Pandemics and Oil Shocks

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Abstract

At the onset of coronavirus in January 2020, crude oil price was around \$51.63 per barrel. But the subsequent spread of the virus across countries all over the world adversely impacted the day-to-day functioning of major industries, corporations, and economies. This adverse impact was amplified by the lockdown measures by governments who were justifiably concerned about the potential devastating effect of the pandemic. As the outbreak intensified, so did oil prices plunge into historic lows (at some point, negative). Is the precipitous drop in oil prices due to the COVID-19 pandemic or are there potentially other factors at play? In this paper, we investigate this question using a pentavariate structural vector autoregression (SVAR) model. Specifically, we identify an exogenous oil price shock arising from the pandemic together with the traditional underlying supply, demand, and financial market shocks to global crude oil markets. We find that a pandemic shock causes a delayed adverse effect on oil prices. In addition, our findings lend support to the view that changes in financial market conditions that affect financial investment decisions also play a significant role in oil price movements. There is however no evidence of a strong impact emanating from the brief Russia-Saudi price war. We also compute the forecast error variance decomposition and find that the impact of a pandemic shock together with aggregate demand and financial market shocks are not trivial in the short run. Taken together, the findings underscore the fruitfulness of research aimed at better understanding the effects of a pandemic shock on oil price movements and highlight the need for policymakers and market stakeholders to explicitly consider global health conditions when analyzing the causes and consequences of oil price shocks.

Keywords: pandemic, oil price shocks, structural VAR, novel coronavirus, COVID-19

JEL Classification: I150, Q41, Q43, Q47

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1 Introduction

We would normally not expect a relationship between pandemics and energy prices because no apparent linkages seem to be evident on the surface. But the scale of the effect the novel coronavirus pandemic may have on the global economy warrants an appraisal of its potential impact on human lives, economic activity, and energy (oil) prices. In early January 2020, Chinese authorities identified the novel coronavirus, now formally known as COVID-19 and the virus that causes it called SARS-CoV-2 or severe acute respiratory syndrome coronavirus 2. Less than three months later, the virus became a global pandemic. United States recoded its first case on January 19 and since then have recorded more than 1 million cases with over one hundred thousand deaths, the highest death in any single country. Globally, there are several hundred thousand deaths.

As containment efforts continue across the world, several sectors are feeling the effects of lockdowns and economic uncertainty brought about by the pandemic. Very early on in February, 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 and no one knows where it is taking us. And alongside the difficulty in predicting the transmissibility of the virus, came increased uncertainty in global commodity markets.

What do pandemics have to do with oil prices? Fluctuations in oil prices are driven by both demand and supply forces. 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, meaning that in recent years (at least since 2018), the supply effect has overshadowed the demand effect causing oil prices to plummet. But in recent months, the outbreak of the novel coronavirus and the uncertainty surrounding its causes and possible repercussions have led to the resurgence of the demand side. But this demand shock is different from the traditional aggregate demand shock because it is inextricably tied to the virus and largely triggered fear and anxiety, which significantly reduce consumer confidence.

To capture fear and anxiety on a global scale, we use the OECD consumer confidence index (OECD CCI), an indicator of future developments of consumer spending and saving based upon answers regarding consumers' expected financial situation, their sentiment about the general economic situation, unemployment and savings capability. The indicator is set at 100 with values above 100 signifying boost in consumer confidence (optimism) whereas values below 100 indicate loss in consumer confidence (pessimism). The paper used the OECD CCI because OECD countries are the hardest hit by the pandemic. To broaden our coverage, we also used OECD plus 6 major economies consumer confidence index (OECD+6 CCI), although the data is not as extensive as the OECD only CCI data. The plus 6 major countries are non-OECD economies including Brazil, China, India, Indonesia, the Russian Federation, and South Africa. Moreover, the study run additional estimation using the OECD business confidence index (OECD BCI) as another measure of fear and anxiety.

