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How is COVID-19 Related to the Global Economy?

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ABSTRACT: Using a structural vector autoregressive model (SVAR) model, this paper attempts to investigate the short-run interrelation between COVID-19 cases, the gold market, the oil market, the global stock market, and the real economy. We find that COVID-19 cases respond predominantly to its own innovations while the crude oil market, the gold market, and global stock returns are interrelated in the short-run. The industrial production index, the price of crude oil, and the price of gold account for approximately 22.64%, 9.5%, and 13.74% of the variations in global stock returns, respectively. Global COVID-19 cases can explain about 6.022% of the variance of the U.S. industrial production index of the 30-day ahead forecast error.

KEYWORDS: COVID-19; Commodity markets; Stock returns; Real economy.

INTRODUCTION

Since the first reported case in late 2019, the number of cases has been increasing significantly around the globe. Pandemics such as the current COVID-19 are large-scale outbreaks of infectious diseases that can greatly increase the mortality over a wide geographic area and cause significant economic, social, and political disruption[1]. The government's actions in response to the pandemic such as lockdowns of cities, suspending travels, and quarantines have impacted economies. Several sectors such as tourism and hospitality sectors have been suffering from these tight measures (i.e. the suspension of travel and tourism activities.)

Commodities such as gold and oil are used as economic and financial indicators by professional analysts and governments since these commodities in general represent commodity markets. Gold has been a consistent lead on inflation expectations over many years (Greenspan, 1994), and the price of crude oil is a good measurement for industrial productions and investment activities. Gold is considered a safe haven to avoid the increase in financial market risks (Kanjilal and Ghosh, 2017). Gold is also known as the lead indicator in the precious metal markets. It is also an instrument that investors use to hedge against inflation. In a situation like COVID-19 pandemic, investors and governments tend to increase their investments in gold attempting to mitigate the financial risks. As a result, the price of gold was estimated at US $2058.4 per ounce at the beginning of August of 2020 due to the uncertainty that caused by the COVID-19 pandemic, which was at a historical high level since the financial crisis in 2008. The price of gold has increased by approximately 21.09 percent in less than one year comparing to 2019 according to S&P Capital IQ data[2].

Unlike gold, oil is the largest source of the world's primary energy. It is anticipated that the share of liquid fuel would fall from 33% in 2012 to 30% in 2040 according to the projection made by US Energy Information Administration (EIA) in its International Energy Outlook 2016. Moreover, oil is the most traded commodity worldwide, and the price of oil is known as highly volatile due to several reasons (i.e., fluctuations in levels of production and consumption). It is reported that 79.4 percent of the world's oil reserves are held by Organization of the Petroleum Exporting Countries (OPEC) since 2018. Brent crude oil prices decreased by approximately 25.38 percent since the spread of COVID-19[3]. This decrease can be attributed to several reasons[4]. Firstly, the increase in oil production level causes a mismatch of the demand and supply condition. In the first quarter of 2020, major oil producers such as Russia and Saudi Arabia increased their production of oil. Moreover, Saudi Aramco (2020) received a directive order from the Ministry of Energy of Saudi Arabia to increase its oil production by the maximum capacity, which was estimated at 13 million

[1] Please see Yamey (2017) and Madhav (2017).

[2] Capital IQ, https://www.spglobal.com/marketintelligence/en/.

[3] The Investing.com website www.investing.com.

[4] Please refer to Rosdini, Rahardi and Nautika (2019) for detailed analysis.

barrels per day as a response to the increase in Russian's oil production of 300 thousand barrels per day[5]. As a result, the price of crude oil collapsed to its lowest level at US $15.98 since the gulf war. Finally, the consumption of oil has fallen due to the lockdown of major industrial countries like China[6]. It is crucial to explore the impact of the current pandemic (COVID-19) on commodities and global stock markets. The main objective of this study is to identify the impact of COVID-19 on the commodity markets and world economies in the short-run. We consider five variables in our study to assess the impact of COVID-19: the price of gold, the price of crude oil, the U.S. industrial production, the FTSE stock index, and COVID-19 cases. The price of gold and and the price of crude oil are chosen to represent the commodity markets. The U.S. industrial production is used as a proxy for real economic activities. And the FTSE-All World index is applied to capture fluctuations in stock markets globally. We expect the COVID-19 pandemic to have a negative impact on the price of oil, real economic activity, stock market indices, whereas the effect on the price of gold is expected to be positive. However, we have a concern with regard to the new pandemic. Since it is a new disease, the information about the ongoing COVID-19 is not enough in order to assess the effects. Although various studies have discussed the impact of pandemics on economies, COVID-19 seems to have different characteristics, and it might have different impacts on these macroeconomic variables after a certain period of time.

The reminder of the article is organized as follows. Section 1 is the literature review. Section 2 describes the data and model construction. Section 3 provides the econometric methodology. And section 4 reports the empirical results.

