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How COVID-19 drives connectedness among commodity and financial markets: Evidence from TVP-VAR and causality-in-quantiles techniques

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ABSTRACT

With many commodity and financial markets reportedly experiencing poor performances during this COVID-19 pandemic, this study intends to examine the effect of the pandemic on the connectedness among the markets. There are several reasons that suggest that apart from the pandemic affecting the performances of the markets, it can also be a driver of their connectedness, coming from the perspective of the global financial cycle channel. Therefore, we first employ the recently developed time-varying parameter vector autoregressions (TVP-VAR) technique to examine the volatility spillover among the commodity and financial assets. We find evidence of strong volatility across the markets, with gold and USD being net receivers of shocks, and others, net transmitters. With this evidence, we proceed to the evaluation of the influence of the COVID-19 pandemic on the connectedness across the markets using both the linear and non-linear (causality-in-quantiles) causality tests. The causality-in-quantiles test outperforms the linear Granger-causality test, and the results show significant causal impacts of the two measures of COVID-19 pandemic (infectious diseases-based equity market volatility and the growth rate of the U.S. COVID-19 reported cases) on the connectedness across the markets, especially at the lower and middle-level quantiles. Overall, these findings prove that the pandemic has been largely responsible for risks transmission across various commodity and financial markets. This is because it has significantly raised investors’ and policy uncertainties and immensely altered global financial cycle which in turn results in global flows of capital, and movements in the prices of assets across different financial markets.

1. Introduction

The growing level of global trade integration and the search for alternative investment assets in the face of market risks has seen the connectedness among global asset markets, particularly since the past few decades. In fact, more than ever before, the recent years have witnessed a high degree of causal relationships among commodity and financial markets, with risks and opportunities in one easily spilling over to others. Commodities are now increasingly being considered as significant components of investment portfolios for both portfolio managers and investors following the vulnerability of common financial markets (especially stock markets) to unfavourable shocks that lead to losses. Choi and Hammoudeh (2010) rightly infer that investors in commodity assets consistently track movements in the prices of commodities and stocks, certainly to make optimal investment choices. Thus, there is substitution mechanism among financial (stocks, and by extension other financial assets including cryptocurrencies, foreign exchanges, etc.) and commodity assets (oil, gold and other precious metals) following the viability of the latter as suitable assets for hedging and safe-haven purposes (Jain and Biswal, 2016).

The literature has revealed different channels through which commodity and financial markets relate. However, these channels largely explain the links among the markets mostly in split, implying that channels that connect all the markets together in one attempt are rare. The foremost seems to be the inflation mechanism which connects the oil market with the metals market. One of the major historic sources of market risks has been traced to inflation (see Rubens et al., 1989) through the business cycle. In the first instance, investors in the economy with high inflation caused by increase in oil price increase their demand for gold in order to serve as hedge against inflation (Jain and Biswal, 2016). On the other hand, due to the relative stability of the value of gold, oil exporting countries increase the proportion of gold in their external reserves portfolios as oil price and revenue increase (see Melvin and Sultan, 1990). As oil price rises due to any external factors, inflation also rises in many countries, and this is consequently followed by hike in the prices of metals. Another prominent channel takes its
stand from the unified currency measurement (U.S. dollar) of most globally traded assets. Assuming the dollar appreciates, the purchasing power of other countries other than the U.S. diminishes, thereby reducing their demand for all the assets denominated in this common currency. Hence, their prices jointly fall (see Adekoya and Oliyide, 2020). The interest rate channel explains how investors in stocks become discouraged when interest rate is low. This could make them consider other high interest-yielding assets in order to gain higher returns.

The last but not the least channel which appears to be the most all-encompassing as it brings more markets together is the macroeconomic factors-based channel. This is also the channel through which we derive the objective of this study. It explains that different global markets (oil, metals and financial) are connected via common economic factors, especially global economic events. Although earliest studies have connected the global markets through global economic activity especially for oil and metals markets since the commodities being traded in these markets are important industrial inputs (see Ahmadi et al., 2016; Reboredo, 2016), subsequent studies are now considering the role of global economic and equity market uncertainties that connect commodity and financial markets in entirety (see Albuclusc et al., 2019)

Against these highlighted mechanisms, the literature is now increasingly being flooded with studies that examine the relationship among oil, metals, stocks, cryptocurrencies and foreign exchange markets in different dimensions (see Singhal et al., 2019; Jain and Biswal, 2016; Akbar et al., 2019; Bedouli et al., 2019, etc.). However, connectedness among the global markets may not just occur unless it is driven by notable factors, particularly policy uncertainty. The pioneers of this theoretical stand (see Pastor and Veronesi, 2012; Gomes et al., 2012) argue that spillovers in returns and volatilities of financial markets can be driven by policy uncertainty via its influence on investment decisions and personal consumption. The recent study of Albuclusc et al. (2019) confirms this by proving that the connectedness between the oil and currency markets is mainly driven by policy-induced uncertainty.

Needless to say, empirical studies on the impact of policy uncertainty on the spillovers across commodity and financial markets are very scarce, as available ones have their focus limited to spillover analysis (see, for instance, Hussain et al., 2019; Malik and Umar, 2019; Jiang and Gu, 2016). What causes the spillover has remained understudied. Worse still, no study has linked such connectedness to the influence of health crisis and the uncertainty induced by such. This serves as the main thrust of this paper. In essence, this paper examines the impact of the current COVID-19 pandemic on the volatility connectedness among oil, gold, and financial (stock, bitcoin and exchange rate) markets.

Notably, the current COVID-19 pandemic has created a dent on the global economy more than what is historically known of past crises, including the Spanish Flu pandemic of 1918 and the latest global financial crisis of 2008. To reveal its impact on global markets, Zhang et al. (2020) reveal that the pandemic has raised the volatility of, and inability to predict, stock markets, while Mhalla (2020) show that it has significant consequences on the global crude oil market. Also, it has resulted in the increased level of market fears and policy uncertainties. For instance, the infectious diseases-based equity market volatility index which measures the extent of investors fear due to the outbreak of notable infectious diseases records the highest value of 112.93 on March 15, 2020 as against the pre-COVID-19 maximum value of 36 on January 29, 2009. Other measures of uncertainties follow similar pattern. This is directly attributed to economic and market uncertainties and the triad of investors, consumers and corporate organizations. Individual investors and corporate firms could be discouraged from investing in new projects while consumers could be led to imbibing conservative spending habits (see Handley and Limao, 2015; Converse, 2017). Similarly, uncertainties raise investors’ sentiments which make them to want to shift attention from the most adversely affected markets to another for safety. An example is seen during this COVID-19 pandemic when investors began to offer their stocks for sale having been pessimistic of the short-run prospects of the stock markets (Salisu and Vo, 2020). This is probably in favour of other assets, hence the spillover across markets during this period. Lastly, if we rely on the global financial cycle channel, the pandemic has induced significantly high global uncertainty which has altered the global financial cycle by affecting capital flows, global credits and movements in assets prices. The eventual outcome of this is the transmission of risks among international markets.