Incorporating the OECD CCI into a pentavariate structural vector autoregression (SVAR) model, we uncover the following results. First, we find that a pandemic shock causes a delayed adverse effect on oil price. Second, changes in financial market conditions that affect financial investment decisions also play a significant role in oil price movements. Third, all initial responses of oil price from the demand-side effects – aggregate demand, pandemic, and oil-market specific demand – are short lived, averaging approximately three months, following which oil price saw a decline. Fourth, we find no

evidence that the brief Russia-Saudi price war caused a major drop in oil price. Specifically, although supply conditions may have played some role in oil price movements, its impact is inconsequential since January 2020. Fifth, forecast error variance decomposition suggest that the effects of a pandemic shock together with aggregate demand and financial market shocks on oil price are not trivial in the short run. These results from the use of OECD CCI are mostly in line with the findings from using the OECD+6 CCI and OECD BCI.

Collectively, the findings underscore the benefits of research aimed at better understanding the dynamic effects of a pandemic shock on oil price movements. The findings also underscore the need for policymakers and market stakeholders to explicitly consider global health conditions when analyzing the causes, consequences, and appropriate reaction to oil shocks.

The rest of the paper is structured as follows. Section 2 provides a brief survey of the five phases of the COVID-19 pandemic and the related slump in oil prices. Section 3 presents the methodology to distinguish between a pandemic shock and other shocks that underlie oil price movements. In Section 4, we present and discuss the results from the structural decomposition of the shocks. We also examine whether the Russia-Saudi price war matters for oil price movements in Section 4. In Section 5, we check the robustness of the results. We compute the forecast error variance decomposition in Section 6 to examine the contributions of different structural shocks to the price of crude oil. Section 7 contains the conclusion.

2 Phases of Covid-19 pandemic and oil price precipitous decline

To understand the relationship between COVID-19 and oil prices, it is useful to understand the unfolding pandemic in five phases.

2.1 Phase I: Wuhan, China

The first phase was in Wuhan, a city in central China in the Hubei province. Wuhan is a major industrial hub where major industries including optical-electronics, biotech, pharmaceuticals, automobile, iron, and steel manufacturing are located. Early January 2020, news began spreading that Wuhan is in a major problem and has shut down most of its major industries. Economists familiar with this news immediately began to worry that this is going to be a major economic shock. The main concern was that since China's economy is the source of nearly one-third of world economic growth and accounts for one-fourth of world oil demand, if China's economy falters then the global economy is certainly going to have a tough time.

At this point in early January, the consensus was that we should expect some disruptions in global supply chain largely due to the shutting down of factories in Wuhan and the surrounding areas which extended to farther industrial and business hubs such as Guangdong and Shanghai. Major global corporations began to revise their earnings and profits downwards and warned about severe supply bottlenecks in the coming months (NYT, 2020). These early supply disruptions were especially evident in the global automobile industry. Consequently, the conventional wisdom was that the economic condition is bad but not too bad as analysts initially predicted. Thus, China and the global economy will quickly rebound. But that changed in the middle of February when suddenly there was a significant spike in the number of coronavirus cases across the globe, especially in Europe, which brings us to the second phase of the COVID-triggered global economic crisis.

2.2 Phase II: Europe

In late February, news began to spread that the extent of cases and the rate of transmissibility of the virus is larger in Italy than in China. And with this surge in the number of cases, the Italian government shut down a large strap of industrial sector by imposing lockdowns beginning in northern Italy which harbors close to half of the country's industrial sector and responsible to nearly a third of the country's economic output. With this public health crisis, the virus has managed to shut down two major industrial centers in the world: Wuhan, China and Lombardy region, Northern Italy. Like Italy, other major industrial economies in Europe including Germany, France, United Kingdom, and Spain became hotbeds of the virus when they began to record significant spike in cases. Governments in these countries also imposed lockdown measures to contain the spread of the virus shutting down major portions of the European economy.

