



# Price and volatility spillovers between global equity, gold, and energy markets prior to and during the COVID-19 pandemic

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## ABSTRACT

This study sets out to provide fresh evidence on the dynamic interrelationships, at both return and volatility levels, between global equity, gold, and energy markets prior to and during the outbreak of the novel coronavirus. We undertake our analysis within a bivariate GARCH( $p, q$ ) framework, after orthogonalizing raw returns with respect to a rich set of relevant universal factors. Under the COVID-19 regime, we find bidirectional return spillover effects between equity and gold markets, and unidirectional mean spillovers from energy markets to the equity and gold counterparts. The results also suggest the presence of large reciprocal shock spillovers between equity and both of energy and gold markets, and cross-shock spillovers from energy to gold markets. Most probably driven by the recent oil price collapse, energy markets appear to have a substantial cross-volatility spillover impact on the others. Our results offer implications for policymakers and investors.

## 1. Introduction

The ongoing COVID-19 pandemic has pushed the global economy to an unprecedented economic abyss. The COVID-19 has triggered a massive spike in uncertainty (Altig et al., 2020), and major suspicions about the health system capacity to combat the pandemic, the economic consequences of the pandemic, and the efficiency of policy responses to the outbreak of the pandemic. The pandemic introduces uncertainties about consumer spending patterns, business survival, and other factors that directly affect productivity (Jorda et al., 2020). Financial markets have been deeply affected by pandemic (Al-Awadhi et al., 2020; Baker et al., 2020; Bai et al., 2020; He et al., 2020; Toda, 2020; Topcu and Gulal, 2020) and the chaos seems to have spread over all markets. These contingent effects of COVID-19 on financial markets (which have crashed down prices of different financial assets and increased their volatility) cast doubt on the notion that specific assets like gold can be a hedge against crises, if they do emerge because of the pandemic. Comprehending how the COVID-19 pandemic affects different markets and furthermore understanding which of these markets can work as a safe

haven is crucial for investors, especially in the midst of a speedily unfolding crisis.

This paper adds to the current literature by being the first to investigate the interactions between the equity, energy, and gold markets during the COVID-19 era, using orthogonalization methodology, comparing these interactions during and before the pandemic period. We examine whether gold is still a viable hedge during unfortunate times, and more specifically against the COVID-19 financial fallout. To answer these questions, we examine the reciprocal relationships between the S&P global Broad Market Stock Index (BMI), S&P GSCI gold index, and S&P GSCI energy index from January 13, 2015 to May 15, 2020. Our econometric framework starts by removing confounders between the three markets. Then, we utilize the residuals from the first stage in GARCH (1,1) systems to test price and volatility spillovers between equity, gold, and energy markets in pairs setting.

We find that the return and volatility transmission relationships between financial markets have strengthened in the aftermath of the COVID-19 outbreak. Interestingly, energy markets have a huge cross-volatility spillover impact on the other markets, most probably

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because of the recent oil price crash. The findings of the entire sample confirm bidirectional spillover effects between returns on the energy market and both equity and gold markets, and unidirectional return transmissions from gold to equity markets. Under the shadow of the pandemic, we find bidirectional return spillovers between equity and gold markets, and unidirectional spillovers from energy returns to equity and gold returns. Moving to the volatility spillovers, our findings refer to bidirectional cross-shock effects between equity and gold markets, together with unidirectional shock spillovers from equity to energy markets and from energy to gold markets during the full sample period. The COVID-19 era witnessed larger bidirectional shock spillovers between equity and both energy and gold markets, and cross-shock spillovers from energy to gold markets.

Our work contributes to the financial markets literature by offering fresh evidence on the interactions among the global financial and commodity markets bearing the economic brunt of the COVID-19 crisis. The pandemic and its consequential adverse impacts on energy market dynamics suggest that the safe-haven characteristic of some investment asset classes is likely to change over time and, therefore, should be periodically assessed. This sustained assessment is a crucial input for the development of appropriate hedging strategies, risk management practices, and optimal portfolio structures.

The remainder of the study proceeds as follows; section 2 describes our sample data, section 3 outlines the econometric framework, section 4 presents the empirical findings and finally, Section 5 gives a brief summary and concluding remarks.

## 2. Prior research

As the world progresses further with dealing with and tracking a pandemic that has nearly completely halted our day-to-day lives, the academic research continues to carefully track the economic and financial consequences caused by COVID-19. The pandemic has had clear and grand effects on the economies of most of the world; as many countries adapt to new strict quarantine guidelines; their economic activities are extremely restricted. The COVID-19 has driven the crash of the stock markets and the rise in their volatilities globally, the US stock market lost 28% from its value from 19 February to March 31, 2020, other major stock markets indices dropped by 10%–30% (Baker et al., 2020; Bai et al., 2020; He et al., 2020; Topcu and Gulal, 2020).

### 2.1. COVID-19 and financial markets

In early studies, Al-Awadhi et al. (2020) and He et al. (2020) find that Chinese stock market returns declined as the number of COVID-19 daily-confirmed cases and deaths increased. Global financial markets have undergone major adversities and risks due to the COVID-19 pandemic, for example, stock markets in the US have reached four circuit breakers over the course of only two weeks (Ji et al., 2020). Furthermore, Bai et al. (2020); Zhang et al. (2020), and Topcu and Gulal (2020) report a significant increase in the volatility of stock returns of most infected during the first two months of the pandemic. This risk level increase can be traced as a product of sentimental factors as different forms of media spread and amplify the market sentiment due to the pandemic. Additionally, knowing that the outbreak is a global threat, an increase in systemic risk is prominently anticipated. The pandemic has clear and grand effects on the economies of most of the world because of the economic look down. These effects appear to be more obvious in certain sectors than others, but the collective need for both practitioners and researchers has become finding safe-haven assets which display a decreased element of volatility.

It is not a surprise to find that the fallout outbreak in other global commodity markets because of the global economic integration. Gold and energy markets have not been an exception to this, as they have shown varying and deep short-term and long-term effects. At less than \$20 a barrel, crude oil prices have dropped to a new significantly low level since the start of the new century. Ji et al. (2020) show that the MSCI-US index and the WTI crude oil futures have faced enormous losses, as they mimic each other's financial trends due to COVID-19. Additional international factors have contributed to the effects of COVID-19 on increasing and producing systematic risk, one of which is the altercations between Russia and Saudi Arabia over oil supply and prices that have had perplexing impacts on stock market volatility. On the March 6, 2020, Russia rejected compliance with the OPEC summit decisions; as a sort of rejoinder Saudi Arabia made price discounts that ranged from \$6 - \$8 per barrel for Asian and European clienteles (Ashraf, 2020). This quarrel has introduced a mass uncertainty with increasing overall risk within the global financial market. Perhaps even more bewildering, on April 20, crude oil futures of the WTI (West Texas Intermediate) closed at -\$37.63 per barrel. An event that could only be described as unparalleled in its potential effects on policy makers, practitioners and overall stock market volatility. Globally, stock markets have responded with a myriad of changing inter-market linkages and growing risks (Zhang et al., 2020).

### 2.2. Links between equity, energy and gold markets

A significant part of the literature confirms the interactions between different financial and commodities markets (See: Bekaert et al., 2005; Eissa and Elgammal, 2015; Ahmed, 2018). The persistence of cointegration and contingency between financial markets in the crisis periods has been documented by a stream of research (e.g., Longin and Solnik, 1995; Bekaert et al., 2005) that reports higher correlations between financial markets in crises. The relationships between equity, gold and energy markets draw considerable attention from global investors because of the major role of energy and stock markets in economic activities from one side and the vital role of gold as a safe-haven asset hedging against other markets' fluctuations. Not only do these three markets provide a diverse universe of lucrative investment opportunities, but also their fluctuations can give early warnings to the policy-makers regarding the health and stability of the economy. Furthermore, assets in these three markets can interchangeably work as a hedging instrument against a range of macroeconomic risks (Gevorkyan, 2017).

Basher and Sadorsky (2016) and Jones & Kaul (1996) provide two theoretical channels for the transmission of oil prices to equity markets; these channels are expected future dividends and discount rates. The oil price variations are likely to affect corporate cash flows, as oil is a vital element in producing and supplying of almost all products. On the other hand, the unexpected oil price spikes usual raise inflation ahead. Consequently, monetary authorities will apply restrictive policy stances and raise interest rates to slow down the inflation. And in turn, the discount rates for future corporate earnings will increase, thereby ultimately causing stock prices to decline. The links between stock markets and energy markets has been documented by Ahmed (2018), who confirms mean and volatility transmission effects from natural gas prices in Qatar stock prices (a main gas producer). Recently, Sharif et al. (2020) show that oil prices drive the US stock markets over short-term while; He et al. (2020) indicate that oil is a source of positive (negative) return transmissions to the Chinese (US) equity markets.

O'Connor et al. (2015) demonstrate that oil markets can affect gold market through inflation channel, the increase in oil prices speeds up the inflation which then increases demand on gold and pushing its price up.

The volatility of gold is affected by oil shocks. This argument is supported by the findings of Baffes (2007) who reports that a rise in the price of oil by \$1 would result in a \$0.34 increase in the gold price. Zhang and Wei (2010) show that the oil market and gold market are cointegrated at all maturities indicating that the markets are jointly efficient. Ewing and Malik (2013), using neural network methodology, confirm the association between oil and gold market. Furthermore, several studies (e.g., Khalifa et al., 2014; Ahmed, 2018; Pandey and Vipul, 2018; Liu et al., 2020) report a convergence of bidirectional spillovers between oil market and gold market. Ahmed and Huo (2021) find reciprocal shock transmissions between oil prices and the Chinese stock market, and one-way volatility spillovers from oil to gold. These findings support the results of Zhang and Wei (2010) who report that oil Granger causes gold price volatility.

Finally, Reboredo (2013) suggests limited hedging but some safe haven characteristics for gold against crude oil. Their results are consistent with negative association between returns on oil and gold during the last financial crisis (2007–2009) reported by Shahzad et al. (2019). However, Selmi et al. (2018) suggest that the ability of gold to act as a hedge and a safe haven against oil price movements will be based on micro mechanisms of the two markets. Recently, Ji et al. (2020) suggest that the role of oil commodity futures, as a safe-haven candidate, deteriorated during the outbreak of the COVID-19.

