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Modeling economic policy issues

COVID-19 pandemic’s impact on intraday volatility spillover between oil, gold, and stock markets

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**A B S T R A C T**

This study examines the volatility spillovers between the US stock market (S&P500 index) and both oil and gold before and during the global health crisis (GHC). We apply the FIAPARCH-DCC model to the 15-minute intraday data. The results showed negative (positive) conditional correlations between the S&P500 and gold (oil). The time-varying conditional correlations between markets were higher during COVID-19 spread. Moreover, gold offers more diversification gains than oil does during the pandemic. Hedging is more expensive during a pandemic than before. Oil provides higher hedging effectiveness (HE) than gold for all sub-periods. HE was lower during the COVID-19 outbreak for both oil and gold. These findings have important implications for both equity investors and policymakers.

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1. Introduction

With over 476,549,503 confirmed cases and causing about 6,128,426 deaths in March 24, 2022, the COVID-19 pandemic has paralyzed real economic activity in the world (Goodell, 2020). Both oil commodities and financial markets showed a spectacular price plunge during the global health crisis (GHC). In addition to Brazil, China, France, India, Iran, Italy, Russia, and the UK, the US is one of the countries most affected by COVID-19. The US stock market (S&P500 index) has experienced a significant decline since January 2020. Ashraf (2020) shows a negative link between the number of confirmed cases and US stock market returns. The author also concludes that stock markets reacted more proactively to the growth in COVID-19 confirmed cases relative to the growth in the number of deaths. Bakas and Triantafyllou (2020) found that pandemic uncertainty has negative (positive) effects on the volatility of the oil (gold) commodity market. Goodell and Goutte (2021) examined the multiscale co-movement between Bitcoin and COVID-19 deaths using the wavelet approach. Sharif et al. (2020) investigated the time-scale relationships between the COVID-19 pandemic, economic policy, geopolitical risk, and the US stock market using the wavelet approach. Azimli (2020) tested the impact of COVID-19 on the return–risk relationship using a quantile regression approach. Drobetz et al. (2020) examine the role of catastrophe bonds as a hedge or safe haven for global stocks, bonds, real estate, commodities, private equity, and

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infrastructure markets. The West Texas Intermediate oil contract cost $37 per barrel on April 20, 2020, for the first time in history. The spread of COVID-19 has significantly decreased global oil demand due to lockdowns. The International Energy Agency estimated that global oil demand would decline by 30% in April 2020, followed by a second important year-on-year decline of 26 million barrels/day in May 2020.\(^2\) It is evident that GHC influences the stock and oil market prices.

Theoretically, these two markets are interdependent, and volatilities are easily passed from the stock market to oil, and vice versa (Ding et al., 2016; Li et al., 2012; Madaleno and Pinho, 2014). Crude oil price shocks impact corporations’ expected cash flows and discount rates, and as a result, market stock prices (Fisher, 1930; Williams, 1938). A vast amount of empirical literature has addressed the relationships between the oil and stock markets and showed mixed results (Jones and Kaul, 1996; Kilian and Park, 2009; Wang et al., 2013). In contrast, gold plays the role of a safe-haven instrument in times of high inflation rates and extreme downward stock markets (Baur and Lucey, 2010; Hillier et al., 2006; Summer et al., 2010). Increasing integration in international stock markets has limited diversification gains (Billio et al., 2017), pushing international investors to find alternative investments such as gold and oil. On the other hand, investment in oil and gold has significantly increased following financialization. In addition, the low correlations between commodity and stock markets have attracted the attention of market participants who rely on these new alternative assets as alternative investments. Therefore, to minimize risk without reducing expected returns, retailers and fund managers have considered these strategic commodity assets in their stock portfolios to hedge their positions against extreme downward stock price movements (Hung and Vo, 2021).

Assessing the degree of dependence and dynamic spillovers among markets is useful for identifying the potential diversification benefits and detecting markets vulnerable to international shocks, as well as the market constituting the source of contagion. It is worth noting that in recent years, gold and oil prices have become more dependent on stock market shocks (Dai et al., 2022; Kang et al., 2019). Nevertheless, monitoring the cross-market linkages between these two strategic commodities and the US stock market is important for portfolio risk management and fund allocation. This study analyzes the dynamic conditional correlations and portfolio risk management between the S&P500 stock index, Brent crude oil, and gold futures markets before and during COVID-19 spread. The rapid increase in uncertainty during the COVID-19 pandemic is the principal motivation for this study.

The results show negative conditional correlations between the S&P 500 and gold and positive conditional correlations between the S&P 500 and oil. Moreover, the time-varying conditional correlations between markets were higher during COVID-19 spread. Gold offers more diversification gains than oil does during the pandemic. Hedging is more expensive during the pandemic. Oil provides higher hedging effectiveness (HE) than gold for all sub-periods. Finally, HE was lower during the COVID-19 outbreak for both oil and gold.

