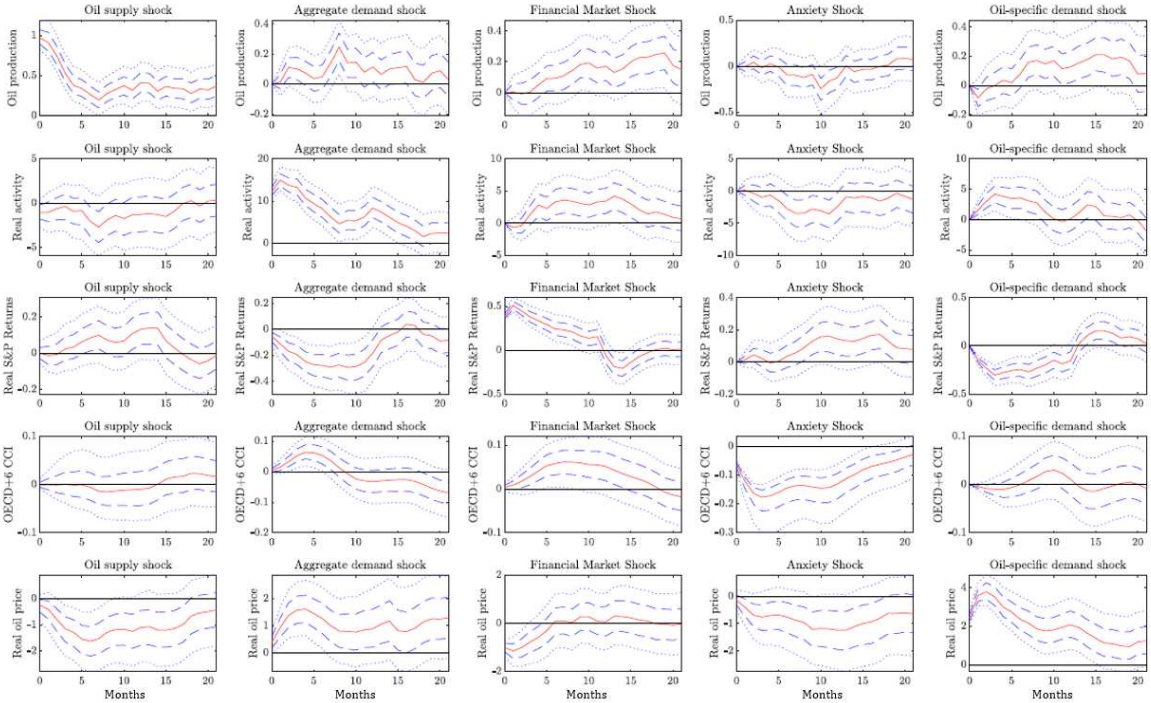

Fig. 3. Responses to one S.D. structural shocks using OECD+6 CCI
Note: dashed and dotted lines represent one- and two-standard error bands.