### 2.3. Is gold still a safe-haven in the COVID-19 era?

The role of gold as a safe-haven and as a hedge against other financial assets during financial uncertainty and global turbulence is well documented in investment literature (see: Baur and McDermott, 2010; Baur and Lucey, 2010; Reboredo, 2013; Baur and McDermott, 2016; and Bouoiyour et al., 2019). There are two theoretical mechanisms for the role of gold as a hedge tool; the first mechanism is the flight-to-safety behavior of risk-averse investors who move away from other financial markets once their volatility increase. Which in turn, prompts a rush in demand for gold, thereby pushing its prices up and increasing investors' wealth. Another interpretation is introduced by Baur and McDermott (2016) who argue that gold is more preferable than other safe haven assets due to the behavioral prejudices associated with gold's history as a currency, a store of value and a safe haven. Baur and McDermott (2016) also introduce evidence that gold was a particularly strong safe haven during the aftermath of political and financial crises.

In contrast, Hood and Malik (2013) show that gold is not a good hedging tool in periods of extremely low or high volatility. They confirm that S&P Dynamic Volatility Futures (VIX) is performing much better than gold as a safe haven during the 1995–2010 period. This is consistent with the results of Hillier et al. (2006) who find that gold is not a good diversification or safe-haven tool in poor equity return periods. Concurrently, Choudhry et al. (2015) report a breakdown in the safe haven during the financial crisis following Sumner et al. (2010) who show that gold volatility and returns spilled over strongly to stocks during the 2008 financial crisis. However, Cohen and Qadan (2010) suggest that the gold derived the VIX to be a better safe haven asset during the 2008 financial crisis. It appears that the empirical evidence regarding the characteristics of gold as a hedge and a safe haven for stocks is based on the market and methodology selections. For example, Baur and Lucey (2010) confirm such characteristics in US, UK for only 15 days after a market crash. Contrary to Bredin et al. (2015) who used wavelet analysis to conclude that gold can be a safe haven for up to a year. Moreover, Baur and McDermott (2010) introduce empirical evidence that gold's role as a safe haven for stock markets is not predominant in all countries.

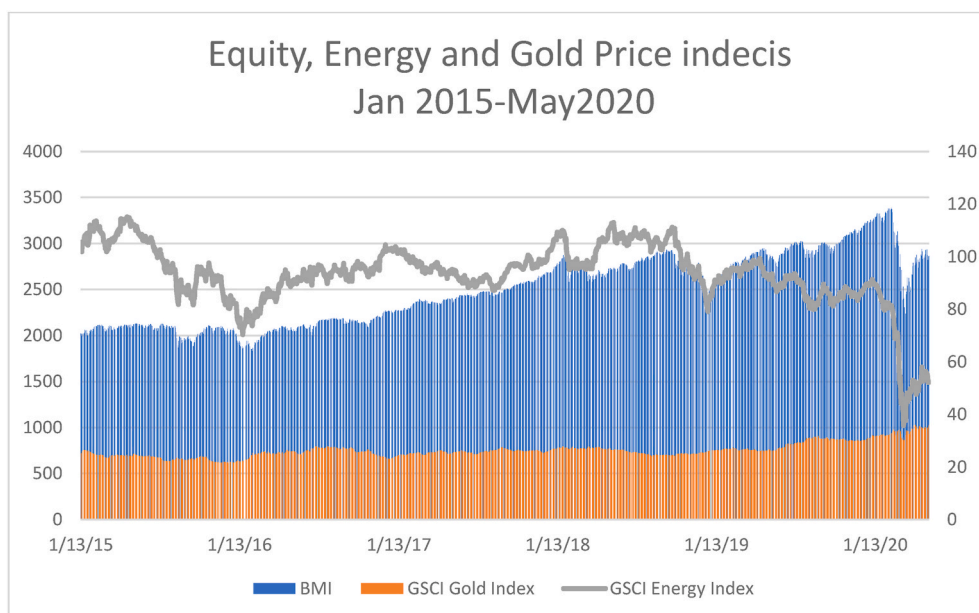
The behavior of commodities which are traditionally sought out to be

safe-haven assets have dramatically changed since the financial crisis of 2008 (Bouri et al., 2020; and Wu et al., 2020). Ji et al. (2020) suggest that their previous function as safe-haven assets begins to be questioned and gathers much needed attention towards the exploration of these commodities regarding the current global health crisis. Surprisingly, even gold as an asset (which has long-been acting as a complete safe-haven), is subjected to questions of its ability as a safe-haven commodity. O'Connor et al. (2015) explain the inconsistent empirical support for the role of gold as a safe haven by the change of the gold pricing and holding mechanism based on behavioural economic issues. Baur and Glover (2012) claim that the safe-haven function of gold has been eroded by the increase in holding gold for purely speculative purposes, which makes gold vulnerable to suffer in times of economic instability like other financial assets. This argument is supported Ivanov (2013), who argue that traders in gold future markets are the main drivers of its price over the long term, rather than hedgers.

Additionally, Batten et al. (2010) and Hammoudeh et al. (2010) support the theoretical expectation that monetary shocks influence gold volatility. In a similar context, Byers and Peel (2001) report that employment reports, economic growth and inflation news are significant triggers for gold volatility. On the other hand, Pandey and Vipul (2018) report volatility spillovers from gold to BRICS equity markets, especially following the global financial crisis, while Uddin et al. (2020) uncover symmetric risk spillovers between gold and the S&P 500 index in tranquil and extreme market conditions. Altogether, this invites us to believe that the current pandemic (COVID -19) which triggered an economic slowdown and an increase in unemployment rates accompanied with a fall on the stock markets and oil prices, will have a significant mark on the volatility of the gold market. Safe-haven property is subject to changes and be contingent on certain characteristics of market turmoil. What we may consider as safe-haven asset during the COVID-19 pandemic, could be separate from those that presided during the financial crisis of 2008. The effectiveness of an asset as a safe haven is prone to change due to its particular asset class and/or the market it is studied within. The current questions that surface are: Does gold remain a safe haven amid the current pandemic? And is it truly immune to the contagion of volatility and overall market risk?

The literature does not reach conclusive evidence whether gold is a safe haven during the ongoing COVID-19 era nor about the spillover between gold markets and stock markets. Ji et al. (2020) find that gold proves a robust safe-haven asset during the COVID-19 crisis, in comparison with Bitcoin and foreign exchange currencies. However, Corbet et al. (2020) establish that neither gold nor Bitcoin has a significant relationship with stock prices of the Shanghai and Shenzhen Stock Exchanges during the rapid spread of the coronavirus in China. Ali et al. (2020) document that as the COVID-19 outbreak shifts from an epidemic to pandemic, gold returns become negative but with less swing. These controversial findings suggest that the safe-haven property is sensible to the choice of markets and highlight the need for further investigation to the spillover between stock, oil, and gold markets.

Our work can be distinguished from the above papers from methodological and sample aspects. From the sample point of view, Corbet et al. (2020) and Ji et al. (2020) use a short data set from March 11, 2019 (August 2019 in Ji et al., 2020 and December 2019 in Ali et al., 2020) to March 2020, which may be insufficient in capturing the complete impact of COVID-19 on financial markets. Our paper uses longer data set from January 13, 2015 to May 15, 2020 for three different sub sample periods (the entire period, 91 days pre-COVID-19 period, and 91 days after COVID-19 period). Finally, we consider global equity data that is not limited to a single country or regional data; as such the case with Corbet et al. (2020) who only study Chinese stock market data or Ji et al. (2020) who use only three regions China, Europe (EU), and the United



**Fig. 1.** This figure shows over 5 years timeframe prices from January 13, 2015 to 13/5/2020. For S&P Global Broad Market Stock Index (BMI) in Blue, GSCI Gold index in orange and GSCI Energy Index in blue. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

States. The reason behind global market selection is that the COVID-19 outbreak has led to international economic lockdown, which has hit firms' cash flows, consumer spending, economic activities, employment, and economic growth expectation. This turmoil has increased investor uncertainty, which in turn, affects financial and commodity markets' return and volatility all over the world.

Our methodology is different from previous studies; for example, Corbet et al. (2020) investigate the dynamic correlation, using a GARCH model, between Chinese main financial markets and gold, bitcoin, and oil as other investment alternatives. Ali et al. (2020) use an EGARCH model to investigate the behavior of return and volatility of the main affected stock markets using COVID-19 as an explanatory variable. Moreover, Ji et al. (2020) use a sequential monitoring procedure to assess whether a tail change in the equity index can be offset by introducing a safe-haven asset. On the other hand, we apply multistage methodology. In the first stage, we control the main common drivers for the equity, gold, and energy markets. In addition, the two markets under investigation are also orthogonalized on the third market. In the second stage, we applied a set of multivariate GARCH models to investigate the spillover in main returns and volatility using the residual of the first stage. Another important contribution of our work is that we investigate under a more comprehensive set of research questions regarding the spillover between equity, gold, and energy markets (returns and volatilities) before and during the pandemic and whether gold can hedge against COVID-19 financial fallout.

### 3. Sample and variables

We use daily data over the period from January 13, 2015 to May 15, 2020, which allows us to investigate the spillover effects between global stock, gold, and energy markets before and during the COVID-19 period. Our main variables are closing prices for the S&P Global Broad Market Stock Index, the CSCI gold index, and the GSCI energy index. To control for the confounders of the three markets we use four control variables, which are well documented in the literature as main drivers for the three market returns. These control variables are S&P Dynamic Volatility Futures (VIX), US trade-weighted exchange rate index (EXR), China Volatility Index (VXFXI), and Bitcoin in the US dollar index (e.g., Goodell and Vähämaa, 2013).