This study contributes to the existing literature on two main fronts. First, it investigates the volatility transmission between the U.S. stock market and both gold and crude oil futures before and during the global health crisis (GHC). COVID-19 has been the worst pandemic in the current century. The restrictive measures implemented by governments to control the spread of this virus did not limit its adverse effects on both commodity and financial markets. The stock market is widely affected by the spread of the virus (Zeinedini et al., 2022). COVID-19 is a systemic risk factor. Moreover, contagion among stock markets is high, reducing the likelihood of diversification opportunities. Therefore, the nexus of stock and strategic commodity markets is worthy of investigation before and during the COVID-19 pandemic. Cross-market correlations provide useful insights for market participants in terms of financial risk management and market regulations. We selected the U.S. stock market for three reasons: (i) the US is one of the largest oil producers and a net importer of oil; (ii) the US is severely affected by the pandemic, resulting in more than 10.4 million confirmed cases (about 21% of the total confirmed cases in the world) and 244,448 deaths in November 2020 (20% of total deaths in the world); (iii) the S&P500 index is a benchmark index for international equity investors, and any shocks in the S&P500 market will be transmitted to the international stock and commodity markets. Gold and crude oil are strategic resources in any economy and are important assets for risk management. In March 2022, the U.S. was the largest oil producer in the world, accounting for 12.108 million barrels per day (20% of the world’s production). The U.S. also imports approximately 7.5 billion barrels of oil-related items. The U.S. is one of the largest consumers of oil (19.69 million barrels per day).\(^3\) Second, we analyze hedging effectiveness strategies useful for investment decisions and financial risk assessment before and during the pandemic. Our study considers 15-min prices for a better understanding of the dynamics of volatility transmission between the gold, oil, and stock markets and their changes during the GHC spread. The advantage of high-frequency data results from the very fine temporal sampling interval for better identification and analysis of temporal volatility transmission patterns between the considered markets. Li et al. (2021) argued that high-frequency data provide an accurate estimation of jumps, volatility, and information transmission of market structure noise.

The remainder of this paper is organized as follows. Sections 2, 3, and 4 present the literature review, data, and outline the methodology. Section 5 discusses the results and Section 6 concludes the paper.

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\(^2\) https://www.bruegel.org.

\(^3\) https://worldpopulationreview.com/.
2. Literature review

Many empirical studies have examined the relationships between oil, gold, and stock markets using different econometric methods. For example, Lin et al. (2019) examine the contagion between Brent crude oil, London gold, and stock market indexes (the Chinese Shanghai Composite Index and European Stoxx 600 Index) using the wavelet approach, empirical mode decomposition, multivariate GARCH models, and linear and nonlinear Granger causality tests. They find evidence of unidirectional contagion from strategic commodity market returns to the Chinese and European markets during irregular events. The European market drove the Brent crude oil market during irregular events. In contrast, significant bidirectional risk contagion exists during extreme events. Naeem et al. (2020) find that the dependence between the oil, gold, and BRICS emerging stock markets varies across different frequencies. The authors claim a positive lower tail dependence between the gold and BRICS markets after the onset of the GFC. Gold acts as a diversifier asset and oil serves as a hedge asset for BRICS equity investors. These results are inconsistent with the findings of Juntila et al. (2018), who found that gold assets provide a better hedge instrument than oil against US stock market risk. Singhal et al. (2019) find significant returns and volatility transmission between the oil, gold, exchange rates, and stock markets in Mexico. Gold (oil) prices have a positive (negative) influence on the Mexican stock market. These findings corroborate the results of Tursoy and Faisal (2018), who show that gold prices, oil prices, and stock prices in Turkey are cointegrated, and that gold prices have a negative influence on Turkey stock prices. Sakurai and Kurosaki (2020) show that the upside and downside correlations between the oil and US stock markets increased during the COVID-19 crisis.

More recently, Enwereuzoh et al. (2021) used structural VAR and smooth transition regression models to study the relationships among crude oil supply shocks, oil demand shocks, oil price shocks, and stock markets in the African continent. They found that oil demand shocks have an insignificant impact on stock markets in oil-importing African economies. Oil supply shocks have little impact on African stock market returns. The authors find that negative price shocks have a greater impact on stock markets than positive price shocks. Adekoya et al. (2021) examine whether gold serves as a hedging asset against extreme downward price movements of oil and stock markets during the spread of COVID-19, using threshold regression and Markov regime switching models. The results show significant nonlinear relationships among the considered markets. Moreover, gold hedges the stock and oil markets during the pandemic period. In addition, equity investors earn higher diversification benefits in the short term by using yellow metals. Vo and Hung (2021) explore spillovers and co-movements between the US stock, crude oil, and gold markets. The authors find time–frequency dependence between the gold, oil, and US stock markets. Furthermore, they reported evidence of significant return transmission during the COVID-19 crisis. Zeinedini et al. (2022) find a negative dependence between the oil and Iranian stock markets, whereas insignificant dependence occurs for the gold and stock markets. Zhao and Wang (2021) investigate the effects of economic policy uncertainty and monetary policy uncertainty in the US and China on commodities (gold and oil) and stock correlations. The authors find that uncertainty indices have heterogeneous impacts on both oil-stock and gold-stock pairs. Table 1 summarizes previous empirical studies (in chronological order) examining the relationships between oil, gold, and stock markets.

3. Data and preliminary statistics

We consider the 15-min prices for the S&P500 index, Brent oil, and gold futures. The intraday data span from April 23, 2018, to April 24, 2020. Tick data were obtained from Tick Data Inc. We split the entire sample period into two subperiods: (i) the pre-COVID-ranges from April 23, 2018, to December 31, 2019, and (ii) the ongoing-COVID-19 period from January 1, 2020, to April 24, 2020. Our breakpoint is January 1, 2020, when the pandemic outbreak occurred in Hubei province and then in the US. The difference in the natural logarithm of two consecutive 15-min prices is our measure of continuously compounded returns.