In short, the gap this study covers is examining how COVID-19 drives the spillover connectedness among oil, gold and various financial markets. This is the first paper, to the best of our knowledge, to explore this. The other contribution is in terms of methodologies which are in two folds following the dual nature of this study’s objective. We first employ the time-varying parameter vector autoregressions (TVP-VAR) approach of Antonacci and Gabauer (2017) to explore the spillover connectedness across the markets unlike the dynamic connectedness methods of Diebold and Yilmaz (2009, 2012, 2014). The superiority of the TVP-VAR is that it avoids the problem of choosing the optimal size of rolling window, as well as the avoidance of the loss of observations during estimation. Secondly, we favour the use of the causality-in-quantiles test suggested by Balcilar et al. (2016) which is an improvement over the test of Jeong et al. (2012) to further evaluate the causal impact of the COVID-19 variable measures on the connectedness across the markets. Since financial and high frequencies series often exhibit nonlinearities, asymmetries, structural shifts and regime changes, linear models can produce spurious results due to functional misspecification and dependence of series.

The remainder of this paper has the following structure: the review of relevant studies is done in Section 2, while the methodologies are developed in Section 3. Section 4 is meant for the discussion of the estimated results. We provide the conclusion in Section 5.

2. Literature review

The linkages among different markets have been extensively analyzed in extant literature. However, the studies are largely in parts, with the important role of oil market in influencing other markets appearing to dominate. Major researchers unravel that stock markets can be influenced directly or indirectly by oil shocks (see Broadstock and Filis, 2014; Arouiri et al., 2011a). The direct link relates to oil price shocks influencing the current and future cash flows, while the indirect link relates to the influence oil shocks have on interest rates that is often used to influence future cash flows (see Arouiri et al., 2011a; Jones and Kaul, 1996). In another way, the exclusive relationship between stock and oil markets has also been recently modelled through financialization (see Zhang, 2017, 2018; Peng et al., 2018). Thus, the increased financialization process has also strengthened the inter-connectedness between oil and stock markets (see Menst et al., 2017).

On the issue of spillover, there has been a high evidence of the presence of spillovers between oil and stock markets. Different studies analyze the spillovers between these markets while noting the level of stock aggregation (see Basheer et al., 2018; Zhang, 2017; Maghyereh

\footnote{This direct and indirect relationship has been established by many studies. For instance, the works of Arouiri et al., 2011 and Basheer et al. (2018) note that in the long run, stock prices should equal the summation of discounted values of expected future cash flows at different investment periods. Evidently, oil is one of the major factor inputs in the production of goods and services, thus in a way, its price changes can directly influence firms’ future cash flow (Huang et al., 1996; Jones and Kaul, 1996). Also, the discount rate which encompasses the expected inflation and real interest rate is also affected by oil price fluctuations (see Jones and Kaul, 1996).

\footnote{The work of Zhang (2017) note that studies has increasingly linked oil price changes to stock markets since the 2008 financial crisis. Importantly, the rising number of oil-related financial derivatives has also increased faster the process of financialization in the oil market (See Ji and Zhang, 2013; Ma et al., 2019).}
et al., 2016; Phan et al., 2016; Bouri, 2015 for aggregate stock market level; Narayan and Sharma, 2011; Tiwari et al., 2018; Hamdi et al., 2019; Aroui et al., 2012; Fang and Egan, 2018 for sectoral/industrial stock level; Antonakakis et al., 2018; Peng et al., 2018; Broadstock et al., 2016 for firm level). For instance, through the use of the generalized VAR-GARCH model, Aroui et al. (2011b) note the existence of return and volatility spillovers between oil and stock markets in the Gulf Cooperation Council (GCC) countries. Awatani and Maghyereh (2013) use the Diebold and Yilmaz (2014) technique to unravel the presence of bi-directional spillovers between oil and stock markets in GCC countries. Although, their findings reveal that there is large transmission of form oil markets to equities market, Zhang (2017) shows that a contrast link exists after the global financial crisis of 2008. Basheer et al. (2018) utilize a structural VAR model to unravel that the oil market transmits shocks to the stock returns of major oil exporting countries. Relating to the oil and stock markets relationship at the sectoral/industrial level, Fang and Egan (2018), while considering the oil and stock markets nexus for China, show that shocks spillover from oil to stock market differs across sectors. They further suggest that information at the sectoral-level should not be neglected while analyzing the spillovers between these two markets (see also Ma et al., 2019; Broadstock and Filis, 2014; Zhang and Can, 2013; Degiannakis et al., 2013; Narayan and Sharma, 2011). Through the use of quantile-on-quantile Granger causality test, Peng et al. (2018) analyze the nexus between oil and stock markets at firm level. Their study credits the importance of accounting for stock at firm level. They find that there is extreme risk from oil price shocks to firm returns. However, Mohanty et al. (2010) note that there is no significant relationship between oil and stock prices of oil and gas companies in five Central and Eastern Europe.

Also, oil has been linked with gold (Aguilera and Radetzki, 2017; Reboredo, 2013; Wang and Chueh, 2013; Zhang and Wei, 2010) and industrial metals (see Adekoya and Oluyide, 2020). For example, Wang and Chueh (2013) note that oil and gold nexus follows a mixed relationship in the long run, but only a positive relationship experienced in the short run. They further indicate that both gold and oil have been serving as prime benchmarks in the international market (see also Beckmann and Czudaj, 2013a, 2013b; Zhang and Wei, 2010). Gokmenoglu and Fazlollahi, 2015 disclose that movement in oil price augments inflation and price of gold. Also, a good number of studies have shown that gold price can be explained from the fluctuations in oil prices (Beckmann and Czudaj, 2013a, 2013b; Soucek, 2013; Wang and Chueh, 2013; Narayan et al., 2010; Le and Chang, 2012; inter alia). Furthermore, since the advent of the financial crisis of 2008, studies have emanated to determine whether investors can find succor in gold against oil price risks. However, most of these studies are unable to establish evidence in favour of the hedging ability of gold (see Reboredo, 2013; Rehm et al., 2018; Saliu and Adeghan, 2020).

In another regards, oil has been connected with currency markets. One can relate the linkages between these markets through the portfolio and wealth channel (see Bénassy-Quéré et al., 2007; Buechter et al., 2012; Coudert et al., 2008; Ding and Vo, 2012; Fedoseeva, 2018; Volkov and Yuh, 2016), and the terms of trade channel (see Amano and Van Norden, 1998a, 1998b; Chen and Chen, 2007; Huang and Guo, 2007; Lizardo and Mollick, 2010). Beckmann and Czudaj (2013b) and Zhang et al. (2008) document the evidence for risk and return spillovers from US dollar to international oil prices. However, recent studies of Brahmasrene et al. (2014), Uddin et al. (2013), Tiwari et al. (2013a, 2013b), among others, reveal that the relationship is bidirectional. Wang and Wu (2012) through the use of vector error correction and Markov-switching frameworks observe that a unidirectional causality runs from oil prices to US dollar, while the study of Beckmann and Czudaj (2013a) shows a reversal.