Markets began to absorb the fact that this is not a China story but a global one. As fear and uncertainty rose, markets started to get very volatile. The reaction of oil prices to the market rattlings was swift. On February 28, 2020 crude oil price was \$47.09 per barrel, down from \$53.78 just a week ago. As conditions in Europe got worse and the coronavirus became a global pandemic, the global supply chain bottlenecks story became firmly entrenched and fear and uncertainty continued to increase (NYT, 2020). At this point, markets moved into a new phase where investors want to get rid of anything that looks risky, which exacerbated the already volatile conditions sending ripples throughout markets.

2.3 Phase III: The U.S. Feds' dramatic move

On Mar 15 2020, The Fed took an unprecedented measure by slashing interest rates to zero and launched a new round of quantitative easing, all in an effort to calm financial markets. To markets participants, this move by The Fed was both good and bad. It was good because it signaled to markets that The Fed is ready to do whatever it can to minimize the downside risks and losses. But at the same time the move was so dramatic, so much so that, it made investors wonder how bad things were. The markets' logic was that if The Fed is taking such a move then things may have been really bad than what markets thought. In other words, The Fed's swift action worsened investors' fear. Unsurprisingly, markets plunged again soon after the Fed's rate cut.

2.4 Phase IV: The surge in U.S. cases and other countries in the Americas

The fourth phase stretched from March 17 - 31 when the number of COVID-19 cases in the U.S. saw an exponential growth. The U.S. went from under 100,000 cases per day in mid-March to about 900,000 cases per day by the end of March, the fastest rate of transmissibility worldwide (USCDC, 2020). Similar surges were observed in Mexico, Argentina, and Brazil, especially in the latter (Worldmeters, 2020). This explosive growth in the number of new cases called for even more stringent measures to flatten the infection curve. Such moves were disparately necessary but further heighten fears among consumers and uncertainty in financial markets. Throughout this period, oil price continue its free fall. Combine with the Russia-Saudi oil price war that worsened the oversupply of oil in global energy markets, oil price plunged to a record low of \$14 per barrel, prompting oil executives to meet with Trump to discuss the oil price crash.

2.5 Phase V: Negative oil price

Right around the beginning of April, while other countries were battling the swift acceleration of the spread of COVID-19, U.S. reached an inflection point in the number of new cases. The number of daily cases continue to rise compared to the previous day but not as rapidly as before (TIME, 2020). Policy interventions such as school closings, stay-at-home orders, and social distancing, though implemented late, began to yield some positive results. Congress also passed the coronavirus response bill bringing some relief to consumers and investors. Markets calmed down and rebounded slightly. Oil prices also trended back upwards.

And just about when investors thought markets will continue their upward rebound, oil prices plunged into negative territory (WSJ, 2020). The negative oil price implies that traders who purchased oil futures are paying the sellers of the contract to cancel the contract because if the contract is not cancelled, the traders risk having to take physical delivery of the oil, which most are incapable of doing. Ultimately, this is bad for oil producers because it puts downward pressure on oil prices, which immediately manifested in the oil markets as the S&P 500's energy sector plunged more than 40%.

To summarize, at the onset of coronavirus in January 2020 (Phase I), crude oil price was around \$51.63 per barrel. But the subsequent spread of the virus across countries all over the world adversely impacted the day-to-day functioning of the major industries, corporations, and economies. This adverse impact was amplified by the lockdown measures by governments who were concerned about the potential devastating effect of the pandemic. As the outbreak intensified, so did oil prices nosedive into historic lows. By Phase V, crude oil prices plunged to a low of \$9 per barrel and at some point, negative.

Is this precipitous drop in oil price due to the COVID-19 pandemic or are there potentially other factors at play? We investigate this question in the next section by estimating a structural VAR model to disentangle the structural shocks that underlie oil price movements.

3 Methodology and Data

This study defines a pentavariate structural VAR model for the global crude oil market as:

$$\mathbf{A}_0 \mathbf{z}_t = \alpha_0 + \sum_{i=1}^{24} \mathbf{A}_i \mathbf{z}_{t-i} + \varepsilon_t \quad (3.1)$$

where $\mathbf{z}_t$ is a vector of monthly time series consisting of five endogenous variables: 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.