Fig. 1 plots the evolving 15-min price returns of (a) S&P500, (b) gold, and (c) Brent oil. We observe a sudden shift during the times of GHC in the three markets, but it is more pronounced for oil market. Moreover, the fat tails and volatility clustering are higher and significant during the pandemic period compared to the tranquil period (before the GHC). This result suggests that 15-min price return dynamics and market volatility are significantly different before and during the GHC.

Table 2 presents the preliminary statistics of S&P500, gold, and Brent oil returns for the entire period before and during the GHC. We find positive mean returns for gold futures before and during the pandemic. More interestingly, the mean returns of the yellow metal were higher during the COVID-19 period than before. This may be attributed to the high demand for gold during the turmoil period. Conversely, the mean returns are negative for Brent oil. Furthermore, the negative mean returns of the oil market are high during GHC. Similarly, the S&P500 market showed a negative mean return during the COVID-19 spread. The three markets are more volatile during the GHC period than before; the oil market has the highest volatility, followed by the S&P 500 and gold for different market episodes. The skewness and kurtosis values deny a normal distribution for the different sub-periods and indicate asymmetric and leptokurtic features in the residual series. The results of the Jarque–Bera test support evidence of non-Gaussian distributions. The results of the Ljung–Box tests (Q(20) and Q^{2}(20)) of standardized and squared standardized residuals and the ARCH-LM(10) test of Engle (1982) reject the null hypothesis of no serial correlation and ARCH effects, indicating the appropriateness of the GARCH model. The unit root (Augmented Dickey–Fuller), Zivot–Andrews (with a structural break), and stationary (Kwiatkowski–Phillips–Schmidt–Shin) tests show that the gold, oil, and S&P500 return series are stationary irrespective of the sub-periods.
Table 1
Previous empirical studies.

| Authors                  | Data period                          | Sample                                                                 | Methodology                                                                 | Main conclusion                                                                 |
|-------------------------|--------------------------------------|------------------------------------------------------------------------|----------------------------------------------------------------------------|--------------------------------------------------------------------------------|
| Dai et al. (2022)       | Daily data from December 2014 to May 2021 | 5 Chinese sector stock indexes, WTI crude oil, and gold prices         | Spillover method of Diebold and Yilmaz (2012a, 2012b, 2014) and Granger causality test | Gold and oil are the net receivers of the systemic shocks and all Chinese sectors are net transmitters of the systemic shocks. |
| Mensi et al. (2022)     | Daily data from September 2010 to December 2020 | 22 sub indices of the STOXX 600 index, Brent oil, and gold futures     | Spillover method of Diebold and Yilmaz (2012a, 2012b, 2014)                | Similar findings with Dai et al. (2022)                                          |
| Ali et al. (2022)       | Daily data from January 2019 to March 2021 | WTI and Brent oil. Stock markets of US, Russia, China, Canada, Venezuela | Wavelet-based Granger causality method                                    | Increase of co-movement between the oil futures markets during COVID-19.       |
| Costola and Lorusso (2022) | Weekly data from January 2005 to December 2020 | MSCI indices of US, China, and Europe. Russian sector stocks, Brent oil, natural gas, and gold | Time-domain spillover index                                                 | Oil and gas are the highest transmitters of spillovers during Russian geopolitical uncertainty. |
| Wen et al. (2022)       | Daily data from January 2002 to October 2020 | WTI oil prices, Shanghai Composite Index, and CCFI index               | MODWT and vine-quantile regression model                                  | Volatility spillovers within the Chinese market are higher compared to the spillovers from oil to the Chinese domestic market. |
| Mensi et al. (2021a)    | Daily data from January 2005 to May 2020 | 10 Chinese sector stocks, WTI oil, and gold                           | Spillover method of Diebold and Yilmaz (2012a, 2012b, 2014)               | Bad return spillovers dominate the good return spillovers. The major events (COVID-19, oil crisis, and financial crises) intensify the asymmetric spillovers and the hedging strategy. |
| Bouri et al. (2021)     | 5-min data from April 2006 to April 2019 | S&P 500 index, gold, and oil                                          | Time-varying parameter vector autoregression (TVP-VAR) model and Spillover in high moments (jumps, kurtosis, realized volatility, and skewness) | Realized volatility spillovers are relatively stronger than spillovers in skewness, kurtosis and jumps. The US stock index is the main net transmitter of realized volatility and net receiver of realized skewness and jumps spillovers. |
| Zhang et al. (2021)     | Daily prices from January 2008 to January 2019 | Brent oil, gold, CSI300 index and CSI Aggregate Bond index to represent stock and bond markets of China | Multivariate GARCH models                                                  | Chinese gold spots and futures are not an effective hedge asset for oil, bond, stock markets. |

(continued on next page)

4. Methodology

4.1. Bivariate FIAPARCH model

To determine the dynamic volatility correlation, we applied a bivariate FIAPARCH-DCC model to evaluate the time-varying correlation between S&P500 and commodity (gold and Brent oil) futures returns. In the first step, we fit a univariate FIAPARCH model to each set of sample returns (see Appendix). In the second stage, we apply Engle’s (2002) model.
Table 1 (continued).