After the global financial crisis of 2008, there has been a debate as regards the hedging ability of bitcoin, its diversification importance, safe haven features and characteristics as a currency or a commodity (see Guensi et al., 2019; Pieters and Vivanco, 2017; Katsiampa, 2017; Cheah and Fry, 2015; Dyhrberg, 2016a, 2016b). For instance, Dyhrberg (2016a) enquire into the nature of the relation between bitcoin, stock index, US/EUR and USD/GBP exchange rates. The study unravels that bitcoin exhibits similar returns with gold and US dollar. This is also corroborated by the findings of Dyhrberg (2016b) which disclose that bitcoin offers hedging and safe haven opportunities just like gold, and can be categorized just as US dollar and gold. However, Baur et al. (2018) establish contrasting results to the findings of Dyhrberg (2016a, b). They prove that bitcoin has extremely different features when compared with gold and US stock.

Following the increasing level of integration among international markets, the recent strand of literature is evaluating the interaction among several markets at a time. For instance, Gajardo et al. (2018) employ the MF-ADCCS to analyze the existence of cross-correlation among gold price, oil market, bitcoin, exchange rates and the DJIA. The results from their study show differences between bitcoin’s relationship with stock markets, and its relationship with commodities. Relating to the spillover between bitcoin and other markets, Symitsi and Chalvatzis (2018) indicate that there are significant return spillovers from technology and energy stocks to bitcoin. Through the use of DCC-GARCH models, Guensi et al. (2019) analyze volatility spillover and conditional cross effects between bitcoin and financial assets. Their findings show that the inclusion of bitcoin among hedging strategies that comprise gold, oil and emerging stocks reduce portfolio risks considerably compared to the one without them. In contrast, Trabelsi (2018) adopts the generalized forecast error variance decomposition methodology of Diebold and Yilmaz (2012) and Barunik and Krehlik, 2018 to analyze the volatility spillover among cryptocurrencies and widely traded assets. The study finds no significant evidence for spillover between cryptocurrencies and other assets classes. On the other hand, Bouri et al. (2018) adopt the VAR-GARCH-in-mean model to explore the return and volatility spillovers among bitcoin, commodities, equities, currencies and bond. Evidence is found for bitcoin being a receiver of more shocks than it transmits to other markets.

2.1. Connection of uncertainty with commodity and financial markets

Very recent years have seen to the increased concern about uncertainty and how it affects economic indicators. This has attracted a handful of studies on the impact of various forms of uncertainty on economic activities and different markets (see Converse, 2017; Rodrik, 1991; Handley and Limao, 2015, etc.). For instance, Pástor and Veronesi (2012) use the political uncertainty to establish a negative influence of uncertainty on stock markets. Corroboratively, studies including You et al. (2017), Liu et al. (2017), Aroui et al. (2016), Aroui and Roubaud (2016), Chang et al. (2015) confirm that uncertainty negatively influences stock market returns, and further contributes to stock market volatility. Apart from stock market performances, other studies have also focused on the commodity and currency markets. Aloui et al., 2016 disclose that policy uncertainty is connected to oil prices during financial stress. However, Reboredo and Uddin (2016) find opposing evidence for causal relationship between policy uncertainty and commodity market. For the currency market, Han et al. (2019), using quantile-on-quantile approach, confirm the presence of state-dependent spillover effects of uncertainty.

From the foregoing, it is obviously seen that numerous studies have been conducted on the interactions among commodity and financial markets, at least in part, and the literature is now witnessing increasing consideration of the effect of uncertainty on the performances of these

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3 The portfolio channel relates the benefits (that is, wealth transfer) oil exporting countries gain from a rise in the oil price. This channel relates the nominal exchange rate to the current oil prices. The terms of trade channel relate oil prices to fluctuations in real exchange rate through its pertinent effect on the terms of trade.
markets. However, how uncertainty drives the connectedness among the commodity and financial markets remains exclusively understudied. Meanwhile, in line with the global financial cycle channel, uncertainty can affect the capital flows, global credits and asset prices, thereby leading to significant risks transmission among international markets. The recent work of Albuvescu et al. (2019) seems to be notable in this move as it considers and confirms the impact of the U.S. economic policy uncertainty on the interactions among oil and commodity currencies.

However, Rather than economic policy uncertainty, this study focuses on the role of COVID-19 pandemic, measured through the infectious diseases-based equity market volatility and the growth rate of the U.S. COVID-19 reported cases. Uncertainty seems to loom more in the period of crisis. With the current pandemic, the high nature of market volatility, significant oil price fall and the instability of markets are definitely not palatable for governments, investors and investment analysts. Among major happenings, Baker et al. (2020) indicate that the period of crisis. With the current pandemic, the high nature of market

coutes on the role of COVID-19 pandemic, measured through the infection

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3. Methodology

3.1. Time-varying parameter vector autoregressions (TVP-VAR)

We take a step towards achieving the first objective of this study by adopting the TVP-VAR methodology of Antonakakis and Gabauer (2017) which extends the extensive works of the originally proposed dynamic connectedness by Diebold and Yilmaz (2009, 2012, 2014). Antonakakis et al. (2020) disclose two main merits of this technique. First, it helps to overcome the challenge of arbitrarily choosing the optimal rolling-window size. Second, it circumvents the problem of loss of valuable observations, thus making it suitable for short sample also. By adopting this method therefore, we allow the variance to vary through a Kalman Filter estimation with forgetting factors. To start with, the TVP-VAR model is specified as

\[ y_t = \mu + \mu_t \rho_{t-1} + \epsilon_t \sim N(0, \tau) \]

(1)

\[ vec(C_t) = vec(C_{t-1}) + \rho_{t-1} \epsilon_{t-1} \sim N(0, \epsilon_t) \]

(2)

with

\[ V_{t-1} = \begin{pmatrix} y_{t-1} \\ y_{t-2} \\ \vdots \\ y_{t-p} \end{pmatrix} \text{ and } C_t = \begin{pmatrix} C_{01} \\ C_{10} \\ \vdots \\ C_{0p} \end{pmatrix} \]

where \( y_t \) and \( V_{t-1} \) represent \( n \times 1 \) and \( np \times 1 \) vectors respectively, \( \rho_{t-1} \) depicts all the information available until \( t - 1 \). \( C_t \) and \( C_u \) are \( n \times np \) and \( n \times n \) dimensional matrices respectively. As regards the error term, \( \mu_t \) is an \( n \times 1 \) vector, while \( \gamma_t \) is an \( np \times 1 \) dimension vector. The time varying variance-covariance matrices, \( \tau_t \) and \( \epsilon_t \), are \( n \times n \) and \( np \times np \) dimensional matrices respectively. However, the vectorization of \( C_t \) as depicted by \( vec(C_t) \) is an \( n \times 1 \) dimensional vector.