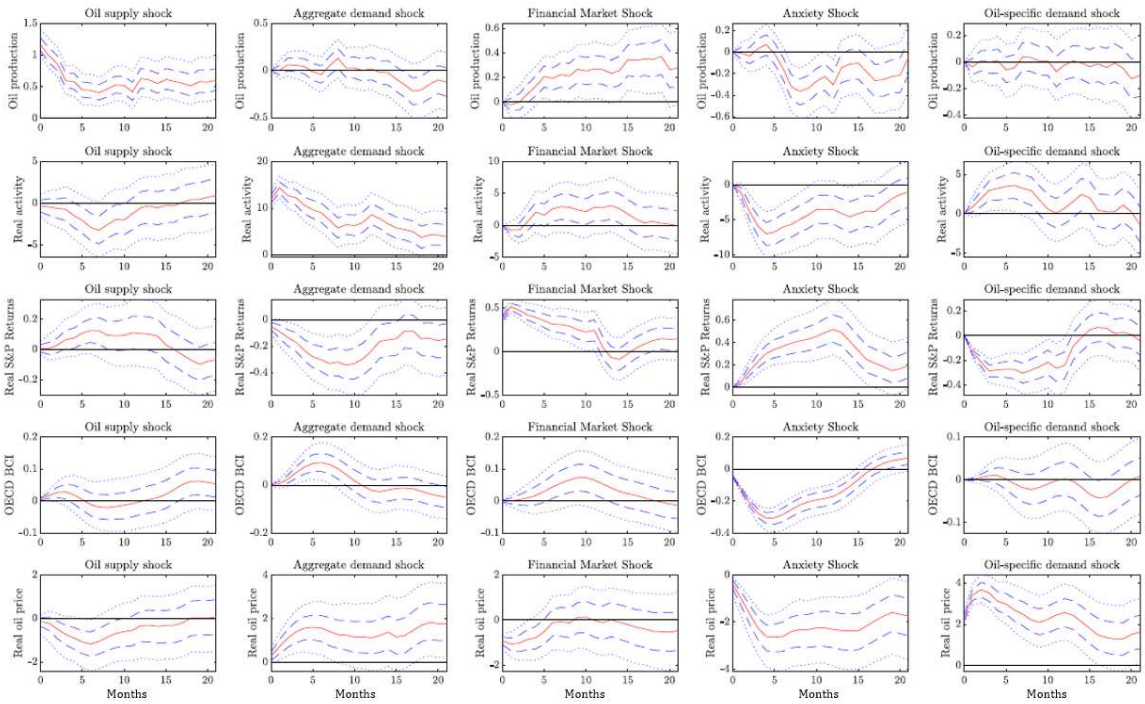

Fig. 4. Responses to one S.D. structural shocks using OECD BCI
Note: dashed and dotted lines represent one- and two-standard error bands.

5 Robustness checks

To test the robustness of the results, we use alternative data set for the measure of global economic activity (REA), real oil price (ROP), and financial market conditions (RSP). We discuss each in turn.

5.1 Real economic activity: Baumeister-Hamilton World IPI

The first robustness check is conducted using the same data set in Section 3. However, instead of using the REA from Kilian (2009, 2019), we use the monthly world industrial production index (WIPI) constructed by Baumeister and Hamilton (2019) as an alternative measure of REA. This index is contained in the OECD MEI database and covers the OECD+6. The impulse response results from the WIPI are reported in Fig. A1 in the Appendix. As the figure shows, the nature of the reactions to the structural shocks is invariant to the choice of real global economic activity index.

5.2 Real price of oil: WTI

We also estimated the VAR model using the WTI deflated by the U.S. consumer price index instead of the U.S. crude oil imported acquisition cost by refineries. As reported in Fig. A2 in the Appendix, the responses are not different from the main results using the U.S. crude oil-importer acquisition cost.

5.3 Speculative demand shock

Most recent oil market VAR studies also include inventories, which is particularly relevant to this study given the unprecedented accumulation of oil inventories. For this reason, to indirectly capture speculative/financial market conditions, we substitute the real S&P (RSP) returns with above-ground crude oil inventories (INV). The oil inventories are measured using total U.S. crude oil inventories and scaled by the ratio of OECD petroleum stocks over U.S. petroleum stocks as in Kilian and Murphy (2014) and Cross et al. (2020). The inventory data are obtained from the EIA and expressed in changes. The impulse responses reported in Fig. A3 in the Appendix indicate that the main results are invariant to this change.

6 Variance decomposition

In this section, we investigate the contribution of different structural shocks to the fluctuations of ROP by estimating the forecast error variance decomposition of the main model that uses OECD CCI as a measure of anxiety. The results reported in Table 1 show that on impact, 16.12% of the variations in ROP are associated with oil supply, aggregate demand, financial market, and anxiety shocks. After three months, these shocks are collectively responsible for 16.79% of fluctuations in ROP, with financial market shock explaining approximately 8.82% while aggregate demand shock accounts for 6.66%, anxiety shock accounts for 0.61%, and oil supply shock accounts for 0.70%.