1. LITERATURE REVIEW

Even though various studies have discussed the relationship between gold and oil, it seems that the direction of the relationship is unclear. Kanjilal and Ghosh (2017) examine the dynamic relationship between crude oil and gold after the financial crisis in 2008 and find that the price of oil has a positive impact on gold price in the long-run with normal circumstances while the price of gold price has a limited effect on oil. Chang (2012) suggests that gold and oil are not associated with each other in the long-run but oil prices have a positive impact on gold returns within one month of shock. Using a wavelet analysis, Alshammari et al. (2020) explore the impact of the exchange rate, the price of oil, and the price of gold on Kuwaiti's stock market, and find that gold has a negative impact on the stock market in the short-run while the price of oil is indirectly correlated with the stock market. According to Gisser and Goodwin (1986), the increase in oil prices have a negative impact on the financial markets. The rise of the price of oil increases the cost of shipping and decrease the future cash flows that a firm would generate, which leads the stock price to decrease. David (2020) studies the impact of pandemics on global stock markets, and find that tock markets have been affected by COVID-19. The author reports that stock indices have heightened volatilities during the period of the COVID-19 pandemic among three pandemics. Ashraf (2020) explores the impact of COVID-19 on stock market returns using daily data of 64 countries from January 22, 2020 to April 17, 2020. The study shows that COVID-19 has a negative impact on stock market returns and that stock markets are affected by the growth of confirmed cases more than the growth in deaths. The author also suggests that stock markets response strongly during early days of confirmed cases and then between 40 to 60 days. Bakas and Triantafyllou (2020) investigate the impact of economic uncertainty related to global pandemics on the volatility of the broad commodity price index as well as on the sub-indexes of crude oil and gold using the daily excess returns data of the S&P GSCI broad commodity index and the sub-indexes of crude oil and gold. They find that the uncertainty of the current pandemic has a negative impact on the price of crude oil while it positively affects the price of gold.

Various studies use the cost of shipping index as a proxy for the world real economic activity[7]. However, Hamilton (2019) argues that the Kilian's index or the cost of shipping is not a good indicator of the world real economic activity for the original and the adjusted cost of shipping indexes are not statistically significant correlated with the annual world real GDP growth rates and they have a small correlation with the future changes in commodity prices. It appears that industrial production index provides a much better measurement of the world real economic activity instead of the cost of shipping based on the author OLS estimation. The author uses world industrial production of the OECD index plus other six major countries against the world real GDP growth rate and finds that the industrial production is strongly correlated with the GDP growth rate while the cost of shipping has a little correlation. We believe that the worldwide industrial production has been affected by the pandemic to different degrees due to

[5] Details can be found on https://www.aramco.com/en/news-media/news/2020/aramco-to-raise-maximum-capacity#.

[6] Total world oil consumption made by U.S Energy Information Administration, Short-Term Energy Outlook (December,2020). https://www.eia.gov/outlooks/steo/report/global_oil.php. The total world oil consumption of 2020 decreases by approximately 8.74%.

[7] This index is developed by developed by Kilian (2009). These studies include but are not limited to McPhail (2011), Baumeister and Peersman (2013), Charnavoki and Dolado (2014), Degiannakis, Filis and Kizys (2014), Gargano and Timmermann (2014), Juvenal and Petrella (2014), Kilian and Murphy (2014).

government restrictions like lockdowns of cities and quarantine orders. Following Hamilton (2019), we adopt the industrial production index in our study to assess the impact of the ongoing pandemic on the economy.

Studying the impact of COVID-19 disease on macroeconomic variables provides a perspective about the response of commodities and the overall economy to shocks generated from unexpected events such as pandemics. It also helps governments and other relevant authorities better understand the possible impact of future pandemics on the economy. In addition, this investigation expands our knowledge on finding proper measures in responding to global pandemics.

2. DATA DISCERPTION AND THE VAR MODEL

2.1 Data

The data employed in this study are daily observations of the Crude Brent oil prices (in U.S dollar) obtained from the S&P Capital IQ. We adjust these daily observations for inflation using the U.S Consumer Price Index obtained from the U.S. Bureau of Labor Statistics to obtain the real values. The daily real gold prices are collected from S&P Capital IQ and are deflated by dividing the U.S Consumer Price Index. We obtain daily observations of FTSE-All World index covering both developed and emerging markets from the Investing.com website[8]. The daily total world COVID-19 cases are retrieved from the World Health Organization. The monthly U.S industrial production data are adjusted for inflation using the U.S producer price index and converted into daily frequency through the quadratic based average method. We adopt the quadratic based average method to convert the U.S monthly industrial production into daily data to match the period of the other variables. The selection of the industrial production as a measurement of the world real economic activity is based on Hamilton (2019). We adopt the U.S industrial production index instead of the OECD industrial production index due to the data availability. As Figure 1 shows, both the levels and growth rates of the OECD index and U.S industrial production indices tend to move together. We transform all variables into the natural logarithm so the interpretation is in terms of percentage. The sample period for this study is from January 2020 to November 27, 2020.