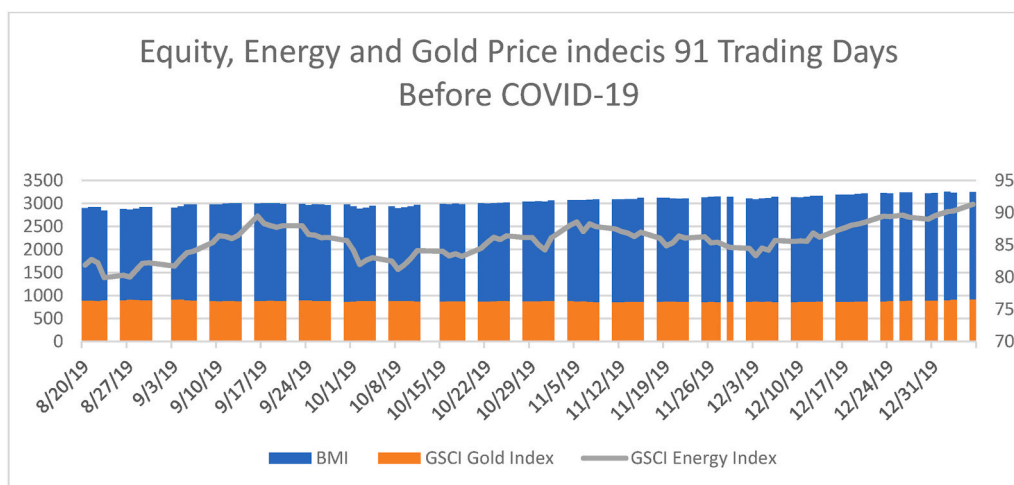
Our sample is divided into three subsamples, the entire period from January 13, 2015 to May 13, 2020, 91 trading days before the Covid-19 pandemic from August 20, 2019 to January 6, 2020, and 91 trading days during the pandemic period from January 7, 2020 to 13 May 2, 2020<sup>2</sup>. The dataset is adjusted to fit the trading days for each benchmark index from Monday until Friday for each week, so the Bitcoin weekend trading is excluded. Besides, we adjust public holidays to fit the trading days in the US market and remove all trading days that do not fit with trading days in the US market. The S&P500, CSCI energy index, GSCI gold index, and VIX are obtained from S&P Dow Jones Indices. Bitcoin, China volatility index, and the US trade-weighted exchange rate index (EXR) are extracted from the Federal Reserve Bank of ST. Louis.

Fig. 1 shows that (BMI) global index price has an increasing trend in the last five years till February 2020 when it moves down sharply to more than 1000 points by mid of March 2020. The situation for the GSCI energy index was more severe as it loses more than 2000 points. The GSCI energy index shows high speculations during the Covid-19 effected by the lockdowns around the globe and the oil war between Russia and Saudi Arabia. The GSCI Gold price index presents relatively a flat trend with a slight increase in 2019 and 2020.

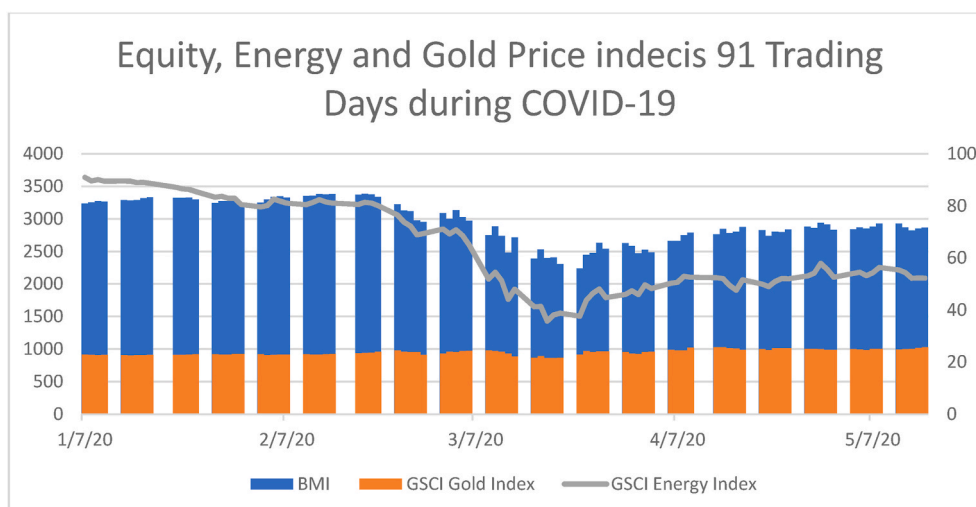
To gain more insight, Figs. 2 and 3 show the behaviour of prices of the three markets respectively in the 91 days before and during the pandemic era. We can see the markets has been very aggressive during

<sup>2</sup> On January 7, 2020, Chinese health authorities announced that the reported cases of pneumonia in Wuhan City had been caused by a novel infectious coronavirus. Since then, the number of positive COVID-19 cases has soared across the globe. On January 9, 2020, World Health Organization (WHO) issued its first COVID-19 Outbreak News report using public, web-based platform, which target the global media (WHO, n.d). This news immediately had its shadow on the global financial markets including global equity market and energy market as we can see in Figs (1) and (3). In addition, China is a major buyer in the energy markets and its official announcement of COVID-19 followed by the Lockdown in China dragged down the Chinese stock markets in January 2020 (Wu et al., 2021) and in turn affected oil prices, which dropped dramatically by February followed by global stock markets. Therefore, the official announcement of COVID-19 followed by the lockdown in China were the trigger for volatility in the global financial markets, which is investigated in this paper. The relationship between China Volatility Index and global markets are well documented in the literature (e.g., Goodell and Vähämaa, 2013).





**Fig. 2.** This figure shows the price Indices over 91 trading days timeframe form August 20, 2019 to January 07, 2020. For S&P Global Broad Market Stock Index (BMI) in Blue, GSCI Gold index in orange and GSCI Energy Index in blue. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)



**Fig. 3.** This figure shows the prices over 91 days timeframe form January 7, 2020 to May 13, 2020. For S&P Global Broad Market Stock Index (BMI) in Blue, GSCI Gold index in orange, and GSCI Energy Index in blue. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

the Covid-19 pandemic especially in March. As shown in Fig. 2, the GSCI Energy Index shows a considerable increasing trend in the period before COVID-19 (from 79 points to 91 points). The GSCI Energy Index turns to take a sharp decrease during COVID-19 period to reach its lowest historical point at 35 points in March 18, 2020 following with a slight recovery in May 2020. Similarly, the BMI global stock index shows a decreasing trend started in the last week of February until reaching its bottom by March 20, 2018 when it starts recovering driven by economic bailouts.

Furthermore, Table 1 shows the descriptive statistics for the BMI index, CSCI energy index, GSCI gold index, and VIX, Bitcoin, China volatility index, and the US trade-weighted exchange rate index (EXR). Table 1 shows an increasing in the two volatility indices (in terms of mean, median, minimum, and even maximum values) and their standard deviations in the 91 trading days after COVID-19 compared to 91 trading days before COVID-19. Moreover, there are clear decreases in the BMI global stock index and energy index in the 91 trading days after COVID-19 compared to 91 trading days before COVID-19 where the gold index shows better performance in the same period.

#### 4. Econometric framework

As indicated in the introductory section, this study aims to provide fresh evidence on the interrelationships, at both return and volatility levels, between global financial markets prior to and during the outbreak of the COVID-19. To address these issues, we run two empirical procedures. First, since the behavior of equity, gold, and energy markets is most likely to be affected by other global forces, our first task is to purge their respective raw returns of the potential influences of these common factors. Second, we assess the dynamic interactions between the three markets, utilizing a GARCH( $p, q$ ) process. The following subsections offer a concise description of both steps.

##### 4.1. Variable orthogonalization

It is well documented that asset prices are sensitive to changes in international financial markets, due to the rapidly growing economic integration of the world. Whether developed, emerging, or frontier, all markets are not isolated from the vicissitudes of the global economy.

**Table 1**  
The descriptive statistics for the three sub samples.

	91 trading days before Covid- 19 20/8/2019- January 06, 2020					91 trading days After Covid- 19 January 7, 2020 - May 13, 2020					The entire period of the investigation January 13, 2015 -13/5/2020				
	Mean	Median	SD	Min	Max	Mean	Median	SD	Min	Max	Mean	Median	SD	Min	Max
CSCI	873.6	873.1	106	849.6	916.57	949.2	953.5	42.1	862.2	1029.9	753.9	741.9	78.9	611	1029.8
GSCI	85.6	86.1	17.4	79.9	91.31	64.3	55.6	16.9	35.7	90.9	93.4	94.4	12.1	35.7	115
BMI	3051	3036.9	417.6	2847.1	3257.85	2961.2	2929.8	319.1	2237.4	3386.2	2491.4	2473.9	377.1	1829.1	3386.1
VIX	14.7	14.1	18.5	11.5	20.56	34.4	33.6	18.8	12.1	82.7	16.3	14.2	7.98	9.14	82.69
VXFXI	19.7	19.6	11.7	16.2	25.63	32.6	31.5	11.8	16.4	69.3	25	23	7.19	15.09	69.28
Bitcoin	8568.5	8263.6	1570	6618.6	10935.67	8175.9	8652.3	1347.8	4980	10380	4259	3569	3979.2	120	19039
EXR	110.4	111	12	106	111	112.1	111.8	1.98	108	117	108.5	109	2.8	101	117

**Notes:** The table shows descriptive statistics for the three investigated samples. CSCI is the gold price index, GSCI is the energy index, BMI is S&P Global Broad Market Stock Index, VIX is the S&P Dynamic Volatility Futures, VXFXI is the China Volatility Index (VXFXI) Bitcoin is the US dollar Bitcoin index, EXR is the US trade-weighted exchange rate index.