$PROD$, REA , and ROP are variables 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.¹ 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.² 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 boost in consumer confidence (optimism) whereas values below 100 indicate loss in consumer confidence (pessimism).³ The study also includes real S&P 500 returns to capture the role financial market conditions. The RSP is constructed by subtracting the consumer price index inflation rate from the log S&P 500 closing price obtained from yahoo finance.

The VAR model in Eq. [1] is estimated using data for the sample period January 1974 to April 2020. The lag length of the VAR model is 24, 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). Baumeister and Hamilton (2019) use 12 lags. Although AIC indicates a lag length of 15, the estimation results based on 15 lags are similar to those based on the 24 lags.

In order to get the reduced-form of the structural model, we simply multiply both sides of Eq. [1] with $\mathbf{A}_0^{-1}$, such that:

$$\mathbf{z}_t = \gamma_0 + \sum_{i=1}^{24} \mathbf{B}_i \mathbf{z}_{t-i} + e_t \quad (3.2)$$

¹ Because the world oil production series most recent available month is November 2019, we supplemented it with world oil production forecasts from EIA Monthly Energy Outlook from December 2019 - April 2020.

² The U.S. crude oil importer acquisition cost by refiners from EIA was available until February 2020. We supplement the series with Brent crude oil price from St. Louis FRED database to extend the ROP series to April 2020.

³ We broaden 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 additional estimation using the OECD business confidence index (BCI) as another 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 begins in July 1983 and ends in October 2019.

where $\gamma_0 = \mathbf{A}_0^{-1}\alpha_0$; $\mathbf{B}_i = \mathbf{A}_0^{-1}\mathbf{A}_i$; $\mathbf{e}_t = \mathbf{A}_0^{-1}\varepsilon_t$; and the latter term implying that $\varepsilon_t = \mathbf{A}_0\mathbf{e}_t$. From here, the structural disturbances are derived by imposing suitable restrictions on $\mathbf{A}_0$. For the purpose of this study, the following short-run restrictions are imposed in the model:

$$\begin{bmatrix} \varepsilon_{1,t}^{OSS} \\ \varepsilon_{2,t}^{ADS} \\ \varepsilon_{3,t}^{FSS} \\ \varepsilon_{4,t}^{ANXS} \\ \varepsilon_{5,t}^{OSDS} \end{bmatrix} = \begin{bmatrix} a_{11} & 0 & 0 & 0 & 0 \\ a_{21} & a_{22} & 0 & 0 & 0 \\ a_{31} & a_{32} & a_{33} & 0 & 0 \\ a_{41} & a_{42} & a_{43} & a_{44} & 0 \\ a_{51} & a_{52} & a_{53} & a_{54} & a_{55} \end{bmatrix} \times \begin{bmatrix} e_{1,t}^{PRDO} \\ e_{2,t}^{REA} \\ e_{3,t}^{RSP} \\ e_{4,t}^{CCI} \\ e_{5,t}^{ROP} \end{bmatrix} \quad (3.3)$$

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 shrouding the state of the global crude oil market. However, oil supply disruption can influence global economic activity, the price of oil, 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 that are not explained by all the aforementioned shocks are captured by the oil-specific demand events.

Our identification scheme generated five structural innovations of interest. These are, as indicated in Eq. [3], the structural shock obtained from the oil supply equation and corresponds to oil supply shock (first row); the structural shock obtained from the aggregate demand equation corresponds to aggregate demand shock (second row); the one obtained from the financial market equation corresponds to a financial speculation shock (third row); the structural shock obtained from consumer confidence equation corresponds to an anxiety shock (fourth row); and the one derived from the real oil price equation corresponds to an oil-specific demand shock (last row). This scheme allows for the computation of the five structural shocks we consider to be the key drivers of oil price. Our working hypotheses are that all five shocks affect the real price of oil, although without *a priori* hypotheses as the nature of the effects.