To further calculate the generalized impulse response functions (GIRF) and generalized forecast error variance decompositions (GFEVD) which are pertinent in estimating the dynamic connectedness, as is the case with the approach of Diebold and Yilmaz (2014), we transform the TVP-VAR to its vector moving average (VMA) representation based on the Wold theorem as specified in Eqs. (3)–(6):

\[ y_t = K (N_t y_{t-1} + \phi_1) \]

(3)

\[ = K (N_t (N_t y_{t-2} + \phi_2) + \phi_1) \]

(4)

\[ \vdots \]

(5)

\[ = K^{N_t} (N_t^{N_t} y_{t-N_t} + \sum_{j=0}^{N_t} N_t^j \phi_j) \]

(6)

where \( N_t \) is an \( n \times np \times 1 \) and \( np \times n \) dimensional matrices. By taking the limit of Eq. (6) as \( k \) tends to \( \infty \), we get:

\[ y_t = \lim_{t \to \infty} K (N_t^{N_t} y_{t-N_t} + \sum_{j=0}^{N_t} N_t^j \phi_j) = \sum_{j=0}^{\infty} K^j N_t^j \phi_j \]

(7)

such that it follows directly

\[ y_t = \sum_{j=0}^{\infty} K^j N_t^j \phi_j \]

(8)

where \( A_{H} \) represents an \( n \times n \) matrix.

The GIRFs (\( \omega_{ij}(H) \)) term defines the responses of all variables \( j \) to a shock in variable \( i \). Due to the absence of a structural model, the differences between an \( H \)-step-ahead forecast are computed, for where variable \( i \) is shocked and another where variable \( i \) is not shocked. This difference can be regarded to be due to shock in variable \( i \), which is consequently computed by:

\[ GIRF(H, \theta_i, \rho_{-1}) = E(\hat{y}_{i,k} | d_j = \theta_j, \rho_{-1}) - E(\hat{y}_{i,k} | \rho_{-1}) \]

(10)

\[ \omega_{ij}(H) = \frac{A_{ij}}{\sqrt{\sum_{i=1}^{n} d_{ij}}} \frac{\theta_j}{\sqrt{\sum_{j=1}^{n} d_{ij}}} = \sqrt{\sum_{i=1}^{n} d_{ij}} \]

(11)

\[ \omega_{ij}(H) = \sum_{j=1}^{n} A_{ij} \sum_{i=1}^{n} d_{ij} \]

(12)

where \( d_j \) is an \( n \times 1 \) selection vector with \( 1 \) in the \( j \)th position, and zero otherwise. Also, we compute the GFEVD(\( \hat{\theta}_{ij}(H) \)), which is the pairwise directional connectedness from \( j \) to \( i \) and further demonstrates the influence variable \( i \) has on variable \( j \) in terms of its forecast variance share. However, the variance shares are then normalized by summing up all rows to one. This depicts that all variables together explain 100% of variable \( i \)’s forecast error variance. The GFEVD is calculated as follows:

\[ \hat{\theta}_{ij}(H) = \frac{\sum_{j=1}^{n} w_{ij}(H)}{\sum_{j=1}^{n} \sum_{j=1}^{n} w_{ij}(H)} = n. \]

(13)

where \( \sum_{j=1}^{n} \hat{\theta}_{ij}(H) = 1 \) and \( \sum_{j=1}^{n} \hat{\theta}_{ij}(H) = n. \) Also, the numerator term de-
notes the cumulative effect of a shock in variable \( i \), while the denomi-
nator term represents the cumulative effect of all the shocks. Thereafter, we compute the total connectedness index through the use of the GFEVD thus:

\[
T_i(H) = \frac{\sum_{j=1}^{n} \tilde{\theta}_{ij}(H) \ast 100}{\sum_{j=1}^{n} \tilde{\theta}_{ji}(H) \ast 100} \tag{14}
\]

The connectedness approach in Eq. (14) generally shows how a shock in one variable spills over to other variables under investigation. However, to further analyze the directional connectedness, the method under consideration divides it into three: total directional connectedness to others; total directional connectedness from others; and net total directional connectedness.

First, the total directional connectedness to others as shown in Eq. (15) analyses a situation where variable \( i \) transmits its shocks to all other variables \( j \).

\[
T_{ij}(H) = \frac{\sum_{j=1}^{n} \tilde{\theta}_{ij}(H) \ast 100}{\sum_{j=1}^{n} \tilde{\theta}_{ji}(H) \ast 100} \tag{15}
\]

Second, we account for the shocks variable \( i \) receives from other variables \( j \) in Eq. (16). That is, the directional connectedness from others:

\[
T_{ji}(H) = \frac{\sum_{j=1}^{n} \tilde{\theta}_{ij}(H) \ast 100}{\sum_{j=1}^{n} \tilde{\theta}_{ji}(H) \ast 100} \tag{16}
\]

Lastly, we subtract Eq. (16) from (15) to derive the net total directional connectedness. In other words, to obtain the net total directional connectedness, we subtract the total directional connectedness from others to the total directional connectedness to others.

\[
T_{ij}.T_{ji}(H) = T_{ij}(H) - T_{ji}(H) \tag{17}
\]

Intuitively, Eq. (17) can be interpreted as the influence variable \( i \) has on the analyzed network. Thus, a positive \( T_{ij} \) means that variable \( i \) influences the network more than itself being influenced, while a negative \( T_{ij} \) means that variable \( i \) is driven by the network.

Finally, we dissect the net total directional connectedness to further examine the bidirectional relationships by computing the net pairwise directional connectedness (NPDC) as shown in Eq. (18).

\[
NPDC_{ij}(H) = \left( \tilde{\theta}_{ij}(H) - \tilde{\theta}_{ji}(H) \right) \ast 100 \tag{18}
\]

If \( NPDC_{ij}(H) < 0 \), it implies that variable \( i \) is dominated by variable \( j \). However, if \( NPDC_{ij}(H) > 0 \), then variable \( i \) dominates variable \( j \).

### 3.2. Causality tests

After the derivation of the total and the net spillovers through the use of the TVP-VAR, we proceed to the second phase of our analyses. Here, we examine the causal effect of the current COVID-19 pandemic (proxied by the equity market volatility due to infectious diseases and the growth rate of the U.S. COVID-19 reported cases) on the connectedness across the oil, gold, bitcoin, stock and USD (measured through the volatility spillover series). To achieve this, we adopt the linear causality test of Granger (1969) and the non-linear causality (causality-in-quantiles) test of Jeong et al., 2012 which was later improved by Balclir et al. (2016).

Starting with the linear causality test, it analyzes the relationship between two variables at a time, where \( y_t \) is the dependent variable and \( x_t \) is the independent variable, which in this study are the proxies for the connectedness across the assets and the COVID-19 measures. The VAR model is specified thus:

\[
y_t = \alpha + \sum_{p=1}^{k} \beta_{p} x_{t-p} + \sum_{q=1}^{l} \theta_{q} y_{t-q} + \mu_t \tag{19}
\]

\[x_t = \theta + \sum_{p=1}^{k} \tau_{p} x_{t-p} + \sum_{q=1}^{l} \pi_{q} y_{t-q} + \epsilon_t \tag{20}\]

where \( \mu_t \) and \( \epsilon_t \) are error terms which are uncorrelated. Granger (1969) shows that Granger-causes \( y_t \) if the lagvalues of \( x_t \) can predict the current value of \( y_t \).

However, financial and high frequency series have often been fraught with nonlinearity, structural shifts and regime changes. Due to the presence of these undesirable statistical features, there have been a quite number on non-linear causality techniques. Among other options, we adopt the causality-in-quantiles test of Jeong et al., 2012 due to two pertinent reasons. First, its robustness to functional misspecification error and ability to detect general dependence between time series makes the technique unique. Second, the test does not only test for causality in the mean, but also causality that may exist in the tail area of the joint distribution of the series.