Bekaert et al. (2005) show that co-movements between country returns and regional or world market returns tend to increase over time. Carrieri et al. (2007) indicate that financial market development and financial liberalization policies are chief drivers of market integration in emerging markets. Methodologically, this critical aspect of globalization reinforces the importance of accounting for the influence of notable determinants when it comes to modeling asset price variations. Hence, for instance, modeling the behavior of gold prices as a function of equity prices solely, or vice versa, will, in all likelihood, generate questionable conclusions. To avoid the potential for omitted-variable bias, we utilize an orthogonalization procedure, by which stock, gold, and energy raw returns are cleansed of the confounding impact of variables largely recognized in the literature for their huge explanatory power regarding asset returns. This practice is frequently used in empirical research works (e.g., Harvey and Liu, 2021; Goodell and Vähämaa, 2013; Gulen and Mayhew, 2000). As elaborated in Section 3, our select price determinants include the US trade-weighted exchange rate index (EXR), the CBOE US VIX option volatility index (VIX), the CBOE China ETF volatility index (VXFXI), and Bitcoin price index (BIT). Since we are interested in exploring price and volatility interactions in a bivariate setting, the two markets under investigation are also orthogonalized on the third (i.e., excluded) market. Thus, we orthogonalize equity, gold, and energy returns with respect to five control variables by estimating an OLS regression model *twice* for each return series, as follows:

concerns over endogeneity and multicollinearity, and to allow for the possibility that the regressand may display delayed, rather than immediate, reactions to common global shocks. To ensure whiteness of the six return residuals  $\tau_t^\perp$ , we fit an autoregressive filter AR(p) for each series as follows:

$$\tau_{s1,t}^\perp = \mu + \sum_{i=1}^p \delta_i \tau_{s1,t-i}^\perp + \delta_{s1,t}^\perp \tag{7}$$

$$\tau_{g1,t}^\perp = \mu + \sum_{i=1}^p \delta_i \tau_{g1,t-i}^\perp + \delta_{g1,t}^\perp \tag{8}$$

$$\tau_{s2,t}^\perp = \mu + \sum_{i=1}^p \delta_i \tau_{s2,t-i}^\perp + \delta_{s2,t}^\perp \tag{9}$$

$$\tau_{n1,t}^\perp = \mu + \sum_{i=1}^p \delta_i \tau_{n1,t-i}^\perp + \delta_{n1,t}^\perp \tag{10}$$

$$\tau_{g2,t}^\perp = \mu + \sum_{i=1}^p \delta_i \tau_{g2,t-i}^\perp + \delta_{g2,t}^\perp \tag{11}$$

$$\tau_{n2,t}^\perp = \mu + \sum_{i=1}^p \delta_i \tau_{n2,t-i}^\perp + \delta_{n2,t}^\perp \tag{12}$$

$$R_{s,t} = C + \phi_1 ENERGY_{t-1} + \phi_2 VIX_{t-1} + \phi_3 VXFXI_{t-1} + \phi_4 EXR_{t-1} + \phi_5 BIT_{t-1} + \tau_{s1,t}^\perp \tag{1}$$

$$R_{g,t} = C + \phi_1 ENERGY_{t-1} + \phi_2 VIX_{t-1} + \phi_3 VXFXI_{t-1} + \phi_4 EXR_{t-1} + \phi_5 BIT_{t-1} + \tau_{g1,t}^\perp \tag{2}$$

$$R_{s,t} = C + \phi_1 GOLD_{t-1} + \phi_2 VIX_{t-1} + \phi_3 VXFXI_{t-1} + \phi_4 EXR_{t-1} + \phi_5 BIT_{t-1} + \tau_{s2,t}^\perp \tag{3}$$

$$R_{n,t} = C + \phi_1 GOLD_{t-1} + \phi_2 VIX_{t-1} + \phi_3 VXFXI_{t-1} + \phi_4 EXR_{t-1} + \phi_5 BIT_{t-1} + \tau_{n1,t}^\perp \tag{4}$$

$$R_{g,t} = C + \phi_1 STOCK_{t-1} + \phi_2 VIX_{t-1} + \phi_3 VXFXI_{t-1} + \phi_4 EXR_{t-1} + \phi_5 BIT_{t-1} + \tau_{g2,t}^\perp \tag{5}$$

$$R_{n,t} = C + \phi_1 STOCK_{t-1} + \phi_2 VIX_{t-1} + \phi_3 VXFXI_{t-1} + \phi_4 EXR_{t-1} + \phi_5 BIT_{t-1} + \tau_{n2,t}^\perp \tag{6}$$

where the subscripts *s*, *g*, and *n* denote stocks, gold, and energy, respectively, *C* is a constant term, and  $\phi_i$  denotes slope coefficients. The residual terms  $\tau_{s1,t}^\perp$  and  $\tau_{g1,t}^\perp$  in Eqs. (1) and (2) represent the components of stock and gold returns, respectively, that are, by construction, orthogonal to energy returns and control variables. Similar interpretations can be given to the residual terms in Eq. (3) through (6). Of particular note, all predictors are lagged a single period to alleviate

where  $\delta_{j,t}^\perp$  (i.e.,  $\delta_{s1,t}^\perp, \delta_{s2,t}^\perp, \delta_{g1,t}^\perp, \delta_{g2,t}^\perp, \delta_{n1,t}^\perp, \delta_{n2,t}^\perp$ ) is a sequence of uncorrelated residuals. Accordingly, the  $\delta_{s1,t}^\perp - \delta_{g1,t}^\perp$  pair from Eqs. (7) and (8) is utilized to examine mean and volatility transmissions between equity and gold markets, while  $\delta_{s2,t}^\perp - \delta_{n1,t}^\perp$  pair from Eqs. (9) and (10) is employed to explore mean and volatility transmissions between equity and energy markets. Likewise, we rely on the  $\delta_{g2,t}^\perp - \delta_{n2,t}^\perp$  pair from Eqs. (11) and (12) to investigate the mean and volatility spillovers between

gold and energy markets. For each filtering model, the appropriate number of autoregressive lags,  $p$ , is determined by Akaike's Information Criterion (AIC).

#### 4.2. Bivariate GARCH models

Having obtained the orthogonalized returns,  $\delta_t^\perp$ , we proceed to the second step, which is concerned with capturing the dynamics of cross-market return and volatility transmissions. To this end, we adopt a bivariate GARCH( $p, q$ ) model, which is well recognized for its potential to handle the stylized facts observed in our series, including heavy tails, volatility clustering, and nonlinear dependence. There is a plethora of research that relies on variants of GARCH models to explain the stochastic behavior of time series, and to explore the price and volatility information spillovers between assets (e.g., Ahmed and Huo, 2021; Andersen and Bollerslev, 1997; Hamao et al., 1990; Hou et al., 2019; Izquierdo and Lafuente, 2004; Symitsi and Chalvatzis, 2018; Sun et al., 2020; Yu et al., 2019). To determine the appropriate number of autoregressive lags (i.e., ARCH terms) and moving average lags (i.e., GARCH terms), various models with combinations of  $p = 1, 2$ , and  $3$  and  $q = 1, 2$ , and  $3$  are examined.<sup>3</sup> In all cases, a bivariate GARCH(1, 1) specification appears to be the best-fitting one, since it consistently ensures the lowest value of the AIC statistic.

In our analysis, we identify the period from January 7, 2020 to the end of our sample as the COVID-19 pandemic. Since the data points at hand for the pandemic period is too small to provide reliable GARCH estimates, we make use of the entire sample, instead of partitioning it into two separate subperiods, in a similar spirit to Chau et al. (2014). Taking January 7, 2020 as an event date, we investigate whether certain exogenous events (i.e., the onset of COVID-19 disease) alter the nature of the interdependence structure between markets over two non-overlapping subperiods of equal length. The first one is labeled as the pre-pandemic, which extends from August 20, 2019 to January 6, 2020, whereas the second one is as defined above. Both subsamples include 91 daily observations. As indicated by Baur and Lucey (2010) and Jana and Das (2020), this modeling approach helps to reveal how investors behave over shorter crisis periods. Two multiplicative dummy variables,  $D_1$  and  $D_2$ , are then incorporated in the conditional mean and variance equations of our GARCH model.  $D_1$  and  $D_2$  are assigned a value of one during the designated pre-pandemic and pandemic periods, respectively, and zero otherwise.

The conditional mean representations of daily returns of markets  $a$  and  $b$  are as follows:

$$\delta_{a,t}^\perp = \alpha_{10} + \alpha_{11} \delta_{b,t-1}^\perp + \alpha_{12} \left( \delta_{b,t-1}^\perp * D_1 \right) + \alpha_{13} \left( \delta_{b,t-1}^\perp * D_2 \right) + \varepsilon_{a,t} \quad (13)$$

$$\delta_{b,t}^\perp = \alpha_{20} + \alpha_{21} \delta_{a,t-1}^\perp + \alpha_{22} \left( \delta_{a,t-1}^\perp * D_1 \right) + \alpha_{23} \left( \delta_{a,t-1}^\perp * D_2 \right) + \varepsilon_{b,t} \quad (14)$$

$$\varepsilon_t \equiv \begin{pmatrix} \varepsilon_{a,t} \\ \varepsilon_{b,t} \end{pmatrix} \Big| \Phi_{t-1} \sim N(0, H_t), \quad H_t \equiv \begin{pmatrix} \sigma_{a,t}^2 & \rho \sigma_a \sigma_b \\ \rho \sigma_a \sigma_b & \sigma_{b,t}^2 \end{pmatrix}$$

where  $\alpha_{10}$  and  $\alpha_{20}$  are long-term drift coefficients,  $\alpha_{11}$ ,  $\alpha_{12}$ , and  $\alpha_{13}$  ( $\alpha_{21}$ ,  $\alpha_{22}$ , and  $\alpha_{23}$ ) measure the cross-mean spillover effects from market  $b$  ( $a$ ) to market  $a$  ( $b$ ) over the whole, pre-pandemic, and pandemic periods, respectively.  $\varepsilon_{a,t}$  and  $\varepsilon_{b,t}$  denote zero-mean return innovations conditional on the information set  $\Phi$  available at time  $t-1$ , and are distributed with a conditional covariance matrix  $H$ .  $\rho$  measures the time-invariant correlation between returns of markets  $a$  and  $b$ . To check whether cross-market return spillovers during the pandemic period are statistically different from those of the pre-pandemic one, we examine the null

<sup>3</sup> For space considerations, results are not reported here, but are available upon request.

hypotheses  $H_0 : \alpha_{12} = \alpha_{13}$  and  $H_0 : \alpha_{22} = \alpha_{23}$ . To this end, a Wald  $\chi^2$  test of equality of paired coefficients is carried out. Moreover, to determine the potential role of gold (i.e., a hedge, diversifier, or safe-haven asset) during the three samples (i.e., the entire, pre-pandemic, and pandemic periods), we adopt the definitions of Baur and McDermott (2010). Specifically, gold serves as a diversifier if it is, on average, weakly positively correlated with stocks or energy. Gold acts as a weak (strong) hedge if it is, on average, uncorrelated (negatively correlated) with stocks or energy. Finally, the precious metal acts as a weak (strong) safe haven if it turns out to be uncorrelated (negatively correlated) with stocks or energy in times of acute market stress.