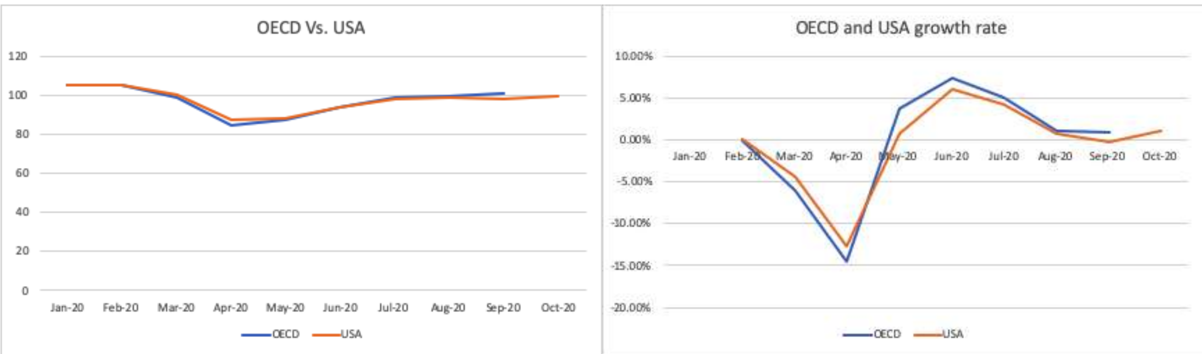

Figure 1: OECD and U.S industrial production in 2020

COVID-19 can be seen either as a demand shock or a supply shock to the real economy. It is treated as a demand shock because Covid related lockdowns and other restrictions negatively affect the aggregate demand through lowered personal consumption and private investment. In the meantime, constraints enforced due to COVID-19 reduce work hours by employees, which lead to fall in the output. Both the supply of gold and crude oil productions are relatively inelastic in the short term measured by daily production, especially the supply of gold. Changes in the price of gold and changes in the price of crude oil in the short term are mainly caused by demand shocks.

2.2 The Structural VAR model

COVID-19 can be seen either as a demand shock or a supply shock to the real economy. It is treated as a demand shock because coronavirus related lockdowns and other restrictions negatively affect the aggregate demand through lowered personal consumption and private investment. In the meantime, constraints enforced due to COVID-19 reduce work hours by employees, which lead to fall in the output.

Both the supply of gold and crude oil production are relatively inelastic in the short term measured by daily production, especially the gold supply. Changes in the price of gold and changes in the price of crude oil in the short term are mainly caused by demand shocks.

We construct a structural VAR model to investigate the cause and effect among COVID-19 cases, the real economy, the price of crude oil, the price of gold, and the stock price. This structural VAR model relates the world stock market to measures of demand shocks in the crude oil market, the gold market, and coronavirus.

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[8] FTSE- All world index represents the global stock market.

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We estimate a structural VAR model based on daily data for the vector time series Y_{t-1}, consisting of the percent change in COVID-19 cases, the percent change in industrial production, the percent change in gold prices, the percent change in global crude oil price, the percent change in stock returns. The structural VAR form is as follows

$$A_0 Y_t = z + AY_{t-1} + e_t$$

where e_t denotes the vector of serially uncorrelated errors, Y_{t-1} represents the vector of macroeconomic variables of interests, A is an appropriately defined companion matrix, and A_0 is an unidentified matrix containing the contemporaneous terms. We put restrictions to the A_0 matrix and transform the structural VAR representation into a properly defined reduced-form VAR.

We attribute fluctuations in the price of crude oil to three shocks: e_{1t} represents covid-19 cases and is defined as either a supply shock or a demand shock; e_{2t} denotes innovations in the global demand for industrial production; and e_{3t} captures the crude oil specific demand shock. We define the crude oil specific demand shock in a spirit similar to Killian and Park (2009), in which this type of demand arises because of the uncertainty about shortfalls of expected supply relative to expected demand. The gold market is designed in a way that it get affected by the real economy as well as innovations to the price of gold not driven by the real market.

Let ϵ_t represent the reduced-form VAR shocks so that $\epsilon_t = A_0^{-1} e_t$. Therefore, the model with identifying assumptions is written as follows

$$\epsilon_t = \begin{pmatrix} \epsilon_{1t}^{\Delta covid-19} \\ \epsilon_{2t}^{\Delta globalindustrialproduction} \\ \epsilon_{3t}^{\Delta realpriceofoil} \\ \epsilon_{4t}^{\Delta realpriceofgold} \\ \epsilon_{5t}^{\Delta realworldstockreturns} \end{pmatrix} = \begin{bmatrix} \alpha_{11} & 0 & 0 & 0 & 0 \\ \alpha_{21} & \alpha_{22} & 0 & 0 & 0 \\ \alpha_{31} & \alpha_{32} & \alpha_{33} & 0 & 0 \\ \alpha_{41} & \alpha_{42} & \alpha_{43} & \alpha_{44} & 0 \\ \alpha_{51} & \alpha_{52} & \alpha_{53} & \alpha_{54} & \alpha_{55} \end{bmatrix} \begin{pmatrix} e_{1t}^{covid-19shock} \\ e_{2t}^{globaldemandshock} \\ e_{3t}^{oilspecificdemandshock} \\ e_{4t}^{goldspecificdemandshock} \\ e_{5t}^{shockstostockreturns} \end{pmatrix}$$

COVID-19 can be viewed as either a demand shock or a supply shock that potentially affects the real economy and asset prices. Both gold and crude oil are thought to have relatively inelastic supply curves in the short run. Because we investigate the dynamic relationships between these variables in the short run, we treat the supply of gold and the supply of crude oil as inelastic. The restrictions on industrial production and the price of oil are consistent with vertical short-term global supply curves. Therefore, in the short-run changes in global industrial production, the real price of oil, and the real price of gold are predominantly determined by downward sloped demand curves. The real-world stock returns are allowed to respond to shocks to covid-19, the world real economy, the global crude oil market, and the gold market. However, the real-world stock returns do not affect COVID-19 and these markets in the reverse direction in the short-term.