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 lower left of the bottom panel, 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 an immediate statistically significant decrease in ROP.

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. Because this paper is the first to quantify pandemic-related oil shocks, this result is new. The impulse response shows that unanticipated anxiety shock has a negative statistically significant effect on ROP. Specifically, ROP reacts negatively to unanticipated anxiety shock approximately two months after the shock and the negative reaction accelerates after five months. This suggest that consumer pessimism about future general economic conditions, unemployment, and savings capacity triggers a decline in ROP. Finally, an unexpected increase in oil market-specific demand has an immediate positive impact on ROP, which is also statistically significant.

Overall, the findings in this section indicate that anxiety (pandemic) shock is an important driver of oil prices. In addition, the results lend support to the view that changes in financial market conditions that affect financial investment decisions also play a significant role in oil price movements. Another interesting observation is that all the initial responses of oil price from the demand-side effects – aggregate demand, anxiety, and oil-market specific demand – are short lived, averaging approximately three months. The eventual decline in oil price following these demand shocks could result from an inverted Maslow hierarchy of needs (Maslow, 1943). Specifically, as Covid-19 unfolded and lockdowns intensified, demand food and other basic necessities superseded the demand for crude oil and gasoline, which may have contributed to the delayed but dramatic decline in oil prices.

4.2 Does the Russia-Saudi Price War Matter?

A question of considerable interest is the role of the Russia-Saudi price war in during the pandemic. Figure 2 plots the time path of the structural shocks from January 2020-April 2020. Clearly, since January 2020, oil production does not exhibit much variation even with the transitory oversupply of oil caused by the Russia-Saudi price war. Rather, the bulk of drop in oil price is driven by oil-specific demand, followed by aggregate demand, financial market conditions, and consumer anxiety conditions, with consumer anxiety becoming more evident in the collapse in oil price from March 2020. Taken together, the structural residuals from January 2020-April 2020 signify that although supply conditions may have played some role in oil price movements, its impact is inconsequential since January 2020. And even after the Russia-Saudi price war in March which should have stabilize price, oil price kept declining and stayed in the negative territory mostly due to demand and financial

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

market conditions and the pandemic-triggered consumer anxiety.

4.3 Other measures of anxiety

As already noted, we broaden our coverage by extending our measure of confidence/anxiety beyond OECD countries. Specifically, we used the OECD+6 CCI to capture fear and anxiety on a relatively bigger global scale. The +6 major countries are non-OECD economies of Brazil, China, India, Indonesia, the Russian Federation, and South Africa, who together with OECD countries account for 80.03% of global Covid-19 cases. The OECD+6 CCI data is available from January 1980 - March 2020. The impulse response of ROP from the incorporation of the OECD+6 CCI are reported in Fig. 3. As Fig. 3 shows, the results are broadly consistent with the main findings from using the OECD CCI. 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 to include the 6 major non-OECD economies to the OECD to measure fear and anxiety on a relatively bigger global scale captured additional effects originating from the dynamics in consumer sentiments.

Furthermore, we run additional estimation using the OECD BCI as another measure of fear and anxiety, particularly from the producer side of the global economy.⁴ 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, here producer anxiety shock triggers an immediate and persistent fall in ROP. This signifies that when producers are anxious or uncertain

⁴The study did not use the business confidence index for OECD+6 major economies (OECD+6 BCI) because available data begins in July 1983 and ends in October 2019.

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.

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.

about future market conditions, their anxiety immediately affects ROP.