The conditional variance representations for returns of markets  $a$  and  $b$  are given by:

$$\sigma_{a,t}^2 = \beta_{10} + \beta_{11} \varepsilon_{a,t-1}^2 + \beta_{12} \sigma_{a,t-1}^2 + \beta_{13} \varepsilon_{b,t-1}^2 + \beta_{14} \left( \varepsilon_{b,t-1}^2 * D_1 \right) + \beta_{15} \left( \varepsilon_{b,t-1}^2 * D_2 \right) + \beta_{16} \sigma_{b,t-1}^2 \quad (16)$$

$$\sigma_{b,t}^2 = \beta_{20} + \beta_{21} \varepsilon_{b,t-1}^2 + \beta_{22} \sigma_{b,t-1}^2 + \beta_{23} \varepsilon_{a,t-1}^2 + \beta_{24} \left( \varepsilon_{a,t-1}^2 * D_1 \right) + \beta_{25} \left( \varepsilon_{a,t-1}^2 * D_2 \right) + \beta_{26} \sigma_{a,t-1}^2 \quad (17)$$

where  $\beta_{10}$  and  $\beta_{20}$  are constants,  $\beta_{11}$  and  $\beta_{12}$  ( $\beta_{21}$  and  $\beta_{22}$ ) denote the sensitivity of the conditional variance of market  $a$  ( $b$ ) to its own ARCH and GARCH effects, respectively, and  $\beta_{13}$ ,  $\beta_{14}$ , and  $\beta_{15}$  ( $\beta_{23}$ ,  $\beta_{24}$ , and  $\beta_{25}$ ) measure the magnitude of cross-volatility shocks from market  $b$  ( $a$ ) to market  $a$  ( $b$ ) over the entire, pre-pandemic, and pandemic periods, respectively.  $\beta_{16}$  ( $\beta_{26}$ ) gauges the cross-volatility persistence from market  $b$  ( $a$ ) to market  $a$  ( $b$ ). We also use the Wald  $\chi^2$  test of coefficient equality to investigate whether cross-volatility shocks during the pandemic period are statistically different from those of the pre-pandemic one, under the null hypotheses  $H_0 : \beta_{14} = \beta_{15}$  and  $H_0 : \beta_{24} = \beta_{25}$ . The stationarity and non-negativity constraints of the conditional variance dictate that:

$$\beta_{10} > 0; \quad \sum \beta_{11} + \beta_{12} < 1; \quad \sum \beta_{21} + \beta_{22} < 1$$

For each market pair, the parameter estimates of the GARCH(1,1) system are obtained by maximizing the following conditional log-likelihood function:

$$L_t = -\log(2\pi) - 0.5 \log |H_t| - 0.5 \varepsilon_t'(\Theta) H_t^{-1}(\Theta) \varepsilon_t(\Theta), \quad L(\Theta) = \sum_{t=1}^T L_t(\Theta) \quad (18)$$

where  $\Theta$  denotes the parameter vector to be estimated,  $T$  is the sample size,  $H_t$  is a  $2 \times 1$  conditional variance-covariance matrix, and  $\varepsilon_t$  is a  $2 \times 1$  column vector that contains  $\varepsilon_{a,t}$  and  $\varepsilon_{b,t}$ . We employ both the BHHH algorithm of Berndt et al. (1974) to perform the numerical maximization of  $L(\Theta)$  and the Quasi Maximum Likelihood Estimation (QMLE) method of Bollerslev and Wooldridge (1992) to compute robust standard errors of the coefficient estimates.

## 5. Empirical evidence

### 5.1. Results of raw data filtering

Our empirical work begins with removing the possible effects of common global influences from the raw return series of equity, gold, and energy. The robust parameter estimates of the OLS regressions are listed in Table 2.

Several observations are worth highlighting. First, in terms of reciprocal relationships, the estimated coefficients  $\phi_1$  in Columns (1) and (6) are positive in sign and statistically significant at the 0.01 level, suggesting that stock and energy price movements affect each other. The estimates of  $\phi_1$  are also positively signed in Columns (2) and (3), which

**Table 2**  
Estimation results of the orthogonalizing regression models.

Parameter	$R_{s1,t}(1)$	$R_{s2,t}(2)$	$R_{g1,t}(3)$	$R_{g2,t}(4)$	$R_{n1,t}(5)$	$R_{n2,t}(6)$
$C$	0.042*** (3.186)	0.024 (1.149)	0.028 (1.411)	0.031 (1.523)	-0.051 (-1.172)	-0.079** (-2.444)
$\phi_1$	0.332*** (8.234)	0.055** (2.031)	0.056 (1.148)	0.024 (1.060)	0.083 (0.973)	0.148*** (13.894)
$\phi_2$	-0.052*** (-10.679)	-0.076*** (-12.271)	0.015** (2.147)	0.013** (2.154)	-0.069*** (-6.800)	-0.017** (-2.372)
$\phi_3$	-0.018*** (-2.755)	-0.047*** (-9.539)	-0.002 (-0.011)	-0.001 (-0.073)	-0.087** (-2.306)	-0.033** (-2.549)
$\phi_4$	0.099 (1.256)	-0.084 (-1.407)	-0.970*** (-11.022)	-0.960*** (-10.637)	-0.632*** (-5.465)	-0.555*** (-6.947)
$\phi_5$	0.105* (1.722)	0.115*** (3.568)	0.014*** (3.699)	0.015*** (3.694)	0.028 (1.286)	0.012 (1.406)

**Notes:** This table presents the regression parameter estimates based on Eq. (1) through (6).  $\phi_2, \phi_3, \phi_4,$  and  $\phi_5$  are the coefficient estimates on the CBOE US VIX option volatility index, the CBOE China ETF volatility index, the US trade-weighted exchange rate index, and Bitcoin returns, respectively.  $\phi_1$  represents the coefficient estimate of energy returns in Columns (1) and (4), of gold returns in Columns (2) and (5), and of stock returns in Columns (3) and (6). Figures in parentheses are the Newey and West (1987) adjusted  $t$ -statistics. \*\*\*, \*\*, and \* indicate statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.

imply a bidirectional impact between stock and gold price changes. Still, the influence of gold on equities proves statistically significant, whereas the reverse case does not hold. There is a positive bidirectional relationship between gold and energy markets, but it lacks statistical significance, as shown by the respective estimates of  $\phi_1$  in Columns (4) and (5). Evidently, the equity-gold and energy-gold nexuses turn out to be very weak in strength. Second, the global gauge of investor anxiety and market risk, VIX, appears to have lagged negative (positive) effects on stock and energy (gold) markets at the 0.05 significance level or better, as indicated by the corresponding estimates of  $\phi_2$ . However, in terms of magnitude, such forward-looking volatility influences are quite small. This finding supports previous literature that reports evidence of an inverse link between global stock markets and VIX (e.g., Ahmed, 2019; Basher et al., 2016; Bollerslev et al., 2012). A plausible explanation of the positive gold-VIX nexus is that when the VIX takes on an upward trend, risk-averse investors may shift focus from traditional financial assets (e.g., equities) to gold, thanks to its well-acknowledged safe-haven and diversification attributes. Such a flight-to-safety behavior may trigger a surge in demand for gold, thereby pushing its prices up. Employing data for 23 economies, Baele et al. (2013) find that flight-to-safety episodes are broadly associated with increases in the VIX.

Third, lagged changes in the CBOE China ETF volatility index (VXFXI) exert negative effects on equity and energy (gold) markets, albeit such effects are small (negligible) in size. The sensitivity of gold returns to the VXFXI changes has no statistical support, as suggested by the corresponding coefficients,  $\phi_3$ , in Columns (3) and (4). It is obvious that stock (energy) markets are more sensitive to changes in the VIX (VXFXI) than to changes in the VXFXI (VIX). Fourth, interestingly, the sensitivity of stock returns to lagged changes in the US trade-weighted

exchange rate index (EXR) is inconsistent, in terms of coefficient signs, and fails to accomplish statistical significance. Gold and energy returns are negatively correlated with the EXR, implying that both commodity prices tend to decline when the EXR strengthens. The respective coefficients,  $\phi_4$ , are sizable and statistically distinguishable from zero at the 0.01 level. Similarly, Ma et al. (2020) demonstrate a negative link between the US trade-weighted exchange rate and a common factor of commodity returns. Balcilar et al. (2014) point out that swings in the US dollar exchange rate reveal shifts in investors' risk appetite, since they could lure investors into or drive them away from the USD-denominated investment assets.

Fifth, although rather small in magnitude, the estimated coefficients on Bitcoin returns,  $\phi_5$ , in Columns (1) through (4) carry a positive sign and are statistically distinguishable from zero at conventional levels, suggesting that rises in Bitcoin prices contribute to higher returns in equity and gold markets. The estimates of  $\phi_5$  in Columns (5) and (6) are positively signed, but with no statistical significance. This finding implies that Bitcoin price changes are irrelevant to explaining the performance of energy markets. Bouri et al. (2018) report evidence of positive (negative) return spillover effects from Bitcoin to global stock, gold, energy, and commodity markets during bear (bull) market conditions. In contrast, the results of Gil-Alana et al. (2020) show no cointegrating relationships between key cryptocurrencies and five benchmark indices representing stock, bond, gold, foreign exchange, and commodity markets.