We transform the structural VAR into a reduced form VAR such that

$$Y_t = \beta_0 + \beta Y_{t-1} + \epsilon_t$$

where $\beta_0 = A_0^{-1} z$, $\beta = A_0^{-1} A$, and $\epsilon_t = A_0^{-1} e_t$. Because we peg down some of the coefficients we can estimate $A_0 andA$ with an OSL method. These identifying restrictions impose a recursive structure on the unrestricted VAR to form the structural VAR. And the structural VAR corresponds to the Cholseky orthogonalized VAR imposed by our restrictions. The impulse response function (IRF) of this structural VAR model is the same as the IRF of a reduced-form VAR with a properly Cholesky transformation. We can write the IRF of the structural VAR form in the following way

$$Y_t = \beta_0 \sum_{i=1}^{\infty} \beta^i + \sum_{j=1}^{\infty} \beta^j L L^{-1} \epsilon_{t-j}$$

where $LandL_{-1}$ are the lower Cholesky factor and its inverse of the companion matrix β. Thus this structural VAR model can be seen as a weighted average of orthogonal shocks defined by the identifying assumptions. The orthogonalized impulse response function (OIRF) are given by the sequence of $\beta^i s$, the sequence of $\beta^j L^{-1} s$, and the orthogonal errors $L^{-1} \epsilon_{t-j}$.

3. EMPIRICAL RESULTS

3.1 Stationarity Tests

We apply the Augmented Dicky Fuller (ADF) test (Said and Dickey, 1984), Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test, and Elliott-Rothenberg-stock point-optimal (ERS) test (Elliott, Rothenberg, and Stock, 1996) to crosscheck stationarity of the time series. The results are provided in Table 1. Table 1(A) exhibits the results of the time series at level, and Table 1(B) shows the stationary tests results in differenced variables. The null hypothesis of the (ADF) test and (ERS) test are defined as the series has a unit root against the alternative of stationarity while the null hypothesis of the KPSS test is defined as the series is stationary. As

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Table 1(A) shows, all variables at levels in logarithm are non-stationary since the p-values exceed 5%[9]. Table 1(B) show that second differenced COVID-19, the U.S. Industrial Production Index (IPI) are stationary according to all tests results, whereas the price of gold, the price of crude oil, and world stock returns are stationary once they are first differenced.

Table 1(A): Stationarity Tests Results

Variable	ADF	KPSS	ERS
COVID	-7.2593***	1.6656	2188.4520
IPI	-2.0277	0.3958	5.3840
GOLD	-2.1343	1.7587	28.5779
OIL	-1.9627	0.2910	28.8772
STOCK	-1.3316	0.6875	6.3516

Table 1(B): Stationarity Tests Results of Differenced Variables

Variable	ADF	KPSS	ERS
D(covid,2)	-17.8938***	0.1577***	924.4700
diff (IPI,2)	-11.8316***	0.2687***	0.2210***
Diff. GOLD	-15.6265***	0.1818***	0.7688***
Diff. OIL	-13.2733***	0.2627***	0.2143***
Diff. STOCK	-8.8244***	0.2211***	0.4204***

In addition, we test these variables for cointegration relations in order to detect any possible long-run connections among them. We conduct Johansen cointegration tests (Johansen, 1991) to investigate the long-run relationship among variables at levels. The trace test results indicate that the series are integrated at 5% level of significance since the p-value exceeds the 5% level of significance, but the series are not cointegrated at 10% level of significance. On the other hand, the Maximum eigenvalue test suggests that the series are not cointegrated at level 5% of significance leading to a failure of rejecting the null hypotheses of no cointegration. The results imply that there is not enough evidence that these variables are associated in the long-run.

3.2 Lag selection and VAR model

The selection of the appropriate lag length is based on Akaike Information Criterion (AIC), Schwarz information Criterion (SC), Hannan-Quinn Criterion (HQ), Akaike's Final Prediction Error (FPE). We also observe the autocorrelation of residuals in the VAR model. Table 2(A) exhibits VAR results for lag selection. The AIC and FPE suggest that ten lags are appropriate while SC and HQ imply that four lags should be chosen. The results of the residual autocorrelation based on the LM test show that serial correlation on residuals are present with lags of ten and four. However, using a lag length of nine, the autocorrelation- LM test indicates that residuals are not serially correlated. Based on the results, we construct a VAR model with nine lags[10].

Table 2: Lag Selection of AIC, SC, HQ, and FPE

AIC	SC	HQ	FPE
10	10	4	4

[9] COVID-19 variable shows that it is stationary at level since the p-value is less than 5% leading to rejecting the null hypothesis according to the ADF test.

[10] Appendix 1 shows the autocorrelation function results. And Appendix 2 exhibits the serial correlation results based on the autocorrelation-LM test.