In the spirit of Jeong et al., 2012, \( x_t \) does not cause \( y_t \) in the \( \rho \)-quantile with respect to the lag-vector of \( \{ y_{t-1}, \ldots, y_{t-p}, x_{t-1}, \ldots, x_{p} \} \) if:

\[Q_{\rho} \{ y_{t}, y_{t-1}, \ldots, y_{t-p}, x_{t}, \ldots, x_{p} \} = Q_{\rho} \{ y_{t}, y_{t-1}, \ldots, y_{t-p} \} \tag{21}\]

Thus, \( x_t \) is a prima facie cause of \( y_t \) in the \( \rho \)-th quantile of \( y_t \) depending on \( t \) and, \( 0 < \rho < 1 \).

Also, assuming \( R_{t-1} \equiv \{ y_{t-1}, \ldots, y_{t-p}, x_{t-1}, \ldots, x_{t-p} \} \), \( U_{t-1} \equiv \{ y_{t-1}, \ldots, y_{t-p}, x_{t-1}, \ldots, x_{t-p} \} \), and \( V_{y|S_{-1}}(y_t, R_{t-1}) \) denote the conditional distribution function of \( y_t \) given \( S_{-1} \) and \( R_{-1} \) respectively. Based on the assumption \( V_{y|S_{-1}}(y_t, R_{t-1}) \), the conditional distribution is absolutely continuous in \( y_t \) for almost all \( S_{-1} \). Denoting \( Q_{S_{-1}}(y_{t}) \) and \( Q_{R_{-1}}(y_{t}) \equiv Q_{y|S_{-1}} \) will then transform to having \( V_{y|S_{-1}}(y_t, Q_{S_{-1}}(y_{t})) = \rho \) with a probability of one.

Therefore, we test for the null and alternative hypotheses of Eqs. (21) and (22) as defined in Eqs. (23) and (24).

\[H_0 = P \{ V_{y|S_{-1}}(Q_{R_{-1}}) | S_{-1} \} = \rho \} < 1 \tag{23}\]

\[H_1 = P \{ V_{y|S_{-1}}(Q_{R_{-1}}) | S_{-1} \} > \rho \} < 1 \tag{24}\]

To consistently test for the null hypothesis as specified in Eq. (23), Jeong et al., 2012 specify the distance measure as follows:

\[K = E \left[ \left| V_{y|S_{-1}}(Q_{R_{-1}}) | S_{-1} \right| - \rho \right] \right] \tag{25}\]

Importantly, the condition of \( K = 0 \) only holds if the null hypothesis as specified in Eq. (23) is true, while \( K > 0 \) holds if the alternative hypothesis is true (Eq. (24)). To proceed, Jeong et al., 2012 note that the feasible kernel-based test statistic for \( K \) can be specified thus:

\[
\hat{K}_T = \frac{1}{T (1 - \frac{1}{p + 1})^2} \sum_{p=1}^{P} \sum_{q=1}^{Q} \left( \frac{S_{-q} - S_{-q}}{r} \right) \tilde{\mu}_q \tag{26}\]

where \( J(\cdot) \) is the kernel function with bandwidth \( \tau \), while \( T, \hat{\mu}_q \) sample size, lag-order and the estimate of the unknown regression error. The regression error is specified below:

\[\hat{\mu}_q = 1 \left\{ y_t \leq Q_{y|S_{-1}}(\rho) \right\} \tag{27}\]

Also, we proceed with Jeong et al., 2012 methodology by estimating the parameter of the \( \rho \)th conditional quantile of \( y_t \) given \( R_{t-1} \) through the non-parametric kernel method as:

\[\hat{Q}_{\rho}(R_{t-1}) = \hat{V}_{y|S_{-1}}^{-1}(\rho | R_{t-1}) \tag{28}\]
where the Nadarya-Watson kernel estimator is given by:

\[
\hat{V}_{\tau}(R_{t}, y_{t}) = \frac{\sum_{\tau=p-1}^{p} W(\frac{(R_{t, \tau} - R_{\tau})}{r}) I\{R_{t, \tau} \leq R_{\tau}\}}{\sum_{\tau=p-1}^{p} W(\frac{(R_{t, \tau} - R_{\tau})}{r})},
\]

(29)

where the kernel function in this case is \(W(\cdot)\) and \(r\) is the bandwidth.

Later, Balcilar et al. (2016) extend the framework of Jeong et al., 2012 by developing a test for the second moment. Therefore, they adopt the nonparametric Granger-quantile-causality approach by Nishiyama et al. (2011). To illustrate the causality in higher order moment, we assume:

\[
y_{t} = h(R_{t, 1}) + \tau(U_{t, 1})\mu_{t},
\]

(30)

where \(y_{t}\) is the white noise process, and \(h(\cdot)\) and \(\tau(\cdot)\) are equal to the unknown functions that fulfill the stationarity condition. Although, this specification does not allow Granger-type causality testing from \(U_{t, 1}\) to \(y_{t}\), however, it could detect the “predictive power” from \(U_{t, 1}\) to \(y_{t}^{2}\) when \(\tau(\cdot)\) is a general nonlinear function. We further reformulate Eq. (30) to account for the null and alternative hypotheses for causality in variance in Eqs. (21) and (22), respectively:

\[
H_{0} = P\left\{ V_{\tau}\{Q_{\tau}(R_{t, 1}|S_{t-1}) = \rho \} = 1 \right\},
\]

(31)

\[
H_{1} = P\left\{ V_{\tau}\{Q_{\tau}(R_{t, 1}|S_{t-1}) = \rho \} < 1 \right\},
\]

(32)

We obtain the feasible test statistic for the testing of the null hypothesis in Eq. (31), and then replace \(y_{t}\) in Eq. (27) – (29) with \(y_{t}^{2}\) (that is, volatility). Unlike the approach of Jeong et al., 2012, we overcome the issue that causality in mean implies causality in variance. More specifically, we can interpret the causality in higher order moments through the use of the following model:

\[
y_{t} = h(U_{t, 1}, R_{t, 1}) + \mu_{t},
\]

(33)

Thus, we specify the higher order quantile causality as:

\[
H_{0} = P\left\{ V_{\tau\{Q_{\tau}(R_{t, 1}|S_{t-1}) = \rho \} = 1 \right\}, \quad \text{for } k = 1, 2, \ldots, k,
\]

(34)

\[
H_{1} = P\left\{ V_{\tau\{Q_{\tau}(R_{t, 1}|S_{t-1}) = \rho \} < 1 \right\}, \quad \text{for } k = 1, 2, \ldots, k
\]

(35)

We test that \(x_{t}\) Granger-causes \(y_{t}\) in \(m\)th quantile up to the K-th moment by using Eq. (34) to construct the test statistic of Eq. (26) for each \(k\). Although, Nishiyama et al. (2011) note that combining different statistics for each \(k = 1, 2, \ldots, K\) into one statistic for the joint null in Eq. (34) which is mutually correlated appears not to be easy, circumventing this issue requires the adoption of a sequential-testing method described by Nishiyama et al. (2011) with some modifications. We start by testing for the nonparametric Granger-causality in mean (\(k = 1\)). Failure to reject the null hypothesis of \(k = 1\) does not translate into non-causality in variance. Therefore, we construct the tests for \(k = 2\). We select the bandwidth by employing least squares validation technique and then employ the Gaussian kernels for \(J(\cdot)\) and \(W(\cdot)\).