Since the orthogonalized returns – i.e., estimated regression residuals of Eq. (1) through (6) – could be temporally autocorrelated, we prewhiten each series by fitting a univariate AR( $p$ ) model. Based on the AIC criterion, nine, seven, and eleven lags are sufficient to obtain white-noise innovations for  $\tau_{s,t}^\perp, \tau_{g,t}^\perp,$  and  $\tau_{n,t}^\perp$  series, respectively. Table 3 lists

**Table 3**  
Coefficient estimates of the residual AR( $p$ ) models.

Parameter	$\tau_{s1,t}^\perp$	$\tau_{s2,t}^\perp$	$\tau_{g1,t}^\perp$	$\tau_{g2,t}^\perp$	$\tau_{n1,t}^\perp$	$\tau_{n2,t}^\perp$
$\mu$	-9.18E-05 (-0.006)	-0.001 (-0.014)	-0.001 (-0.053)	-0.001 (-0.052)	0.003 (0.006)	-4.93E-05 (-0.001)
$\delta_1$	-0.096*** (-7.858)	-0.148*** (-12.101)	-0.014 (-0.719)	-0.019 (-1.036)	-0.034* (-1.672)	-0.042** (-2.160)
$\delta_2$	0.033*** (2.755)	0.058*** (4.278)	-0.029 (-1.562)	-0.028 (-1.438)	0.012 (0.623)	-0.043** (-2.114)
$\delta_3$	-0.125*** (-8.974)	-0.049*** (-4.283)	0.017 (0.749)	0.015 (0.662)	0.006 (0.449)	-0.029 (-1.549)
$\delta_4$	-0.147*** (-10.999)	-0.141*** (-9.303)	0.027 (1.235)	0.031 (1.419)	0.022 (1.383)	0.017 (0.796)
$\delta_5$	0.003 (0.202)	0.039** (2.538)	-0.081*** (-3.914)	-0.077*** (-3.775)	0.049*** (2.971)	-0.011 (-0.642)
$\delta_6$	-0.032** (-2.246)	-0.109*** (-7.209)	-0.047** (-2.506)	-0.050*** (-2.793)	-0.053** (-2.196)	0.057*** (3.607)
$\delta_7$	0.161*** (10.623)	0.169*** (11.300)	-0.049** (-2.149)	-0.048** (-2.119)	0.167*** (11.400)	0.116*** (7.743)
$\delta_8$	-0.086*** (-5.719)	-0.022 (-1.399)	-	-	-0.020 (-1.116)	-0.016 (-0.934)
$\delta_9$	0.075*** (5.095)	0.117*** (7.168)	-	-	-0.039* (-1.797)	-0.082*** (-4.906)
$\delta_{10}$	-	-	-	-	0.062*** (2.695)	0.023 (1.122)
$\delta_{11}$	-	-	-	-	-0.091*** (-5.294)	-0.098*** (-5.081)

**Notes:** This table presents the estimation results of the AR( $p$ ) model based on Eq. (7) through (12).  $\delta_i$  denotes the autoregressive coefficient estimates of the return residuals. The optimal number of autoregressive lags is identified by Akaike's Information Criterion (AIC). Figures in parentheses are the Newey and West (1987) adjusted  $t$ -statistics. \*\*\*, \*\*, and \* indicate statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.



**Table 4**  
Descriptive statistics and diagnostic tests for filtered return series.

	$\hat{\delta}_{s1,t}^+$	$\hat{\delta}_{s2,t}^+$	$\hat{\delta}_{g1,t}^+$	$\hat{\delta}_{g2,t}^+$	$\hat{\delta}_{n1,t}^+$	$\hat{\delta}_{n2,t}^+$
<b>Panel A: Basic statistics and diagnostic tests</b>						
Mean	4.15E-05	3.14E-05	7.01E-06	6.81E-07	-2.54E-07	1.99E-06
Standard deviation	0.583	0.717	0.790	0.791	1.421	1.273
Skewness	-0.657	-0.850	0.670	0.679	-1.330	-1.011
Kurtosis	16.773	21.050	10.602	10.591	28.089	19.477
J-B	1.07E+03***	1.83E+04***	3.32E+03***	3.31E+03***	3.55E+04***	1.54E+04***
L-B(5)	0.084	0.041	0.091	0.089	0.475	0.110
L-B(15)	1.575	1.842	11.801	11.170	1.260	6.224
L-B <sup>2</sup> (5)	1.13E+02***	1.24E+02***	117.480***	136.070***	184.310***	64.074***
L-B <sup>2</sup> (15)	1.79E+2***	2.05E+2***	340.620***	369.350***	411.540***	270.740***
ARCH(15) LM	60.004***	60.373***	11.397***	12.105***	17.297***	9.915***
<b>Panel B: Unit root test results</b>						
ADF test	-36.515***	-36.628***	-36.584***	-36.603***	-36.776***	-36.829***
KPSS test	0.032	0.034	0.114	0.118	0.074	0.083

**Notes:** Panel A reports the estimates of the unconditional mean, standard deviation, skewness, and kurtosis of the filtered return series. It also presents the results of some diagnostic tests. J-B is the Jarque-Bera test that examines the null hypothesis of a normally distributed series. L-B(Q) and L-B<sup>2</sup>(Q) denote the Ljung-Box test that examines the null hypothesis of no serial correlation up to lag order Q in the filtered returns and their squares, respectively. ARCH(15) LM is the Lagrange Multiplier (LM) test for the presence of ARCH effects up to 15 lags in the residuals. The ARCH LM test has the null hypothesis of no heteroskedasticity in the residuals. Panel B reports the ADF and KPSS unit root test results. ADF is the Augmented Dickey-Fuller test, which examines the null hypothesis of a unit root, whereas KPSS is the Kwiatkowski, Phillips, Schmidt, and Shin test with the null hypothesis of stationarity. The 0.01 critical values for the ADF and KPSS tests, both with a drift and trend, are -3.965 and 0.216, respectively. The critical values for the ADF and KPSS tests are obtained from Kwiatkowski et al. (1992), respectively. \*\*\* and \*\* denote rejection of the corresponding null hypothesis at the 0.01 and 0.05 significance levels, respectively.

**Table 5**  
Parameter estimates of the bivariate GARCH(1, 1) model.

	Panel A: Equity and gold		Panel B: Equity and energy		Panel C: Gold and energy	
	$\hat{\delta}_{s1,t}^+$	$\hat{\delta}_{g2,t}^+$	$\hat{\delta}_{s2,t}^+$	$\hat{\delta}_{n1,t}^+$	$\hat{\delta}_{g1,t}^+$	$\hat{\delta}_{n2,t}^+$
<b>First moment equations</b>						
$\alpha_{aa,0}$	0.013 (1.084)	-0.021 (-0.751)	0.019 (1.487)	0.022 (0.746)	-0.187 (-0.376)	0.016 (0.229)
$\alpha_{ba,1}$	0.052*** (2.982)	-0.043 (-1.218)	0.021* (1.684)	0.040 (0.675)	-0.020 (-0.405)	-0.016 (-0.180)
$\alpha_{ba,2}$	-0.059 (-1.057)	-0.111 (-0.579)	0.253*** (8.609)	-0.339 (-1.309)	-0.026 (-0.147)	-0.112 (-0.403)
$\alpha_{ba,3}$	0.078 (1.209)	0.186* (1.838)	0.278*** (6.621)	-0.338* (-1.698)	0.173** (2.076)	0.354 (1.476)
$H_0 : \alpha_{ba,1} = \alpha_{ba,3}$	0.698	0.029	0.000	0.028	0.126	0.193
$H_0 : \alpha_{ba,2} = \alpha_{ba,3}$	0.106	0.171	0.633	0.546	0.279	0.158
<b>Second moment equations</b>						
$\beta_{aa,0}$	0.014*** (2.960)	0.005 (1.151)	0.014** (2.535)	0.028 (1.310)	0.539** (2.119)	0.478*** (3.291)
$\beta_{aa,1}$	0.104*** (5.124)	0.022*** (2.651)	0.108*** (5.804)	0.026** (2.324)	0.104* (1.715)	0.073 (1.119)
$\beta_{aa,2}$	0.819*** (3.177)	0.909*** (7.605)	0.799*** (5.878)	0.934*** (6.076)	0.556*** (2.943)	0.554*** (3.889)
$\beta_{ba,3}$	0.006** (2.532)	0.009* (1.707)	0.011** (2.378)	0.055*** (3.458)	-0.024 (-1.046)	-0.041*** (-7.661)
$\beta_{ba,4}$	-0.005 (-1.271)	0.004 (0.553)	-0.016*** (-3.543)	-0.003 (-0.167)	-0.036 (-1.174)	-0.205*** (-6.386)
$\beta_{ba,5}$	0.031* (1.760)	0.040*** (2.774)	0.026 (1.522)	0.257*** (3.246)	0.172 (1.189)	0.743 (1.382)
$\beta_{ba,6}$	-0.004 (-0.563)	-0.023* (-1.818)	0.002 (0.603)	-0.096*** (-2.833)	-0.005 (-0.178)	-0.041 (-0.264)
$H_0 : \beta_{ba,3} = \beta_{ba,5}$	0.153	0.028	0.374	0.009	0.126	0.144
$H_0 : \beta_{ba,4} = \beta_{ba,5}$	0.041	0.026	0.021	0.001	0.286	0.752
<b>Diagnostic tests</b>						
AIC	1.326	1.591	2.541	1.31E+03***	1.31E+03***	1.31E+03***
J-B	34.550***	102.246***	198.402***	232.127***	1.47E+03***	1.31E+03***
L-B(5)	1.674	4.972	5.660	3.864	2.774	2.323
L-B(15)	3.953	14.347	8.548	6.870	8.222	5.762
L-B <sup>2</sup> (5)	4.278	1.987	1.735	1.769	2.971	1.864
L-B <sup>2</sup> (15)	15.359	5.159	9.477	7.549	6.408	4.333

**Notes:** This table displays the estimation results of the bivariate GARCH(1, 1) models based on the conditional mean Eqs. (13) and (14) and the conditional variance Eqs. (16) and (17).  $\alpha_{aa,0}$  and  $\beta_{aa,0}$  are the intercept terms of the conditional mean and variance equations, respectively.  $\alpha_{ba,1}$ ,  $\alpha_{ba,2}$ , and  $\alpha_{ba,3}$  reflect the cross-mean spillover effects from market *b* to market *a* over the whole, pre-pandemic, and pandemic periods, respectively.  $\beta_{ba,3}$ ,  $\beta_{ba,4}$ , and  $\beta_{ba,5}$  measure the magnitude of cross-volatility shocks from market *b* to market *a* over the whole, pre-pandemic, and pandemic periods, respectively.  $\beta_{aa,1}$  and  $\beta_{aa,2}$  reflect the sensitivity of the conditional variance of market *a* to its own ARCH and GARCH effects, respectively, whereas  $\beta_{ba,6}$  measures the cross-volatility persistence from market *b* to market *a*. J-B denotes the Jarque-Bera test that examines the null hypothesis that the standardized residuals are normally distributed. LB(15) and LB<sup>2</sup>(15) denote the Ljung-Box test that examines the null hypothesis of no serial correlation in the first 15 lags of the standardized residuals and their squares, respectively. Figures in parentheses are z-statistics, while the reported values for the Wald  $\chi^2$  test of parameter equality are critical probabilities. \*\*\*, \*\*, and \* indicate statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.

estimates of the residual AR( $p$ ) models. For both  $\tau_{s,t}^+$  series, the vast majority of autoregressive coefficient estimates are statistically significant at the 0.05 level or better, while for  $\tau_{g,t}^+$  series, we can notice that only farther AR( $p$ ) coefficients (lag 5 and beyond) are statistically different from zero. The autoregressive coefficients of  $\tau_{n,t}^+$  series show no consistent pattern of statistical significance. The white-noise residual series,  $\delta_{j,t}^+$ , derived from each autoregressive model are subsequently deployed in our analysis.