Table 3: Selected Results of the VAR (9) Model

Variable	Estimates	F-Statistic
COVID	= - 0.6318 COVID t-1 - 0.5417 COVID t-2 - 0.4186 COVID t-3 (0.0788) (0.0930) (0.1023) - 0.3001 COVID t-4 + 0.2566 COVID t-5 (0.1071) (0.1071)	4.6047
IPI	= -0.8208 IPI t-1 - 0.5561 IPI t-2 + 1.6207 STOCK t-2 - 0.4572 IPI t-3 (0.0803) (0.1041) (0.6934) (0.1155) -0.31469 IPI t-4 - 0.2399 IPI t-5 + 1.6011 STOCK t-6 (0.1217) (0.1224) (0.8035)	3.8495
OIL	= 0.2250 OIL t-1 + 0.07133 GOLD t-1 + 0.098770 STOCK t-1 (0.0771) (0.0240) (0.0253) + 0.1620 OIL t-4 - 0.06989 STOCK t-6 (0.0782) (0.0243)	2.0815
GOLD	= - 0.0267 IPI t-1 + 0.1649 STOCK t-2 - 0.6342 OIL t-4 (0.0124) (0.0836) (0.2553) + 0.2642 STOCK t-6 - 0.3080 STOCK t-7 - 0.1897 STOCK t-8 (0.0842) (0.0870) (0.0887) + 0.1886 GOLD t-9 (0.0828)	1.3499
STOCK	= -0.5114 OIL t-1 + 0.4637 OIL t-2 + 0.2201 GOLD t-2 (0.2472) (0.2375) (0.0739) + 0.2862 STOCK t-2 - 0.2138 STOCK t-4 + 0.5855 OIL t-6 (0.0778) (0.0767) (0.2279) + 0.7080 OIL t-7 + 0.1423 STOCK t-7 - 0.2146 GOLD t-8 (0.21873) (0.07168) (0.06702) - 0.5636 OIL t-9 (0.2589)	4.4320

In Table 3 we present the results of the VAR (9) model with five variables. We only report variables with test results significant at the 5% level of significance. The first row in Table 3 shows that COVID-19 seems to have a sustained impact on itself in the short-run. The U.S industrial production is positively affected by stock returns at two-day and six-day lags. On the other hand, we are unable to identify any significant effect of the U.S industrial production on the stock markets. Moreover, the price of gold and the stock markets have influences on the price of oil. The price of gold has a positive impact on the price of oil at a one-day la. Stock returns have effects on the price of crude oil after six days and on the price of gold eight days out. The price of oil, the U.S industrial production, and stock returns are all negatively related to the price of gold. Interestingly, we can infer from these estimates that the price of gold has positive impact on the crude oil market whereas the price of gold is negatively affected by the price of crude oil. Furthermore, oil and gold prices both affect the global stock returns. The crude oil market affects stock returns negatively at a one-day lag and a nine-day lag. We conclude that the impact of the price of oil on the stock markets is unclear. The gold market seems to have a positive effect on stock returns immediately while the effect turns negative with an eight-day lag. Surprisingly, we find that the COVID-19 pandemic, measured by daily worldwide cases, has no significant effects on the U.S industrial production, the price of crude oil, the price of gold, and stock returns in the short-run. We find evidence of immediate short-run dynamic effects among all other variables except for COVID-19. Specifically, the crude oil market and the market gold seem to be relevant indicators as they both have impact on stock returns. In addition, the two markets affect the U.S industrial production through the stock markets indirectly.

3.3 Impulse response functions (IRFs)

We report orthogonalized impulse response functions so the orthogonal innovations are consistent with the structural VAR model. One unit of orthogonal innovation is represented by one-standard deviation shock. The impulse response function (IRF) represents the response of one variable to the shock of another variable, and it can help researchers find out the direction of the relationship among variables of interest. The first row in Figure 2 shows that responses of COVID-19 to shocks of real economic activities, the crude oil market, the gold market, and the global stock market. We can see that COVID-19 only responses to itself while effects of other variables fluctuate around the line of zero. A one standard deviation shock of the price of crude oil initially has no noticeable impact on global COVID-19 cases, but the impact turns negative with four-day and nine-days lags. Similarly, a one standard deviation shock of COVID-19 negatively affects the price of oil at three and six day-lag. The price of gold is positively affected by a one-unit shock of COVID-19 with two-day, six-day, and nine-day lags, which is expected as investors turn to gold as a relatively safe asset when the pandemic gets worse. The other variable that gets affected during the pandemic is global stock returns. Although the impact of COVID-19 on stock returns is little to very mild, investors tend to respond to the pandemic with cautions. This phenomenon is reflected in the IRFs in which stock returns dip about five days after the COVID-19 shock. The negative effect does not last and reverts to zero three days later. We find that in the immediate short run the real economy is relatively sensitive to shocks to the gold market while the response to other variables especially COVID-19 is very mild. It doesn't show either a clear positive or a negative effect, instead the response goes up and down around zero. One possible explanation is that in the immediate short-run the uncertainty aggravates as a result people tend to act normal but with cautions. Our results show that the gold market, the crude oil market and the global stock market are connected in the immediate short-run. The global stock market has a sustained positive effect on the crude oil market. The effect of oil shocks on the global stock returns is also positive. The positive impact is likely due to real shocks on the demand side. Investors interpret positive demand shocks as good news which help push up assets prices. The stock market has a longer effect on the gold market than the crude oil market has. The response of the price of gold to oil shocks is immediately positive but drops to zero after three days.