### 4. Discussion of empirical results

#### 4.1. Preliminary analyses

We begin by briefly indicating the nature and sources of the data used. The data obtained for analysis in this study are the various financial and commodity markets series including dollar exchange rate, prices of gold, crude oil, S&P 500 stock and bitcoin, and the COVID-19 proxies which are the equity market volatility due to infectious diseases index and the U.S. COVID-19 reported cases. Since our focus is on the COVID-19 period, the data are on daily frequency from January 21, 2020 to July 2, 2020 so that enough observations are generated. Prices of bitcoin and the U.S. COVID-19 reported cases are respectively sourced from coinmarketcap.com and the website of the Centres for Disease Control and Prevention (covid.cdc.gov), while the remaining data are obtained from Federal Reserve Economic Database (fred.stlouisfed.org).

We provide first-hand information on the descriptive and distribution properties of these series or their transformed values in order to keep up with standard practice in the empirical literature. As observed from Table 1, only oil and stock report average negative returns during the period of global pandemic among all the assets under consideration. Bitcoin, gold and USD show positive returns with the highest reported for gold (0.122%), suggesting that investors in these three markets are likely to enjoy positive gains. This is unlike the evidence of loss associated with the oil and stock markets. Of course, the reasons for these results are not far-fetched. The global crude oil and stock markets are more flexible and sensitive to shocks from whatever source. This is due to their strong connection with the macroeconomy. For instance, crude oil is a crucial input into production processes (see Adeloye and Adebiyi, 2019) such that significant alteration to industrial and commercial activities affects its demand, thus lowering its price. This is true of most economies of the world during the current COVID-19 pandemic that results into the shut-down of most firms and the paralysis of economic activities. Consequently, price of oil significantly fell following a fall in its demand. Whatever creates fear or uncertainty in investors has the tendency of adversely affecting the performance of the stock markets. The pandemic has raised investors’ sentiments so high that it is regarded as the crisis with the greatest impact on stock markets (see Baker et al., 2020). On the other hand, others report positive average returns due to their nature. Bitcoin is not physically traded as it is an electronic asset whose trade is not easily impaired. Although gold is a physical asset, it has a very high intrinsic value and has enjoyed stability over time as a good store of value (see Adeloye and Oliyide, 2020). This has made it to even be a suitable hedge against oil and stock markets risks during this period.

All the returns series, except USD, are also seen to be highly volatile judging from the values of the standard deviation. Oil is associated with the highest degree of variability, followed by bitcoin and then stock. Concerning their distribution, they are all negatively skewed, coupled with excess kurtosis. It is thus not surprising why the Jarque-Bera test rejects the null hypothesis of normal distribution for all of them.

Turning to the health indicators, the extent to which the COVID-19 pandemic hits financial markets and even the so-called advanced countries is seen in the high mean values of the equity market volatility.

### Table 1
Descriptive statistics.

| Asset returns | Health indicators |
|---------------|-------------------|
|               | Average          | SD    | Mean | Std. Dev. | Skewness | Kurtosis | Mean | Std. Dev. | J-Q/S-EMV |
| Bitcoin       | 0.047            | 0.122 | 0.303 | 0.039     | 0.0124    | 13.337   | 3.385 | 0.462     | 4.496     |
| Gold          | 0.263            | 0.330 | 0.253 | 0.150     | 0.0124    | 13.337   | 3.385 | 0.462     | 3.150     |
| Oil           | 0.147            | 0.400 | 0.253 | 0.263     | 0.0124    | 13.337   | 3.385 | 0.462     | 4.496     |
| Stock         | 0.694            | 0.454 | 0.253 | 0.263     | 0.0124    | 13.337   | 3.385 | 0.462     | 4.496     |
| USD           | 0.122            | 0.330 | 0.253 | 0.150     | 0.0124    | 13.337   | 3.385 | 0.462     | 4.496     |

Value in bold suggests the non-rejection of the null hypothesis of normal distribution.
due to infectious diseases (EMV-ID) and the growth rate of COVID-19 reported cases in the U.S. While the average infectious diseases-based uncertainty in the equity market is 24.698, the reported cases of COVID-19 pandemic grow at a daily average of 13.337%. These measures are also followed by high variability. However, while the growth rate of COVID-19 is far from being normally distributed having shown high skewness and kurtosis estimates, the Jarque-Bera test discloses ID-EMV as being normally distributed as also reflected in its fair skewness and kurtosis values.

These descriptive statistics offer basic insights that are worth pointing out as we proceed in the analysis. The first is that the positive returns of some of the assets and the negative returns of the others may suggest the likelihood of give-and-take nexus among them. In other words, as we would find out in the next section, it is most likely that there is significant volatility spillovers and connectedness among the assets. Secondly, both the asset returns and the health-based factors demonstrate high degree of volatility. This suggests that the latter, especially the infectious diseases-based equity market volatility, may be responsible for any inherent volatility spillovers among the former. It is thus necessary to examine the possibility of the COVID-19 health indicators to cause the connectedness among the assets. Lastly, with the series being largely non-normally distributed, coupled with negative/positive skewness and high kurtosis values, it shows that they are heavily tailed either to the right or left, and have excess kurtosis. What this merely indicates is the likelihood of nonlinearity, structural breaks and regime changes in the series. Hence, applying linear models which are basically known for constant parameter estimation would yield results devoid of originality and reliability for appropriate policy formulation and investment decisions. This therefore informs our proposed causality-in-quantiles test which accounts for all the above highlighted features.

4.2. Spillover results

We are more concerned in this study with how the volatility spillovers across the commodity and financial markets are affected by the considered COVID-19 health indicators rather than the individual returns of the assets. Therefore, it becomes necessary to first estimate the volatility spillovers among the assets. The estimates of the spillover analysis are presented in Table 2. Three things matter in the results, which are the unidirectional spillovers, the total spillover from and to a particular asset, and the net directional spillovers for individual asset. The net directional spillover is obtained by subtracting the total contributions received by an asset from others from the total contributions it gives to others. This makes the asset in question to be a net transmitter of shocks if a positive net spillover value is obtained. Otherwise, it is a net shock receiver. Summarizing the results, it can be seen that there is a very strong spillover effect among the assets with all of them significantly giving and receiving. On average, stock and oil are the highest givers of shocks with values being 65.5% and 63.7% respectively, while gold is the least giver (32.9%). USD and bitcoin also give much with their individual values exceeding 50%. Interestingly, the assets that give less appear to be those that receive more. For instance, gold and USD receive more shocks from others (71.6% and 73.7% respectively), while oil receives the least (10.5%). Since all the assets transmit and receive, it is important to determine whether each of them receives more shocks or gives more, as revealed by the net spillover. Obviously, only gold and USD are net receivers of shocks, implying that they receive more than they transmit. The net spillover results in Table 2 are also consistent with the net spillover graphs in Fig. 2. These results strongly align with expectations, and they corroborate the descriptive results in Table 1 where it is shown that gold and USD/EUR have positive returns. Their relative stability during this period seems to be the reason why shocks from other assets move in their direction. Gold particularly stands as a good hedge against the risks from other markets for this time frame. On the other hand, oil and stock appear to be the most adversely affected as evidenced from their negative returns and empirical evidences. Investors in these markets are therefore giving attention to other assets.