## 5.2. Univariate stochastic properties

Panels A and B of Table 4 cast light on the univariate characteristics of our main variables. Specifically, Panel A reports estimates of the first four unconditional moments of the filtered return series, together with diagnostic checks, while Panel B shows the results of the unit root tests.

As seen in Panel A of Table 4, the sample averages are very close to zero. Energy (stock) returns appear to be the most (least) volatile, as indicated by their respective standard deviations. Gold (stock and energy) returns exhibit positive (negative) skewness, a feature symptomatic of a greater probability of huge gains (losses) in these markets than would be connoted by a Gaussian distribution. The kurtosis statistics reveal that the individual return distributions are substantially leptokurtic, which implies a high likelihood of occurrence of extreme positive (negative) returns in gold (stock and energy) markets. The Jarque-Bera test statistics are significant at the 0.01 level, further confirming the non-normality of the series under study. The Ljung-Box statistics, testing for autocorrelation up to orders 5 and 15 in the residual levels, are insignificant, which means that the filtering process achieves success in stripping out the predictable portion in our raw returns data. Nevertheless, the same test shows that the squared residuals are temporally correlated up to lags 5 and 15, supporting the existence of ARCH effects in all series. As substantiating evidence, the Lagrange Multiplier (LM) test statistics are highly significant, demonstrating that the residuals are heteroskedastic. In this regard, the presence of fat tails, volatility clustering, and nonlinear dependence in the data entails the adoption of GARCH modeling, which is able to account for such stylized properties.

Next, we run both the Augmented Dickey-Fuller (ADF) unit root test (Dickey and Fuller, 1981) and the KPSS test (Kwiatkowski et al., 1992) to determine the integration order of the individual series. The results are given in Panel B of Table 4. We strongly reject the ADF-test's null hypothesis of a unit root process, while we fail to reject the KPSS-test's null hypothesis of stationarity at the 0.01 significance level. Accordingly, we conclude that our filtered return series are integrated of order zero, i.e.,  $I(0)$ .

## 5.3. Mean spillovers

In this subsection, we investigate whether the nature of return transmissions between stock, gold, and energy markets has altered in the aftermath of the COVID-19 outbreak. The first part of Panels A, B, and C of Table 5 presents estimates of the conditional mean parameters.

As for the equity-gold market pair in Columns (1) and (2), we observe a positive and statistically significant mean spillover from gold to stock markets over the entire sample period, while the reverse case lacks statistical significance. Hence, gold price changes appear to carry important information about future price movements in global stock markets. In the pre-pandemic period, the bilateral spillover effects turn out to be statistically insignificant, as shown by the estimates of  $\alpha_{ba,2}$ . However, in the pandemic period, we notice that the cross-market terms are negative in sign and distinguishable from zero at conventional levels. This finding implies that, with the onset of the COVID-19 disease across the world, there is price interdependence between equities and gold, where past negative returns in either market positively affect current returns in the other. Besides, the cross-mean transmission from stock

markets to gold is somewhat larger in magnitude than that of the reverse case. The respective signs of  $\alpha_{ba,1}$ ,  $\alpha_{ba,2}$ , and  $\alpha_{ba,3}$  in Column (2) suggest that gold can function as a weak hedge against equity market downturns during the overall sample and the pre-pandemic period, while it can serve as a strong safe haven under the shadow of the coronavirus outbreak. The Wald-type test statistics of the null hypothesis  $\alpha_{ba,2} = \alpha_{ba,3}$  have a  $p$ -value less than 0.05 in both specifications, confirming that the sensitivity of either market to lagged return spillovers from the other one is significantly different between pre-pandemic and pandemic periods. In support of our results, numerous studies demonstrate the safe-haven characteristic of gold in tumultuous financial times (e.g., Baur and McDermott, 2010; Bouoiyour et al., 2019; Reboredo, 2013). Ji et al. (2020) find that gold proves a robust safe-haven asset during the COVID-19 crisis, in comparison with Bitcoin and foreign exchange currencies. Still, Corbet et al. (2020) establish that neither gold nor Bitcoin has a significant relationship with stock prices of the Shanghai and Shenzhen Stock Exchanges during the rapid spread of coronavirus in China. Ali et al. (2020) document that as the COVID-19 outbreak shifts from an epidemic to a pandemic, gold returns become negative but with less swings.

Now, we turn to the equity-energy nexus shown in Columns (3) and (4). The estimates of  $\alpha_{ba,1}$  suggest the presence of positive and statistically significant return interdependence over the whole period, with the sensitivity of current stock returns to past energy returns being much greater than that of the other way round. The positive sign implies that higher returns in one market lead to higher returns in the other. The estimates of  $\alpha_{ba,2}$  show that the reciprocal spillovers are positive in the pre-pandemic period, even though the stock price impact of energy becomes less statistically significant and the energy price impact of equities loses its significance. In the pandemic period, we observe unidirectional return spillovers radiating from energy to stock markets. The coefficient  $\alpha_{ba,3}$  in Column (3) is still positively signed and discernible from zero. We strongly reject the null hypothesis of parameter equality, since the  $p$ -value associated with the Wald test statistic is much less than 0.01. This finding implies that the sensitivity of stock markets to energy price movements witnesses considerable changes following the onset of the COVID-19. On the other hand, there is no evidence of mean spillovers from equities to energy markets, as established by the statistical insignificance of the corresponding coefficient in Column (4). This suggests that, over the pandemic period, there may be some dominant factors (e.g., the Russia-Saudi Arabia oil price war), other than global stock market price dynamics, driving energy prices. The response of energy markets to stock price movements proves unaffected by the COVID-19 outbreak, given the Wald test statistic is not significant at even the 0.10 level. Consistent with our findings, Sharif et al. (2020), using the wavelet coherence and the wavelet-based Granger causality tests, document that oil prices lead the US stock markets over short time scales (4–8 days) within the COVID-19 crisis period. The results of He et al. (2020) indicate that oil is a source of positive (negative) return transmissions to the Chinese (US) equity markets. Gatfaoui (2016) finds that the nature and strength of the relationships between the US natural gas, oil, and stock markets differ across structural break-based regimes. Pal and Mitra (2019) report evidence of time-varying co-movements between oil price changes and stock returns of the automobile and parts sector.

Concerning the gold-energy market pair in Columns (5) and (6), we detect mean spillovers in both directions over the full sample period. The corresponding estimates of  $\alpha_{ba,1}$  are statistically distinguishable from zero at the 0.10 level or better and carry a positive sign, implying that higher prices in one market are likely to boost prices in the other. In terms of magnitude, past returns in energy markets exert influence on current gold returns more than twice as large as that of the other way round. The mutual spillover effects in the pre-pandemic period turn out to be negative and statistically insignificant, as shown by the estimates of  $\alpha_{ba,2}$ . With the onset of the COVID-19 outbreak, we observe statisti-

cally significant unidirectional mean transmissions from energy to gold markets, while the reverse direction is denied. In terms of sign, past energy (gold) returns have a negative (positive) influence on current gold (energy) returns. This suggests that, in times of global economic downturn, gold can stand up as a strong safe haven against energy price declines. The Wald test statistic is highly significant in Column (5), but not so in Column (6), which implies that the sensitivity of gold markets to past return spillovers from energy markets differs significantly between pre- and post-pandemic periods, while the impact of lagged gold returns on current energy returns appears to be the same across the two periods. In agreement with our results, [Reboredo \(2013b\)](#) reports evidence of tail independence between oil and gold markets, which confirms the safe-haven property of gold against extreme price movements in oil markets. [Shahzad et al. \(2019\)](#) document a significant negative dependence between returns of oil and gold during the 2007–2009 global financial turmoil. [Selmi et al. \(2018\)](#) find that gold may serve as a hedge, a safe haven, and a diversifier asset against oil price movements, depending on both gold market conditions and oil price states (i.e., low, normal or high).

In brief, our results show that price transmission relationships become more intensified in the aftermath of the COVID-19 outbreak. For the entire sample period, significant mean spillovers are present in both directions across almost all cases. Under the grip of the pandemic disease, we detect bidirectional return spillover effects between equity and gold markets, and unidirectional mean spillovers from energy markets to equity and gold markets.

#### 5.4. Volatility spillovers

In this subsection, we examine whether the level of volatility transmissions between equity, gold and energy markets has changed on the heels of the COVID-19 outbreak. The middle section of [Table 5](#) reports estimates of the conditional variance equation parameters. Several remarks stand out. First, all estimates of  $\beta_{aa,1}$ , reflecting shock dependence, are statistically significant at the 0.05 level or better, which suggest that the respective conditional variances of equity, gold, and energy returns are affected by their own past shocks. It appears that such own-shock effects vary across the three markets, with the stock market exhibiting the largest sensitivity to its own past news shocks, as indicated in Columns (1) and (3). Similarly, the estimated coefficients capturing own volatility persistence,  $\beta_{aa,2}$ , are substantial in magnitude and highly statistically significant in all specifications. We note that GARCH effects are at least five times larger than the corresponding ARCH effects, which suggest that own-volatility spillovers tend to feed much more into forecasts of future conditional variances than do own-shocks. The noticeable small and large sizes of ARCH and GARCH coefficients, respectively, are a manifestation of a gradual evolution of the estimated volatility series over time if there is a shock ([Arouri et al., 2011](#)). The literature is replete with works documenting short- and long-run persistence of past shocks and volatilities, respectively, in financial and commodity markets (e.g., [Ahmed, 2014](#); [Ahmed and Huo, 2021](#); [Hammoudeh et al., 2010](#); [Maghyereh et al., 2017](#); [Yu et al., 2019](#)).