However, the distribution changes significantly after 12 months and even more so after 20 months. After 12 months, the four shocks are responsible for 25.48% of ROP fluctuations, with oil supply shock accounting for 3.32% of ROP fluctuations. In contrast, an aggregate demand, financial market, and anxiety shocks respectively account for 14.57%, 4.46%, and 3.14%. By 20 months, the four shocks collectively account for 33.11% of ROP fluctuations, with the largest fluctuation in ROP driven by aggregate demand shock (19.24%) followed by anxiety shock (7.40%), financial market shock (4.24%), and oil supply shock (2.23%). These

results are broadly consistent with the findings from the impulse responses analysis presented above, suggesting that aggregate demand, financial market, and anxiety shocks are relatively more important for oil price variability in the short run.

Table 1. Forecast error variance decomposition

Period	OSS	ADS	FSS	ANXS	OSDS
1	0.38	1.63	14.02	0.10	83.88
3	0.70	6.66	8.82	0.61	83.21
6	2.33	12.89	6.30	0.75	77.72
9	3.65	14.44	5.13	1.13	75.66
12	3.32	14.57	4.46	3.14	74.52
15	2.69	15.85	3.91	5.24	72.32
18	2.39	17.65	4.00	6.58	69.40
20	2.23	19.24	4.24	7.40	66.89

Note: OSS = oil supply shock, ADS = aggregate demand shock, FSS = financial speculation shock, ANXS = anxiety shock, and OSDS = oil-specific demand shock.

7 Conclusion

The paper investigates the role of the COVID-19 pandemic in oil markets, focusing on the great oil price crash in April 2020. It employs a structural VAR model to identify an oil price shock arising from the pandemic together with the supply, demand, and financial market shocks to global oil markets. In addition to the impulse response analysis, the study also examines the historical evolution of the shocks on the real price of oil and provides estimates of how much each contributed to the evolution of the real price of oil during the January 2020 to April 2020 period. The historical decomposition shows that the bulk of the drop in oil price during this period has been driven by oil-specific demand, aggregate demand, financial market conditions, and pandemic anxiety conditions, with pandemic anxiety becoming more evident from March 2020. The eventual decline in oil price in April 2020 following these demand shocks is attributed to an inverted Maslow's hierarchy of needs because, as the COVID-19 unfolded in the early stage of the pandemic and lockdowns intensified, demand for food and other necessities superseded the demand for crude oil and gasoline, which may have contributed to the dramatic decline in oil prices in April 2020. To a certain extent, crude oil and gasoline became relatively non-essential goods during this period.

A second contribution of the paper is to examine whether the brief Russia-Saudi oil price war that began in March 2020 impacted oil prices in April 2020. The results show that although supply played some role in oil price movements, its impact was inconsequential in April 2020.

Overall, the analyses and findings highlight the importance of research that incorporates economic uncertainty related to pandemics into models of global commodity markets. Additionally, the findings affirm the need for policymakers and market participants to consider changes in global health conditions when analyzing the causes and consequences of oil price shocks.

A final implication of the paper is that although pandemic uncertainty played a crucial role in the decline in oil prices during the early stage of the pandemic when the virus had no mutations, it is unclear how oil prices react to mutations of the virus and associated uncertainties. It is also unclear how oil prices will behave as the pandemic gradually peters out. An attempt to incorporate genetic mutations of the virus to forecast crude oil futures has been made by (Weng et al. 2021).