| Reference                  | Data Source                                      | Analysis Method                      | Findings                                                                 |
|----------------------------|--------------------------------------------------|--------------------------------------|--------------------------------------------------------------------------|
| Uddin et al. (2020)        | Daily data from January 1996 to October 2016    | US stock market (S&P500 index), gold, silver, and platinum, and oil futures | Copula and CoVaR methods. Asymmetric tail dependence between S&P stock market and both silver and platinum. Gold is a diversifier asset for US equity investors. |
| Ashfaq et al. (2019)       | Daily data from September 2009 till August 2018 | WTI oil and stock markets of Saudi Arabia, United Arab Emirates, Iraq (oil-exporting countries), China, Japan, India, and South Korea (oil importing countries) | BEKK-GARCH and dynamic conditional correlation (DCC) GARCH models. The responsiveness of stock markets to oil prices depends on whether the country is oil-importing or oil-exporting. Oil asset helps to minimize the stock portfolio risk. |
| Ansari and Sensarma (2019) | Monthly data from January 1996 to December 2018 | Federal Fund Rate (FFR), gold, Brent crude oil price, and BRICS stock markets | Structural VAR model and ARDL model. Indian market responds positively to the FFR. South African market responds negatively to oil shocks. Russian and Brazilian stock markets respond positively to gold price changes. |
| Maghyereh et al. (2017)    | Daily data from January 2004 to May 2016        | GCC stock markets, Brent oil, and gold prices | DCC GARCH model. Gold and oil are not good hedges for GCC markets but suitable for diversification purposes. Commodity assets provides risk reductions. |
| Salisu and Isah (2017)     | Monthly data from January 2000 to December 2015 | Brent and WTI oil as well as stock markets of Argentina, Australia, France, Germany, Japan, South Korea, Kuwait, Indonesia, Nigeria, Qatar, Saudi Arabia, UK, and US. | Nonlinear panel ARDL model. Asymmetric responsive of stock markets to oil prices. |
| Raza et al. (2016)         | Monthly data from January 2008 to June 2015     | Gold, oil, international stock markets, oil volatility index, and gold volatility index | Nonlinear ARDL model. Gold prices affect negatively the stock market returns. Commodity volatiles impact negatively the stock market prices at both short- and long-run. |
| Basher and Sadorsky (2016) | Daily data from January 2000 to July 2014.      | Oil prices, gold prices, bond prices, VIX, and 23 emerging stock markets | A DCC GARCH model. Dynamic conditional correlations among markets under study. Oil is a good hedge asset for emerging markets. |
| Khalfaoui et al. (2015)    | Daily data from June 2003 to February 2012      | WTI and G7 stock markets             | Multivariate GARCH and wavelet approaches. High correlations between oil and stock markets. Oil market was leading the G7 markets. |
| Guessmi and Fattoum (2014) | Monthly data from September 2000 to October 2010| Brent oil and stock markets of oil-importing (US, Italy, Germany, Netherlands and France) and exporting countries (United Arab Emirates, Kuwait, Saudi Arabia and Venezuela). | DCC-GARCH model. Positive correlations between oil and stock markets. Oil is not a safe haven asset for equity investors during crisis periods. |

Dynamic conditional correlation (DCC) approach, providing time-varying correlations between the two markets. In DCC, we calculate the variance-covariance matrix \( H_t \) as follows:

\[
H_t = D_t R_t D_t^\top,
\]
Table 1 (continued).

| Author(s)           | Data Source                                    | Markets Studied                              | Methodology                          | Findings                                                                 |
|---------------------|------------------------------------------------|----------------------------------------------|--------------------------------------|-------------------------------------------------------------------------|
| Creti et al. (2014) | Monthly data from September 2000 to October 2010 | Brent oil and stock markets of oil importing and oil exporting countries | Evolutionary cross-spectral density function estimation, Interdependence between oil and stock markets is high for oil-exporting countries than oil-importing countries. |
| Chkili (2014)       | Daily data from January 2000 to July 2014       | Gold and BRICS stock markets                | Asymmetric-DCC-GARCH model           | Gold serves as a safe haven for stocks during times of financial stress. |
| Mensi et al. (2013) | Daily data from January 2000 until December 2011 | S&P500 index, WTI and Brent oil, gold, beverage, and wheat | CCC GARCH model                      | Evidence of significant volatility transmission between S&P 500 and commodity markets. |
| Fillis et al. (2011)| Monthly data from January 1987 to September 2009 | Oil and stock markets of oil-exporting countries (Canada, Mexico and Brazil) and oil-importing countries (US, Germany and Netherlands) | DCC-GARCH-GJR model                  | Supply-side oil price shocks do not influence the relationship of the two markets. |

Fig. 1. Time variations of 15-min price returns Note: We divide the entire period into two subperiods. (Pre-COVID-19 from April 23, 2018, to December 31, 2019, and COVID-19 outbreak from January 1, 2020, to April 24, 2020).

where $D_t = \text{diag} \left( h_{11}^{1/2}, \ldots, h_{NN}^{1/2} \right)$ is an $n \times n$ diagonal matrix of time-varying conditional standard deviation from the univariate FIAPARCH model. The evolution of the correlation in the DCC model is given by

$$Q_t = (1 - \alpha_{dcc} - \beta_{dcc}) Q_t + \alpha_{dcc} (\varepsilon_t \varepsilon_t') + \beta_{dcc} Q_{t-1},$$

(2)
Table 2
Preliminary statistics for 15-min returns.