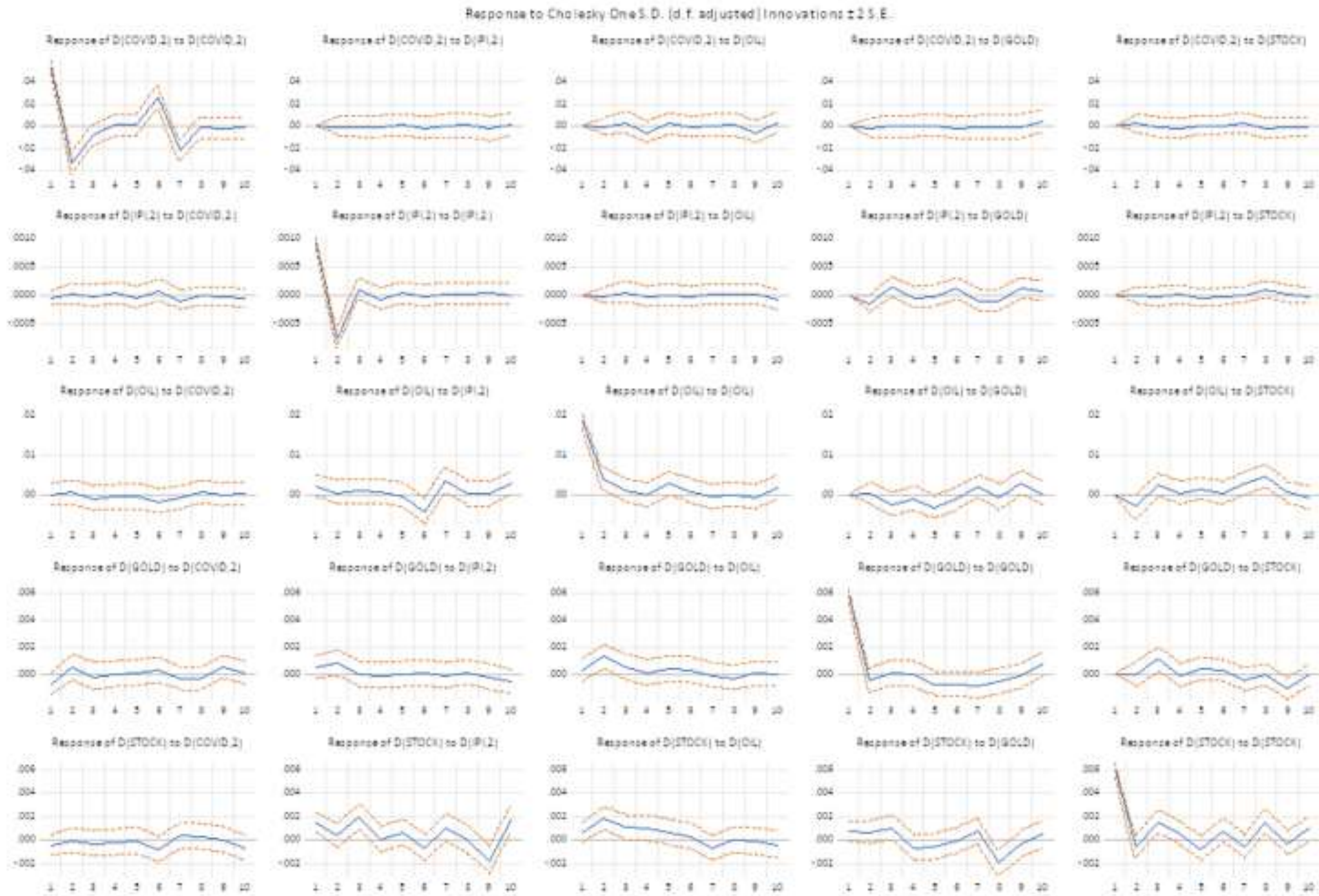

Figure 2 : Impulse Response Functions Results

3.4 Granger causality

We conduct Granger Causality test (1969) to find out whether Granger-causal relationships exist among these variables in the short-run. The null hypothesis is defined as Variable (X) does not Granger cause Variable (Y). Table 4 shows the Granger Causality results that are significant at the 5% level. The results indicate that none of the variables are Granger-caused by COVID-19. In other words, there is no immediate short-run causal relationship between COVID-19 and other variables since the F-statistics are very small and p-values are all higher than the 5% level. This outcome is consistent with the impulse response function results above in which none of these variables are affected by COVID -19 shocks in the short-run. The proxy for the real-world economic activity, the U.S industrial production index does Granger- cause global stock returns and the price of crude oil in a one-way causal relationship based on the p-values. This means that an increase in the industrial production affects both the crude oil market and stock prices in the short-run. Moreover, the crude oil market and global stock returns Granger-causes each other in both ways in the short-run since the p-value is less than 5% level of significance. There also exists a two-way Granger-casual relationship between the world real stock market and the gold market in the short-run. We can conclude that commodities such as gold and oil and global stock markets Granger-caused each other in the short run.

Table 4: Granger causality significant results.

Null hypothesis	Direction	F-statistic	p-value
D(IPI,2) does not Granger cause D(OIL)	One way	3.3518	0.0008***
D(IPI,2) does not Granger cause D(STOCK)	One way	3.7620	0.0002***
D(Stock) does not Granger cause D(OIL) D(OIL) does not Granger cause D(STOCK)	Two-way Two-way	3.9446 2.4512	0.0001*** 0.0113**
D(Stock) does not Granger cause D(GOLD) D(GOLD) does not Granger cause D(STOCK)	Two-way Two-way	1.7059 4.2376	0.0893* 0.0000***

3.5 Forecast Error Variance Decomposition (FEVD) Analysis

Forecasting error variance decomposition shows the relative effect that one variable has on another one. It can be written as the moving average representations of our VAR(9) model. Each component in the forecast error variance decomposition can be interpreted as the contribution of that particular shock to the variance of the n-step ahead forecast error. In our analysis we compute the forecast error variance decompositions for the one-step to thirty-step ahead predictions[11]. The computed results of of forecast error variance are given in Table 5. We only report variables that are statistically signifiant at the 5% level.