Second, the coefficient estimates quantifying shock transmissions between stock and gold markets over the entire period,  $\beta_{ba,3}$ , are positive and significant at conventional levels, as shown in Columns (1) and (2). We can see that the magnitude of past volatility shocks from stock markets to gold markets is much greater than that of the reverse direction. In the pre-pandemic period, the estimates of  $\beta_{ba,4}$  suggest that the two-way shock spillover effects are even more minuscule and without statistical support. Nonetheless, with the global spread of COVID-19, the estimates of  $\beta_{ba,5}$  point to reciprocal shock spillovers, which are positive and statistically discernible from zero at the 0.05 level or better. In terms

of magnitude, volatility shocks from stock markets to gold markets are still larger than the other way round. The consistent positive signs imply that positive shocks in either market are expected to raise the other's future volatility. Moreover, the Wald test statistics of the null hypothesis  $\beta_{ba,4} = \beta_{ba,5}$  display a  $p$ -value less than 0.05 in both specifications, which demonstrate that the sensitivity of either market's current variance to past shocks from the other one differs significantly between pre-pandemic and pandemic periods. In line with our results, [Uddin et al. \(2020\)](#) find symmetric risk spillovers between gold and the S&P 500 index in tranquil and extreme market conditions. The results of [Boako et al. \(2019\)](#) indicate substantial co-jumps between gold and stock prices in Brazil, Indonesia, Mexico, Russia, and Turkey. [Pandey and Vipul \(2018\)](#) document volatility spillovers from gold to BRICS equity markets, especially following the global financial crisis.

Third, the estimated coefficient  $\beta_{ba,3}$  in Column (3) is positively signed, although it lacks statistical significance. Consequently, past shocks from energy markets have no impact on current variance of equities. In contrast,  $\beta_{ba,3}$  in Column (4) achieves a high statistical significance, which implies that energy markets are positively affected by lagged shocks from stock markets over the whole sample. In the period preceding the onset of coronavirus, the estimate of  $\beta_{ba,4}$  in Column (3) becomes negative and reaches a borderline significance, while in Column (4) it also shifts sign to negative but without statistical significance. As the COVID-19 outbreak started to take hold, the estimates of  $\beta_{ba,5}$  in Columns (3) and (4) turn out to be negative and substantial in terms of both size and statistical significance. This finding points to the existence of bidirectional shock spillover effects between stock and energy markets. It is clear that the impact of past energy shocks is greater than that of past stock shocks. We reject the null hypothesis of parameter equality, since the Wald test statistic is significant in both specifications, which suggests that the response of the conditional variance of either market to past shocks from the other is different in crisis times than in ordinary times. Indeed, a stream of literature documents shock and volatility transmissions between energy commodities, particularly oil, and stock markets (e.g., [Khalifa et al., 2014](#); [Ahmed, 2018](#); [Liu et al., 2020](#); [Pandey and Vipul, 2018](#)). [Ahmed and Huo \(2021\)](#) find reciprocal shock transmissions between Brent crude oil and the Chinese stock market, and one-way volatility spillovers from the former to the latter. The results of [Ji et al. \(2020\)](#) suggest that the role of oil commodity futures, as a safe-haven candidate, deteriorated during the outbreak of the COVID-19.

Fourth, the estimated coefficient  $\beta_{ba,3}$  in Column (5) is positive and discernible from zero at the 0.05 level, implying that past shocks from energy markets influence current volatility in gold markets. The same coefficient in Column (6) also carries a positive sign but fails to attain statistical significance, which means that past gold shocks exert no impact on current energy price volatility over the full period. The estimates of  $\beta_{ba,4}$  in Columns (5) and (6) are still positive, albeit without statistical support, thus suggesting the absence of significant cross-shock effects between the said markets in the period preceding the outbreak of the pandemic. Under the COVID-19 regime, the estimate of  $\beta_{ba,5}$  in column (5) reverses sign, grows larger in magnitude, and proves to be highly statistically significant, whereas the same coefficient in Column (6) is still positive and increases in size, though it is statistically indistinguishable from zero. In absolute terms, the shock impact of energy is greater than that of gold. Accordingly, we conclude that there are unidirectional shock spillovers from energy to gold markets. The Wald test statistic is significant in Column (5), but not so in Column (6). This finding suggests that the sensitivity of the gold (energy) market's current variance to past shocks from the energy (gold) market is (not) significantly different between pre-pandemic and pandemic periods. Similar to

our results, Zhang and Wei (2010) find that oil linearly Granger causes gold price volatility, but not vice versa. Ewing and Malik (2013) report evidence of substantial volatility transmissions in two directions between gold and oil futures. Likewise, Yaya et al. (2016) document reciprocal volatility spillovers between the West Texas Intermediate crude oil and gold markets.

Fifth, we observe that the coefficient estimates measuring cross-volatility transmissions,  $\beta_{ba,6}$ , are negative in Columns (1) through (4) and positive in Columns (5) and (6). This implies the presence of bidirectional negative (positive) conditional volatility dependencies between stock and both of gold and energy markets (between energy and gold markets) in the long run. Accordingly, stock market volatility increases tend to reduce future volatilities in gold and energy markets, and vice versa, while when volatility rises in the energy or gold market, the future volatility of the other is likely to climb. It should be noted, nevertheless, that cross-volatility spillover effects from gold to stock and energy markets fail to reach statistical significance at standard levels, as shown in Columns (1) and (6), which indicates that the price fluctuations of gold exert no influence on the respective future volatility of stock and energy markets. Ciner et al. (2013) and Maghyereh et al. (2017) present comparable conclusions. In all specifications, we also notice that cross-volatility spillovers,  $\beta_{ba,6}$ , are considerably less in size than own-volatility spillovers,  $\beta_{aa,2}$ , which suggest that current conditional variances of the three markets respond more strongly to their own lagged volatilities than to those emanating from other markets. These results support previous evidence (e.g., Arouri et al., 2011; Ewing and Malik, 2013; Yaya et al., 2016; Yu et al., 2019, among others).

In sum, our findings suggest that shock and volatility spillovers become more pronounced in the wake of the COVID-19 pandemic. For the full sample period, there are modest bidirectional cross-shock effects between equity and gold markets, along with unidirectional shock spillovers from equity to energy markets and from energy to gold markets. Under the shadow of the global health crisis, we detect comparatively large bidirectional shock spillover effects between equity and both of energy and gold markets, and cross-shock spillovers from energy to gold markets. Importantly, energy markets appear to have a substantial cross-volatility spillover impact on the other markets, most probably due to the recent oil price debacle.

Finally, we carry out a battery of diagnostic checks on standardized residuals and squared standardized residuals from all GARCH model specifications. The results are given at the bottom part of Table 5. By and large, all our models seem to be well specified, even though there are still reduced departures from Gaussianity. The Ljung-Box test statistics in all cases are insignificant, suggesting that there are no significant temporal dependencies, whether linear or nonlinear, in the standardized residuals for up to the 15th order.

## 6. Conclusion

In this study, we re-examine the dynamic relationships, at both return and volatility levels, between the world's stock, gold, and energy markets prior to and during the novel coronavirus outbreak. Our empirical analysis includes two steps. First, since the behavior of equity, gold, and energy markets is most likely to be affected by other global determinants and risk forces, our first task is to purge their respective raw returns of the potential influences of these common factors. Second, we assess the dynamic interactions between the three markets, using a GARCH( $p, q$ ) process.

Our findings are summarized as follows. In terms of return spillover effects, significant mean transmissions are observed in both directions between equity and energy markets as well as between gold and energy markets across the entire sample period. We also detect unidirectional return transmissions from gold to equity markets. Under the shadow of the pandemic disease, we find bidirectional return spillovers between equity and gold markets, and unidirectional spillovers from energy

returns to equity and gold returns. In general, price transmission relationships become more intensified in the aftermath of the COVID-19 outbreak. In terms of volatility spillovers, there are bidirectional cross-shock effects between equity and gold markets, together with unidirectional shock spillovers from equity to energy markets and from energy to gold markets during the full sample period. As the health crisis took hold globally, we detect comparatively large bidirectional shock spillovers between equity and both of energy and gold markets, and cross-shock spillovers from energy to gold markets. Interestingly, energy markets have a huge cross-volatility spillover impact on the other markets, most probably on account of the recent oil price crash. For example, in consequence of the Russia-Saudi Arabia oil price rout, the S&P GSCI crude oil and S&P GSCI energy index benchmarks experienced a free fall from 256 to 69 on March 05, 2020 to as low as 114 and 36, respectively, on the 18th of the same month, thereby shedding nearly 55% and 49% of their respective values. By and large, shock and volatility spillovers are more pronounced on the heels of the COVID-19 outbreak.

Altogether, our empirical analysis offers fresh evidence on the dynamic interactions among the world's financial and commodity markets bearing the economic brunt of the COVID-19 crisis. Indeed, the coronavirus pandemic and its consequential adverse impacts on oil market dynamics corroborate previous evidence suggesting that the safe-haven characteristic of some investment asset classes is likely to change over time and, therefore, should be periodically assessed. This sustained assessment is a crucial input for the development of appropriate hedging strategies, risk management practices, and optimal portfolio structures.

## Author statement

Mohammed M Elgammal: Conceptualization, Writing- Original draft preparation, Visualization, Supervision, Writing- Reviewing and Editing. Waleed Ahmed: Conceptualization, Methodology, Formal analysis, writing- Original draft preparation, Investigation, Writing- Reviewing and Editing. Abdullah Alshami: Conceptualization, Data curation, Writing- Original draft preparation.

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