|                | Whole period | Before GHC | During GHC |
|----------------|--------------|------------|------------|
|                | S&P 500      | Gold       | Brent oil  | S&P 500      | Gold       | Brent oil  | S&P 500      | Gold       | Brent oil  |
| **Mean (%)**   | 0.011        | 0.051      | −0.242     | 0.044       | 0.030      | −0.026     | −0.164       | 0.162      | −1.392     |
| **Max.**       | 3.932        | 2.608      | 14.287     | 1.544       | 1.362      | 12.095     | 3.932        | 2.608      | 14.287     |
| **Min.**       | −5.092       | −2.068     | −22.945    | −1.787      | −1.764     | −4.733     | −5.092       | −2.068     | −22.945    |
| **Std. dev.**  | 142.81       | 61.38      | 676.86     | 33.38       | 36.33      | 357.88     | 44.71        | 31.42      | 210.83     |
| **Jarque–Bera**| 4.1057e+007 | 7.1561e+006| 9.6197e+008| 1.6354e+006| 1.9648e+006| 2.2660e+008| 5.7813e+005| 2.6803e+005| 1.4338e+007|
| **Q (20)**     | 237.53       | 215.41     | 228.48     | 39.30       | 51.39      | 26.39      | 74.17        | 101.83     | 74.94      |
| **Q^2 (20)**   | 715.22       | 7795.1     | 419.31     | 5988.7      | 1340.3     | 9.641      | 790.02       | 1095.2     | 56.22      |
| **ARCH-LM(10)**| 302.72       | 278.52     | 25.89      | 264.03      | 95.20      | 0.799      | 38.34        | 39.75      | 3.688      |

Panel A: Descriptive statistics

|                | S&P 500      | Gold       | Brent oil  | S&P 500      | Gold       | Brent oil  | S&P 500      | Gold       | Brent oil  |
|----------------|--------------|------------|------------|--------------|------------|------------|--------------|------------|------------|
| **ADF**        | −132.34      | −131.65    | −134.04    | −117.97      | −118.78    | −119.4     | −53.207      | −53.240    | −53.943    |
| **ZA**         | −103.93      | −112.09    | −99.871    | −118.04      | −208.40    | −146.81    | −42.149      | −44.205    | −44.123    |
| **KPSS**       | 0.0504       | 0.3372     | 0.5160     | 0.0092       | 0.3761     | 0.0563     | 0.1138       | 0.0594     | 0.1119     |

Notes: ADF statistics of the Augmented Dickey Fuller (1979) unit root test checks a unit root whereas the KPSS of Kwiatkowski et al. (1992) tests stationarity in the time series. Zivot–Andrews (ZA) unit root test of Zivot and Andrews (1992) checks the null hypothesis of a unit root with a structural break in the intercept in time series. ***Denotes the rejection of the null hypotheses at the 1% significance level.
with $\alpha_{dce} > 0$, $\beta_{dce} > 0$, and $\alpha_{dce} + \beta_{dce} < 1$. $\Omega_t = \{q_{ij,t}\}$ denotes time-varying covariance matrix of $\varepsilon_t$. The coefficients $\alpha_{dce}$ and $\beta_{dce}$ are estimated parameters depicting the conditional correlation process. $R_t$ is a matrix of time-varying conditional correlations, given by

$$R_t = (\text{diag}(Q_t))^{-1/2} Q_t (\text{diag}(Q_t))^{-1/2}.$$  

(3)

where $\text{diag}(Q_t) = \sqrt{q_{ii,t}}$ is a diagonal matrix containing the square root of the $i$th diagonal element of $Q_t$. The dynamic correlation is expressed as

$$\rho_{ij,t} = \frac{(1 - \alpha_{dce} - \beta_{dce}) q_{ij} + \alpha_{dce} q_{ii,t-1} q_{jj,t-1} + \beta_{dce} q_{ij,t-1}}{\sqrt{\left[(1 - \alpha_{dce} - \beta_{dce}) q_{ii} + \alpha_{dce} q_{ii,t-1}^2 + \beta_{dce} q_{ij,t-1}^2\right] \left[(1 - \alpha_{dce} - \beta_{dce}) q_{jj} + \alpha_{dce} q_{jj,t-1}^2 + \beta_{dce} q_{jj,t-1}^2\right]}}.$$  

(4)

In the bivariate FIAPARCH-DCC model, the significance of $\alpha_{dce}$ and $\beta_{dce}$ indicates that the estimates are dynamic and time varying. The time-varying $\rho_{ij,t}$ indicates the direction and strength of the correlation (Engle, 2002).

The parameters of the bivariate FIAPARCH-DCC model were estimated using the quasi-maximum likelihood method with respect to the log-likelihood function given in Eq. (5) according to a two-step estimation procedure.

$$l_t(\Theta, \Phi) = -\frac{1}{2} \sum_{t=1}^{T} \left[ n \log(2\pi) + \log|D_t|^2 + \varepsilon_t D_t^{-2} \varepsilon_t \right] + \sum_{t=1}^{T} \left[ \log |C_t| + w_t C_t^{-1} u_t - u_t' u_t \right].$$  

(5)

4.2. Measures of portfolio design

To manage the stock market more efficiently, we computed the optimal portfolio weight and hedge ratio for portfolio diversification and risk management.