5 Robustness checks

To test the robustness of our 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, but instead of using the real economic activity from Kilian (2009) and subsequently revised in Kilian (2019), we use the monthly world industrial production index (WIP) constructed by Baumeister and Hamilton (2019) as an alternative measure of real global economic activity. This measure was originally contained in the OECD MEI database and covers OECD plus 6 major non-member countries namely Brazil, China, India, Indonesia, the Russian Federation, and South Africa, hence, more closely related to our OECD CCI measure. Impulse response results from using the WIP are reported in Figure A1 in the Appendix. As the figure shows, the responses do not vary, signifying that the nature of the reactions to the structural shocks are invariant to the choice of real global economic activity index.⁵

5.2 Real price of oil: WTI

We also estimated the VAR model using the WTI oil price 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 seem particularly relevant to this study given the current crisis where we experienced an unprecedented accumulation of 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*) measured using total U.S. crude oil inventories scaled by the ratio of OECD petroleum stocks over U.S. petroleum stocks as in Kilian and Murphy (2014) and Cross (2020). The inventory data are obtained from the EIA and expressed in changes. The impulse responses reported in Fig. A3 in the Appendix indicate the main results of the paper are invariant to this change.

⁵Our use of a recursive scheme for identification of the structural shocks implies the assumption of a vertical oil supply curve. Given the evidence of oil supply elasticity in Baumeister and Hamilton (2019) and Caldara et al. (2019), a possible extension of the analysis in this paper is to relax this assumption using the Bayesian vector autoregression approach as in Baumeister and Hamilton (2019). A first attempt is made by Mohammed and Barrales-Ruiz (2020).

6 Variance decomposition

In this section, we investigate the contribution of different structural shocks to the fluctuations in ROP by estimating the forecast error variance decomposition of the main model that uses OECD CCI as a measure of anxiety. Results are reported in Table 1. In the short run, the effects of these four shocks – oil supply, aggregate demand, financial market, anxiety – on ROP are not trivial. Specifically, 16.12% of the variations in ROP are associated with these shocks, on impact. After 3 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 (long run). 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 whereas 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 to the findings from the impulse responses analysis presented above.

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 novel coronavirus, now known as COVID-19, emerged in Wuhan, China in early January. Less than three months later, the virus became a global pandemic. In an attempt to contain the spread of the virus, governments and public health authorities imposed nationwide lockdowns. The shutdowns resulted in a massive surge in joblessness globally as economic activity came to an abrupt standstill and market uncertainty spiked. As the outbreak intensified, so did oil prices plunge (at some point, negative), exacerbating the already volatile conditions in energy markets and supporting industries. However, it is unclear whether the precipitous drop in oil prices is caused by the COVID-19 pandemic or some other factor(s).

In this paper, we take a first step toward incorporating pandemics into modeling oil price shocks. Specifically, we examine the phases of COVID-19 pandemic and employ a structural VAR model to identify an exogenous oil price shock arising from the pandemic together with the traditional supply, demand, and financial market shocks to global oil markets. We find that anxiety/pandemic shock causes a delayed decrease in oil price. We also find that changes in financial market conditions that affect financial investment decisions play a significant role in oil price movements. Furthermore, all initial responses of oil price from the demand-side effects – aggregate demand, anxiety, and oil-market specific demand – are short lived, averaging approximately three months. We attribute the eventual decline in oil price following these demand shocks to an inverted Maslow hierarchy of needs because, as Covid-19 unfolded and lockdowns intensified, demand food and other basic necessities superseded the demand for crude oil and gasoline, which may have contributed the delayed but dramatic decline in oil prices.

We also examine the role of the Russia-Saudi price war in the recent oil price slump and find no evidence of a strong impact emanating from the price war. In particular, we find that although supply conditions may have played some role in oil price movements, its impact is inconsequential since January 2020. Finally, our forecast error variance decomposition suggest that the impacts of anxiety/pandemic shock together with aggregate demand and financial market shocks to oil price are crucial in the short run and long run.

Our analyses and findings contribute to the literature in two important ways. First, we show how to incorporate pandemic shocks in oil price movements. Additionally, our findings affirm the need for policymakers and market stakeholders to explicitly consider changes in global health conditions when analyzing the causes, consequences, and appropriate reaction to oil price shocks.

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A Appendix: Robustness checks impulse responses

Fig. A1. Responses to one S.D. structural shocks using OECD CCI and WPI
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.

Figures

Figure 1

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

Figure 2

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

Figure 3

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

Figure 4

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

Supplementary Files

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