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Appendix

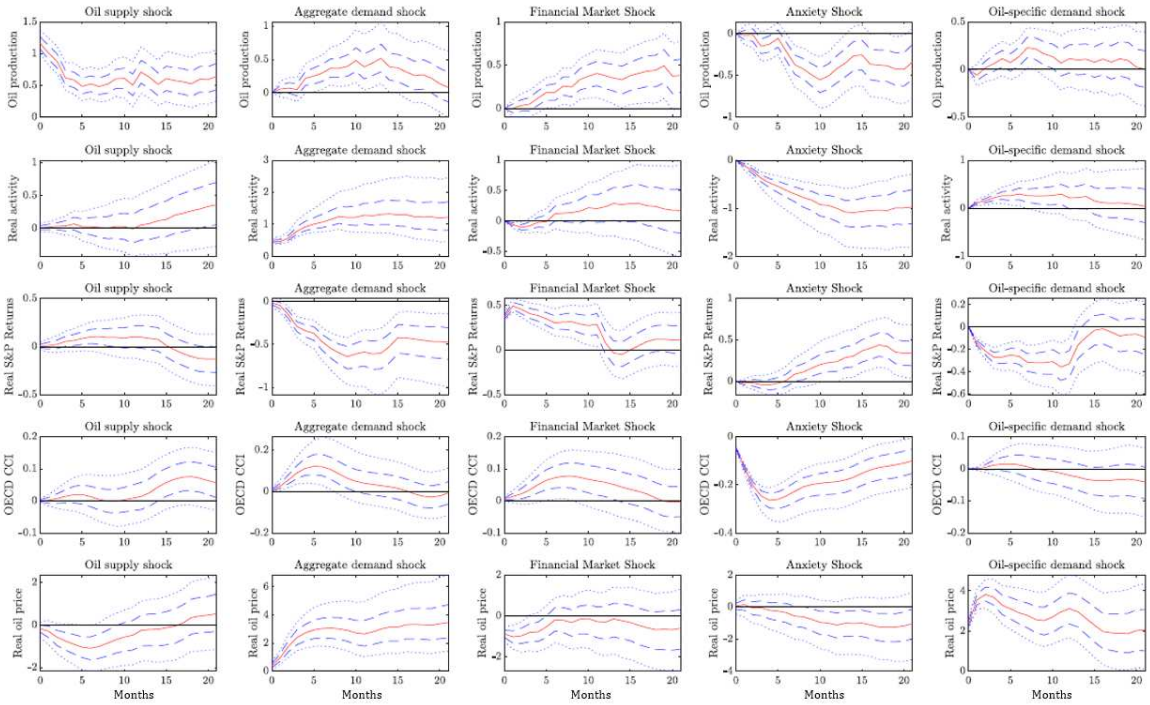

Fig. A1. Responses to one S.D. structural shocks using OECD CCI and WIPI
Note: dashed and dotted lines represent one- and two-standard error bands.