First, we consider a risk-minimizing stock–commodity portfolio without reducing expected returns. Following Kroner and Ng (1998), we define the portfolio weight of commodity assets as follows:

$$w_t^C = \frac{h_{t}^C - h_{t}^{C,S}}{h_{t}^C - 2h_{t}^{C,S} + h_{t}^{S}},$$

with $w_t^C = \begin{cases} 0 & w_t^C < 1 \\ w_t^C & 0 \leq w_t^C \leq 1 \\ 1 & w_t^C > 1, \end{cases}$

(6)

where $h_t^C$, $h_t^S$, and $h_{t}^{C,S}$ are the conditional volatility of the commodity markets (gold and Brent oil), the conditional volatility of the S&P500 stock market, and the conditional covariance between the commodity and S&P500 markets at time $t$, respectively. For each stock–commodity pair, all information needed to compute the weight $w_t^C$ is obtained from the FIAPARCH-DCC model.

Second, to minimize the risk of this stock and commodity portfolio, we measure the degree of hedging of a long position (buy) in the stock by a short position (sell) in the commodity assets (gold and Brent oil). Following Kroner and Sultan (1993), hedge ratio ($\beta_t^C$) is defined as follows:

$$\beta_t^C = \frac{h_{t}^{C,S}}{h_{t}^C}.$$  

(7)

where $\beta_t^C$ is a hedge ratio with a one-dollar long position in the S&P 500 market and a one-dollar short position in commodities (gold and Brent oil). Finally, the hedging effectiveness (HE) to examine the risk-minimization effectiveness of each portfolio with stocks and commodities is estimated as follows:

$$\text{HE} = 1 - \frac{\text{Var}_{\text{hedged}}}{\text{Var}_{\text{unhedged}}}.$$  

(8)

where $\text{Var}_{\text{hedged}}$ is the portfolio variance with optimal weights in a stock and commodity pair, and $\text{Var}_{\text{unhedged}}$ represents the variance of commodity asset returns without any diversification. A higher HE ratio indicates a superior hedging strategy.

5. Results and discussions

5.1. Conditional correlation analysis

To analyze the evolving relationships between the U.S. stock, gold, and oil markets, we apply different GARCH-DCC competing models with different distributed innovations and lag orders. Akaike information criterion (AIC) was used to select the best model. The AR(1)-FIAPARCH (1,d,1)-DCC model with Student’s $t$ distributions fits our data, and the estimation results corresponding to this model are presented in Table 3. As we can see, the autoregressive parameter

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5 We consider all possible combinations for the ARMA(p,q) model with p = 0, 1, 2 and q = 0, 1, 2, based on the Akaike information criterion (AIC) and determine the lowest value of AIC. In this paper, the best mean process is a AR(1) process.
of the mean equation is statistically significant for the S&P500 (except during the pandemic period) and gold markets, indicating that previous returns can be used to predict current returns. For Brent oil, this parameter was statistically significant during the COVID-19 outbreak. The Brent oil market was the most persistent market during COVID-19, followed by the gold and S&P500 markets. Before the pandemic, gold was the most persistent market, whereas the S&P500 was the least persistent. The ARCH and GARCH parameter values are statistically significant for almost all cases, suggesting that previous squared shocks and the 15-min lag conditional variance impact the current conditional variance. This result is consistent with Mensi et al.’s (2013) findings.

Panel B shows negative conditional correlations between the S&P500 and gold for the entire period, as well as before and during COVID-19 spread. This shows that gold is a diversifier and hedge asset against negative stock price movements during tranquil and GCH periods. Our results are in line with those of Omane-Adjepong and Alagided (2021), who found that gold and palladium serve as safe haven assets against African stock market risk. Our result confirms the finding of Salisu et al. (2021), who conclude that gold hedges US stock market risk during the GCH spread. We find moderately positive and statistically significant correlations between the S&P 500 and Brent oil pairs. More precisely, the conditional correlations for the S&P500-Brent oil pair increased during the GCH period relative to before the pandemic spread, indicating a decrease in diversification benefits. This result also supports evidence of contagion effects in the sense of Forbes and Rigobon (2002). Gold is a good diversifier for Brent oil price, as the parameter of dynamic conditional correlations is negative before and during COVID-19 spread, suggesting that energy investors are interested in combining oil and gold for better portfolio risk management. This result is in line with Semlì et al.’s (2018) findings that Bitcoin and gold serve as a hedge, safe haven, and diversifier for oil price movements. The parameters $\alpha_{DCC}$, $\beta_{DCC}$, and the Student’s t-test were statistically significant, indicating the appropriateness of our model. Panel C presents the estimated results of the diagnostic tests, including the standard residuals and squared standardized residuals of the Ljung-Box test statistics.