Table 5: Forecasting Error Variance Decomposition (FEVD)

Variable	Percentage of 30-Day forecast error variance decomposition	
	By itself	By other variables
COVID	96.42%	-
IPI	83.96%	6.022% COVID, 7.19% GOLD,
OIL	68.44%	10.24% IPI, 8.25% GOLD, 9.16% STOCK
GOLD	77.62%	5.74% OIL, 8.34% STOCK
STOCK	51.73%	22.64% IPI, 9.53% OIL, 13.27% GOLD

The results in Table 5 show that the U.S industrial production index, the price of gold, the price of oil, and the world stock market are the most relevant variables in terms of interconnections[12]. As we see in the table, global COVID-19 cases cannot be explained by any other macroeconomic variables nor they are responsible for changes in these variables. This outcome supports the result of both our structural vector autoregressive (VAR) model and the impulse response function (IRF) results. Most of the factors (except COVID-19) can explain variations in the global stock markets. We can see that the crude oil market, the gold market, and the global stock returns are interrelated. Global COVID-19 cases are predominantly determined by its own shocks. The U.S industrial production index seems to play a relatively important role in explaining variations of the global stock markets comparing to the price of gold and the price of oil. In particular, the U.S industrial production index, the price of crude oil, and the price of gold

[11] Since we use daily observations, one step is one day.

[12]Because their shocks have an influence that is higher than 5%.

account for approximately 22.64%, 9.5%, and 13.74% of the variations in global stock returns, respectively. Interestingly, global COVID-19 cases can explain about 6.022% of the variance of the U.S. industrial production index of the 30-day ahead forecast error. This means that global COVID-19 cases do affect the real economy with a lag of thirty days.

CONCLUSION

This paper attempts to empirically investigate the interconnections between global COVID-19 cases, the gold market, the crude oil market, the global stock market, and the overall economy using daily observations of worldwide daily COVID-19 cases, the price of gold, the price of crude oil, the FTSE-All World stock market index, and the U.S industrial production index,. We construct a structural vector autoregressive (SVAR) model and apply orthogonalized impulse response (IRF) analysis (IRF), Granger-causality tests, and forecast error variance decomposition (FEVD) to examine the dynamic effects among these variables. Our results show that none of the variables are Granger- caused by COVID-19, whereas the U.S industrial production index Granger- causes global stock returns as well as the oil market in a one-way direction. Commodities and the global stock market Granger cause each other in both directions. The U.S industrial production index, the price of gold, the price of oil, and the world stock market are the most relevant variables in terms of interrelation among themselves. The U.S industrial production affects both the oil market and stock markets. In particular, it affects the oil market temporarily in the immediate short run and has a sustained effect on the global stock markets for about six days. The U.S. industrial production index, the price of gold, the price of crude oil, and the real-world stock returns are the most relevant variables in terms of forecast error variance decomposition (FEVD). Specifically, the U.S industrial production index, the price of crude oil, and the price of gold account for approximately 22.64%, 9.5%, and 13.74% of the variations in global stock returns, respectively. COVID-19 cases only affect the real economy with a thirty-day lag.

Our study has its limitations. The COVID-19 pandemic is currently in progress, the available data about the ongoing pandemic can only provide limited information for a short-run window. The medium-run and long-run effects of coronavirus on the overall economy remain unclear. We plan to assess the medium-run and long-run impact of coronavirus on different economies and assets markets once the pandemic is over.

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APPENDIX

Appendix 1(A)**:** Autocorrelation Function (ACF) Results

D(COVID,2)

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.428	-0.428	43.714	0.000
		2	-0.034	-0.266	43.996	0.000
		3	-0.040	-0.227	44.378	0.000
		4	-0.220	-0.491	56.046	0.000
		5	0.549	0.259	129.26	0.000
		6	-0.275	0.068	147.66	0.000
		7	0.020	0.076	147.75	0.000
		8	-0.050	0.026	148.36	0.000
		9	-0.175	-0.122	155.97	0.000

D(IPI,2)

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.533	-0.533	62.333	0.000
		2	0.074	-0.294	63.552	0.000
		3	-0.037	-0.217	63.850	0.000
		4	0.004	-0.171	63.855	0.000
		5	0.008	-0.120	63.870	0.000
		6	0.000	-0.084	63.870	0.000
		7	-0.005	-0.067	63.875	0.000
		8	0.001	-0.052	63.875	0.000
		9	0.016	-0.011	63.937	0.000

D(Oil)

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.141	0.141	4.7661	0.029
		2	0.041	0.021	5.1620	0.076
		3	0.009	0.001	5.1823	0.159
		4	0.081	0.080	6.7790	0.148
		5	0.063	0.041	7.7368	0.171
		6	-0.043	-0.064	8.2007	0.224
		7	0.017	0.030	8.2712	0.309
		8	-0.073	-0.084	9.5878	0.295
		9	0.100	0.116	12.052	0.210