Interestingly, our net spillover results largely contradict those of Hussain et al. (2019) despite using similar spillover framework. For instance, they establish that stock is neither a transmitter nor a net receiver of shocks, and that oil and gold are respectively net receiver and net transmitter. We can then argue that the current COVID-19 pandemic is responsible for the dynamic change in the connectedness among the

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5 Only the overall spillover and total net spillover graphs are reported due to space consideration.
financial markets. This is consistent with the total spillover graph in Fig. 1 where it is seen that the overall volatility spillover peaked during the months when the COVID-19 pandemic was really hitting hard on countries of the world, and newspapers reports gathered momentum. This further makes it imperative to examine if the connectedness among the assets is driven by the COVID-19 pandemic health indicators. Meanwhile, Hussain et al. (2019) argue that metals, oil and financial markets are functionally linked via diverse channels. Hence, financial market volatility can sweep into other connected markets via the business cycle (Wang and Chueh, 2013; Kearney and Lombra, 2009). With the current health pandemic having significantly altered business cycle, it is important to examine its effect on the connectedness across the markets. The next section addresses this.

### 4.3. Causality tests results

So far, we have observed very strong volatility connectedness across the commodity and financial markets with gold being the highest net
We proxy the COVID-19 pandemic with two indicators, namely equity market volatility due to infectious diseases (ID-EMV) and the growth rate of COVID-19 pandemic reported cases in the U.S. (COVID), and for which distinct results are reported. For robustness, the causality test reveals just fair evidence of causal relationship between the causality results are in three folds for each category of COVID-19 pandemic indicators: (i) effect of COVID-19 pandemic on the overall spillover; (ii) effect of COVID-19 pandemic on the total net spillover for each asset; and (iii) effect of COVID-19 pandemic on net pair-wise spillover.

We begin with the linear causality test results which are presented in Tables 3 and 4. When ID-EMV is made as the causal variable, Table 3 shows that the null hypothesis of Granger-non-causality cannot be rejected in a relatively large number of cases. The few rejections where rejection is found at either 5% or 10% significance levels are the overall spillover, net spillovers for bitcoin, gold and stock, and net pair-wise spillover between stock and gold, bitcoin and stock, and USD and stock. If we turn to Table 4 where COVID is the causal variable, the causal evidence is just about half of the cases, but those with significant estimates are quite different from when ID-EMV is the causal variable, especially for the net pair-wise spillovers. In this regards, spillover connections with oil find more significance (net spillover for oil, net pair-wise spillover between oil and each of gold, stock and USD) unlike

Table 5
BDS test results: ID-EMV as the causal variable.

| Spillover series                  | Dimension | 2     | 3    | 4     | 5     | 6     |
|----------------------------------|-----------|-------|------|-------|-------|-------|
| Overall spillover                 | 0.068***  | 0.125*** | 0.165*** | 0.181*** | 0.204*** |
| Net spillover for bitcoin         | 0.054***  | 0.118*** | 0.182*** | 0.227*** | 0.250*** |
| Net spillover for gold            | 0.081***  | 0.162*** | 0.218*** | 0.249*** | 0.271*** |
| Net spillover for oil             | 0.052***  | 0.125*** | 0.184*** | 0.218*** | 0.242*** |
| Net spillover for stock           | 0.058***  | 0.131*** | 0.192*** | 0.235*** | 0.257*** |
| Net spillover for USD             | 0.053***  | 0.139*** | 0.195*** | 0.223*** | 0.247*** |
| Net spillover between oil and bitcoin | 0.104*** | 0.173*** | 0.212*** | 0.227*** | 0.231*** |
| Net spillover between oil and gold | 0.071*** | 0.141*** | 0.185*** | 0.212*** | 0.219*** |
| Net spillover between oil and stock | 0.080*** | 0.157*** | 0.215*** | 0.248*** | 0.264*** |
| Net spillover between oil and USD | 0.053*** | 0.102*** | 0.146*** | 0.173*** | 0.190*** |
| Net spillover between stock and gold | 0.066*** | 0.128*** | 0.182*** | 0.209*** | 0.221*** |
| Net spillover between bitcoin and gold | 0.067*** | 0.135*** | 0.185*** | 0.230*** | 0.253*** |
| Net spillover between bitcoin and stock | -0.000 | -0.000 | -0.001 | -0.001 | -0.002 |
| Net spillover between bitcoin and USD | 0.053*** | 0.129*** | 0.174*** | 0.199*** | 0.217*** |
| Net spillover between USD and gold | 0.027**  | 0.081*** | 0.135*** | 0.172*** | 0.198*** |
| Net spillover between USD and stock | 0.037*** | 0.090*** | 0.128*** | 0.170*** | 0.195*** |

***Denotes the rejection of the null hypothesis of serial dependence, and therefore presence of nonlinearity, at 1% significance level.

Table 6
BDS test results: COVID as the causal variable.

| Spillover series                  | Dimension | 2     | 3    | 4     | 5     | 6     |
|----------------------------------|-----------|-------|------|-------|-------|-------|
| Overall spillover                 | 0.068***  | 0.131*** | 0.181*** | 0.204*** | 0.226*** |
| Net spillover for bitcoin         | 0.067***  | 0.128*** | 0.194*** | 0.238*** | 0.260*** |
| Net spillover for gold            | 0.069***  | 0.138*** | 0.196*** | 0.228*** | 0.252*** |
| Net spillover for oil             | 0.063***  | 0.136*** | 0.194*** | 0.227*** | 0.249*** |
| Net spillover for stock           | 0.059***  | 0.130*** | 0.180*** | 0.206*** | 0.219*** |
| Net spillover for USD             | 0.065***  | 0.147*** | 0.197*** | 0.218*** | 0.242*** |
| Net spillover between oil and bitcoin | 0.095*** | 0.165*** | 0.207*** | 0.223*** | 0.227*** |
| Net spillover between oil and gold | 0.076*** | 0.145*** | 0.188*** | 0.211*** | 0.220*** |
| Net spillover between oil and stock | 0.095*** | 0.165*** | 0.207*** | 0.223*** | 0.227*** |
| Net spillover between oil and USD | 0.037***  | 0.093*** | 0.149*** | 0.181*** | 0.198*** |
| Net spillover between stock and oil | 0.041*** | 0.098*** | 0.148*** | 0.174*** | 0.190*** |
| Net spillover between stock and USD | 0.066*** | 0.134*** | 0.182*** | 0.207*** | 0.222*** |
| Net spillover between bitcoin and gold | 0.072*** | 0.151*** | 0.211*** | 0.255*** | 0.277*** |
| Net spillover between bitcoin and stock | -0.000 | -0.001 | -0.00 | -0.002 | -0.003 |
| Net spillover between bitcoin and USD | 0.035**  | 0.088*** | 0.135*** | 0.172*** | 0.190*** |
| Net spillover between bitcoin and USD and gold | 0.038*** | 0.091*** | 0.141*** | 0.184*** | 0.208*** |
| Net spillover between USD and stock | 0.031**  | 0.074*** | 0.104*** | 0.131*** | 0.157*** |

***Denotes the rejection of the null hypothesis of serial dependence, and therefore presence of nonlinearity, at 1% significance level.