### Table 3
Estimation results of the AR (1)-FIAPARCH (1, d, 1)-DCC model.

#### Panel A: Estimates of mean and variance equations

|          | Whole S&P500 | Gold | Brent oil | Pre-COVID 19 S&P500 | Gold | Brent oil | COVID 19 Outbreak S&P500 | Gold | Brent oil |
|----------|--------------|------|-----------|----------------------|------|-----------|--------------------------|------|-----------|
| Const.(M)| 0.0004       | 0.0002 | −0.0009   | 0.0004               | 0.0003 | 0.0007   | 0.0017                   | 0.0024** | −0.0018** |
|           | (0.0004)     | (0.0002) | (0.0014)  | (0.0004)             | (0.0025) | (0.0009) | (0.0013)               | (0.0012) | (0.0005)  |
| AR(1)    | −0.0248***   | −0.0283*** | −0.0158   | −0.0252***           | −0.0239*** | −0.0075 | −0.0206                  | −0.0423*** | 0.0773*** |
|           | (0.0081)     | (0.0078) | (0.0101)  | (0.0075)             | (0.0083) | (0.0083) | (0.0208)               | (0.0151) | (0.0016)  |
| Const. (V)| 0.2778**     | 0.4983*** | 0.0015    | 0.3028               | 0.4992 | 0.0023  | 0.0009                   | 0.0262   | 0.0558*** |
|           | (0.1300)     | (0.0808) | (0.0100)  | (0.2455)             | (0.3563) | (0.0039) | (0.0014)               | (0.0424) | (0.0061)  |
| d-Figarch| 0.3301***     | 0.3427*** | 0.3657*** | 0.3122***            | 0.3673*** | 0.1369 | 0.3589***               | 0.4723*** | 0.9062*** |
|           | (0.0608)     | (0.0266) | (0.0472)  | (0.1082)             | (0.0617) | (0.0990) | (0.0805)               | (0.1162) | (0.2231)  |
| Arch     | 0.4289***     | 0.2618*** | 0.8593*** | 0.3532***            | 0.1489 | −0.3101 | 0.4837***               | 0.3491*** | 0.0406*** |
|           | (0.0626)     | (0.1300) | (0.0499)  | (0.1819)             | (0.1103) | (2.3508) | (0.0946)               | (0.0769) | (0.1471)  |
| Garch    | 0.5839***     | 0.4214*** | 0.9431*** | 0.4810***            | 0.3085*** | −0.2933 | 0.7144***               | 0.7001*** | 0.5726*** |
|           | (0.0760)     | (0.1583) | (0.0252)  | (0.2276)             | (0.1487) | (2.4062) | (0.1083)               | (0.1209) | (0.0761)  |
| APARCH   | 0.1360***     | 0.0107 | 0.3118*** | 0.1066***            | 0.0050 | 0.3578** | 0.2178                   | 0.1061   | 0.4050*** |
| (Gamma)  | 0.0499***     | 0.0357*** | 0.0920*** | 0.0509***            | 0.0341*** | 0.1816  | (0.1910)               | (0.0892) | (0.0439)  |
| APARCH   | 2.0601***     | 2.1126*** | 2.1940*** | 2.0506***            | 1.9565*** | 2.3936*** | 2.1227***               | 2.0719*** | 0.1144*** |
| (Delta)  | 0.0490***     | 0.0432*** | 0.0782*** | 0.2030***            | 0.1946*** | (0.4455) | (0.1708)               | (0.1611) | (0.0083)  |

#### Panel B: Estimates of the DCC model

|            | S&P 500 | Gold | Brent Oil | S&P 500 | Gold | Brent Oil |
|------------|---------|------|-----------|---------|------|-----------|
| Student-t df | 3.0358*** | 3.0878** | 2.8496*** |
|             | (0.0142) | (0.0163) | (0.0307) |

#### Panel C: Diagnostic tests

| Q(20) | Q2(20) |
|-------|--------|
| 17.699 | 2.5382 |
| [0.607] | [0.999] |

Notes: p-values are in brackets, and standardized errors are in parentheses.

*Indicate significance at the 5% level.

**Indicate significance at the 1% level.
The results show evidence of misspecification. These results have significant economic implications for equity investors, which we discuss later.

To better understand the evolving relationships between the three markets under investigation, we plot the trajectory of the DCC coefficients for each pair in Fig. 2. Graphical evidence indicates an evolving relationship over time and its sensitivity to GHC. Taking the S&P500–gold pair, we observed negative correlations before the COVID-19 period, whereas the peak of the correlation reached its highest level during the COVID-19 outbreak (approximately 0.3). Even during the pandemic, equity investors can use gold assets to hedge their positions during GHC. The level of correlation between the S&P500 and Brent oil is high, where the correlation coefficient exceeds 0.5 during the COVID-19 period. Our results are consistent with the findings of Liao et al. (2021), who find a significant increase in return and volatility spillovers between the oil, gold, and stock markets during the COVID-19 pandemic. These results corroborate the findings of Mensi et al. (2021b) and Hung and Vo (2021). In contrast, the relationship between gold and Brent oil is less unstable during the pandemic outbreak, as the correlation coefficient oscillates between negative and positive values during the pandemic. Before COVID-19, the trajectory showed a downward trend, indicating high diversification gains. We notice that the correlations between the S&P500 and gold are more stable than those between the S&P500–Brent oil and gold–Brent oil. The changing correlations show that investors should adjust their positions frequently, especially during GHC.

5.2. Portfolio management analysis

It is crucial to discuss the economic significance of our results in terms of fund allocation and portfolio risk management. Specifically, the estimations of the FIAPARCH-DCC model are used to quantify the optimal portfolio weights, hedge ratios, and hedging effectiveness over the whole period and pre- and during pandemic periods for the three pairs (S&P 500–gold, S&P 500–Brent oil, and gold–Brent oil).