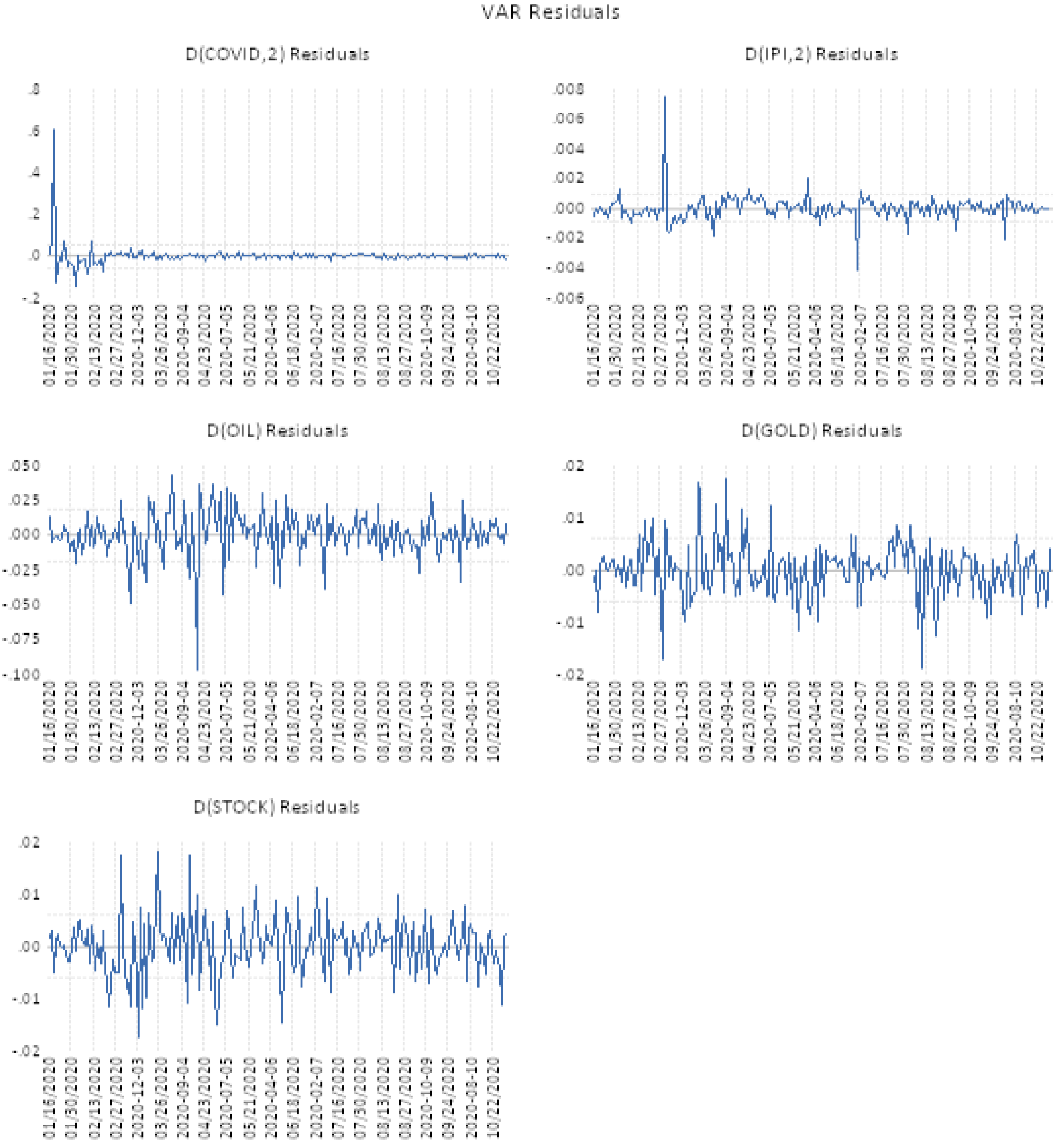
D(Gold)

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.018	-0.018	0.0819	0.775
		2	0.044	0.044	0.5541	0.758
		3	0.019	0.020	0.6373	0.888
		4	-0.113	-0.115	3.7535	0.440
		5	-0.098	-0.105	6.0892	0.298
		6	-0.175	-0.173	13.557	0.035
		7	-0.031	-0.031	13.797	0.055
		8	-0.033	-0.033	14.071	0.080
		9	0.107	0.096	16.912	0.050

D(Stock)

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.164	-0.164	6.4523	0.011
		2	0.288	0.268	26.404	0.000
		3	0.028	0.118	26.597	0.000
		4	-0.076	-0.150	27.988	0.000
		5	0.134	0.072	32.365	0.000
		6	-0.213	-0.141	43.470	0.000
		7	0.266	0.203	60.913	0.000
		8	-0.217	-0.108	72.565	0.000
		9	0.256	0.170	88.809	0.000

Appendix 1(B)**:** Residuals of the SVAR(9) model



Appendix 2: Serial Correlation Test Results

Null hypothesis: No serial correlation at lag h

Lag	LRE* stat	df	Prob.	Rao F-stat	df	Prob.
1	25.76424	25	0.4203	1.032902	(25, 569.9)	0.4205
2	28.68560	25	0.2773	1.152937	(25, 569.9)	0.2775
3	21.72784	25	0.6514	0.868041	(25, 569.9)	0.6516
4	17.00285	25	0.8817	0.676505	(25, 569.9)	0.8818
5	23.27571	25	0.5615	0.931127	(25, 569.9)	0.5617
6	17.88924	25	0.8471	0.712318	(25, 569.9)	0.8472
7	26.74083	25	0.3690	1.072962	(25, 569.9)	0.3692
8	11.86794	25	0.9876	0.470109	(25, 569.9)	0.9876
9	17.46777	25	0.8641	0.695283	(25, 569.9)	0.8642