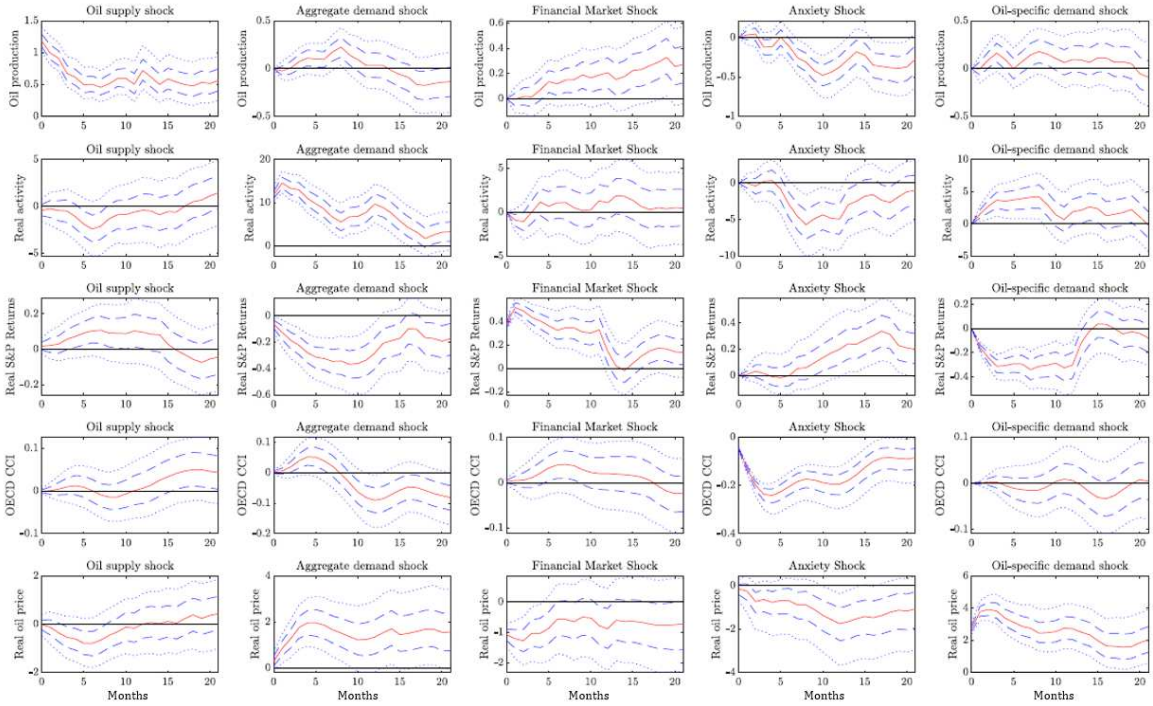

Fig. A2. Responses to one S.D. structural shocks using OECD CCI and Real WTI oil price
Note: dashed and dotted lines represent one- and two-standard error bands.

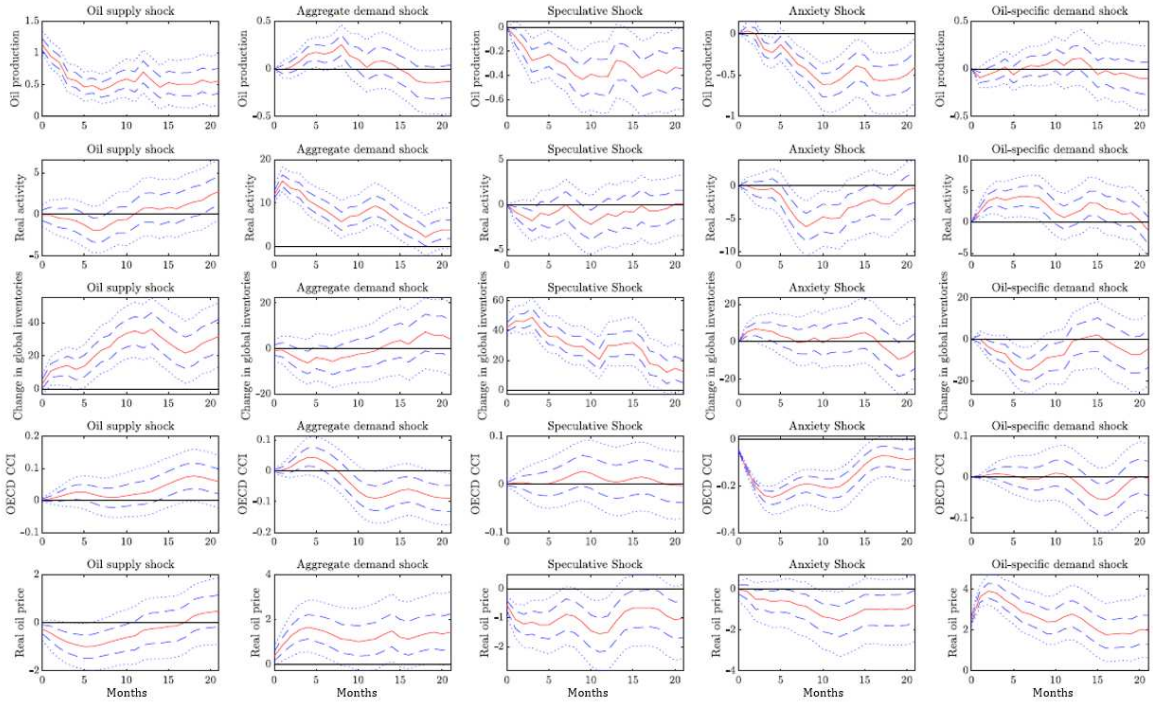

Fig. A3. Responses to one S.D. structural shocks using OECD CCI and Crude oil inventories
Note: dashed and dotted lines represent one- and two-standard error bands.