Table 3. In addition, the net spillovers for stock and USD, net pair-wise spillover between bitcoin and USD, and USD and stock are found to be significant.

We can conclude from the results that, to some extent, the linear causality test reveals just fair evidence of causal relationship between COVID-19 pandemic and the connectedness among the assets. As we pointed out under the statistical description, the series are associated with fat tails, excess kurtosis and non-normality. These undesirable statistical features are first-hand indication of the possibility of nonlinearity, structural breaks and regime changes in the series. It is also known from empirical evidences that financial series often exhibit nonlinear movements and structural shifts along their time paths (see Adekoya and Oliyide, 2020). Against this evidence, linear models become weak in producing reliable results. Hence, we choose to consider causality-in-quantiles test, a nonlinear model, which is flexible and can conveniently account for the aforementioned undesirable statistical issues. To provide formal evidence for the need to use this nonlinear technique, however, we conduct the BDS test which was developed by Brock et al. (1996). The results support the rejection of the null hypothesis of serial dependence of the spillover residual series across all the dimensions regardless of the COVID-19 pandemic indicator used (see Tables 5 and 6). The only exemption is the net pair-wise spillover between bitcoin and stock. Overall, the BDS test suggests that the series are nonlinearly related, thus justifying our choice of causality-in-quantiles
test.

The results for the causality-in-quantiles test are presented in Figs. 3 and 4. Against any reasonable doubt, there are significant improvements in the results when nonlinearity is accounted for compared to those of the linear Granger-causality model. In Fig. 3 which shows the nonlinear effect of ID-EMV on the spillovers (overall, net spillover for each asset...
and net pair-wise spillover between the assets), it can be seen that only for the net pair-wise spillover between bitcoin and stock can we not reject the null hypothesis of causality from ID-EMV. Others are significant at either or both lower- and middle-level quantiles as their causality curves are above the 5% significant line. The causal impact of ID-EMV is exceptionally profound in some cases, such as for total net spillover for bitcoin, net pair-wise spillover between bitcoin and gold, USD and stock, oil and stock, and oil and USD, following their significance in most of the

Fig. 3. (continued).
quantiles.

Considering COVID as the causal variable (see Fig. 4), significance at 5% is mostly found for most of the spillover series at the lower quantiles. Also, COVID ceases to significantly cause overall spillover and net pair-wise spillover between oil and bitcoin. Notwithstanding, similar results as those of ID-EMV are also found. For instance, COVID also causes the net pair-wise spillovers between bitcoin and gold, oil and stock, and oil and USD in most of the quantiles.

Overall, the findings from this study show that the current COVID-19 pandemic has significant causal impact on the spillover connectedness across the commodity and financial assets. The pandemic has serious implications on the interactions across the commodity and financial markets via its alteration of the global business cycle which drives investors’ sentiments and consequently raises risks variance across the markets. Of course, the influence of the pandemic is the reason behind the difference between the volatility spillover results reported in this study and those of Hussain et al. (2019). However, our findings run similar to the evidence provided by the study of Albulescu et al. (2019) which establishes that economic policy uncertainty drives volatility spillover in the oil and commodity currency markets. In addition to this evidence, accounting for nonlinearity in the causal relationship is of utmost importance, as the neglect of such would produce spurious results.

5. Conclusion

This study is motivated by two factors. First, there are theoretical propositions on the connectedness among commodity and financial markets through various channels. This has resulted into the increasing empirical evidences on the connectedness among these markets, although in split forms. Second, the current COVID-19 pandemic has been adjudged as the health crisis of all time with the greatest impact on financial markets, especially the stock markets. Beyond this, it is believed to have significantly altered global business or financial cycle. Meanwhile, changes in the global business or financial cycle are symbolic in the movements in global capital flows and prices of tradable assets across diverse financial markets (see Rey, 2018; Nier et al., 2014) since they induce risks preferences for investors. If the global economy has truly experienced changes in the business cycle during this period, it can then be empirically argued that the COVID-19 pandemic drives the connectedness among the commodity and financial markets.

Thus, the thrust of this paper is to examine the causal effect of the current COVID-19 pandemic on the connectedness among the globally traded commodity and financial assets (oil, gold, stock, bitcoin and dollar-euro exchange rate). To the best of our knowledge, no study has covered this gap in the literature. The analyses are in two folds. We first examine the volatility spillovers among the assets. After this, we
Fig. 4. Causality-in-quantiles test result for the effect of COVID on connectedness across oil, gold and financial markets
determine the causal effect of COVID-19 pandemic (which is proxied by two health indicators namely infectious diseases-induced equity market volatility index and the growth rate of the COVID-19 reported cases in the U.S.) on three categories of spillovers (overall spillover, total net spillover for each asset and net pair-wise spillover between the assets). We find that there is strong volatility spillover among the assets as they are all significant transmitters and receivers of shocks. Moreover, both gold and USD are found to be net receivers of shocks, while others are
net transmitters. Further analysis through graphical illustration reveals
that overall spillover is higher for about the first four and half months of
the pandemic, and these months interestingly coincide with the periods
when global panic over the pandemic was at its peak. Based on this
evidence, we proceed to the causality analysis with the nonlinear cau-
sality test (causality-in-quantiles) proving superior to the linear
Granger-causality test. The findings show that COVID-19 has significant
causal effect on the connectedness across the assets. Particularly, the
effect of the pandemic on the connectedness across the markets is
stronger mostly at the lower- and middle-level quantiles, while only in
very few cases is insignificance established. These results are robust to
the two COVID-19 health indicators used.

Investors and policy makers can draw policy insights from these
findings. There is a strong alignment between the findings of this study
and the postulation of the global business or financial cycle channel
which is in a way driven by the current COVID-19 pandemic that induces
investors’ sentiments and risks, and further transmits the same across
the commodity and financial assets. This is because the pandemic
adversely affects global capital flows, credit transactions and financial
liquidity. It is thus a very smart investment strategy for investors to
close monitor changes in global business cycle, especially during the
period of notable global health crisis, and adjust their investment
portfolios accordingly in order to mitigate or circumvent losses. This can
even be generalized for the periods of any crisis that affects global
capital flow and credit activity which further have the tendency of
altering the business cycle and consequently inducing transmission of
risks. Also, it is crucial for investors to include assets with relative sta-
bility, such as gold, in their investment portfolios so as to advance the
performance of their overall adjusted risks. For policy makers, it is
important to strengthen their financial markets, especially the stock
market, against exposure to risks. The financial markets have for long
been used to gauge the performance of the macroeconomy, thus making
the overall economy to be at the receiving end of the exposure of the the
financial markets to negative shocks. Finally, it would be an interesting
empirical adventure for future studies to examine how the pandemic
connects spillover among commodity and financial markets’ fears rather
than returns.

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