Table 4 presents the estimation results. As shown in this table, equity investors may include gold and/or oil in their U.S. stock portfolios to minimize risks without lowering expected returns. Interestingly, investors should add more gold than oil. This result persisted for the entire period before and during the COVID-19 pandemic outbreak. Our results are not in line with Mensi et al.’s (2013) findings, as they used constant conditional correlations of the GARCH (CCC-GARCH) model.
Table 4
Results of the portfolio weights, hedge ratios and hedging effectiveness.

| Portfolio pairs     | $w_t^C$ | $\beta_t^C$ | HE(%) |
|---------------------|---------|-------------|-------|
| Whole period        |         |             |       |
| S&P 500/Gold        | 0.5639  | −0.147      | 41.96 |
| S&P 500/Brent oil   | 0.1031  | 0.1033      | 73.20 |
| Pre-COVID19         |         |             |       |
| S&P 500/Gold        | 0.5507  | −0.1352     | 58.93 |
| S&P 500/Brent oil   | 0.1017  | 0.0987      | 80.42 |
| COVID19 outbreak    |         |             |       |
| S&P 500/Gold        | 0.6343  | −0.2068     | 25.34 |
| S&P 500/Brent oil   | 0.1105  | 0.1275      | 69.98 |

Fig. 3. Time-varying hedging ratios.

More importantly, we notice that the weight invested in oil and gold commodities was higher during the pre-COVID-19 period. For example, the optimal weight of gold is 0.63 (0.55) during (pre-) COVID-19, suggesting that for equity shares, the optimal weight of gold holding in a one-dollar gold–stock portfolio should be 63% (55%) during (before) GHC, with the remainder budget of 37% (45%) invested in the U.S. stock market. The hedge ratio values are positive for oil and negative for gold. Hedging is expensive when oil is used. The hedge ratio for oil was higher during the COVID-19 period (0.12) than before (0.10). This result implies that one dollar in oil assets should be shortened by about 12 (10) cents of the S&P500 index during the (before) GHC period. Oil provided a higher HE than gold for different periods. More interestingly, HE is lower during the GHC period than before for both oil and gold, confirming the effects of GHC on portfolio risk management.

Fig. 3 displays the dynamic hedge ratios for the S&P 500–oil and S&P 500–gold pairs. Graphical evidence shows that the hedge ratio for the S&P 500–gold pair is negative before COVID-19 and oscillates between negative and positive during the pandemic period. As for oil, the hedge ratio is positive during the sample period and reaches the highest level during COVID-19, indicating that hedging is expensive during GHC. This corroborates the results of Morema and Bonga-Bonga (2020) for the South African stock market.

6. Conclusion

Economic uncertainty has intensified during the COVID-19 pandemic. U.S. stock market volatility at the industry level (petroleum and natural gas, restaurants, hotels, and lodging industries) has increased during the COVID-19 outbreak (Baek et al., 2020). COVID-19 has affected the relationship between commodities and stock markets. This study examines the volatility spillovers between the gold, oil, and U.S. stock markets. It also provides economic implications for portfolio design before and during a global health crisis. We use 15-min data and a bivariate FIAPARCH-DCC model to achieve our objectives.

The results show negative conditional correlations between the S&P500 and gold before and during COVID-19 spread, suggesting that gold is a refuge asset against the extreme S&P500 index movement. On the contrary, we find moderate positive conditional correlations between the S&P500–Brent oil pair, but an increase during COVID-19 spread, indicating that the propitiatory role of the diversifier asset for oil decreases during times of GHC. Moreover, gold is a good diversifier of Brent oil. Overall, equity and energy investors can use gold assets to hedge their positions during the GHC. The portfolio risk implications show the usefulness of adding oil and gold to equity portfolios. In addition, gold provides more protection against downward equity movements than oil does. This result persisted before and during the COVID-19
pandemic. Interestingly, equity investors should add more gold than oil before and during the pandemic. Investment in commodity assets was higher during COVID-19 than pre-COVID-19, suggesting the importance of these assets in financial risk management. Hedging is more expensive during a pandemic. Oil offers the best HE compared with gold for different sub-periods. HE was lower during the pandemic than before the outbreak for both oil and gold.

Our results have important implications for both investors and policymakers. For better portfolio optimization and hedging performance, equity investors should be aware that strategic commodities (gold and oil) are important hedge assets that should be added to stock portfolios during extreme negative US stock price movements. Moreover, we recommend that investors combine gold and stocks during periods of the global health crisis. For prudential supervision and to ensure financial security, policymakers should be aware that the COVID-19 pandemic remarkably intensifies poverty-stock linkages and thus implement measures (e.g., holding enough oil reserves or increasing investment in renewable energies) to protect stock markets against shocks emanating from oil and system health.

Our research can be extended by examining the dynamics, direction, and volatility transmission between oil, gold, and aggregate/disaggregate stock markets across frequencies, using both the trivariate asymmetric BEKK GARCH model and the maximal overlap discrete wavelet transform (MODWT) to decompose the raw series. Another alternative is to consider spillovers in high moments (skewness and kurtosis) between gold, oil, and aggregate/disaggregate stock markets before and during the recent pandemic crisis. Additionally, portfolio design analysis can be improved by considering a portfolio composed of oil, gold, and stock assets.

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Appendix

We apply the multivariate DCC–FIAPARCH model to examine the dynamic correlations between stock and commodity markets. In the FIAPARCH model, we assume that the daily return process is described by an autoregressive moving average (ARMA) model as follows:

\[ r_t = \mu + \phi_1 r_{t-1} + \phi_2 r_{t-2} + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \varepsilon_t, \quad \varepsilon_t = z_t \sqrt{h_t}, \]  

where \(|\mu| \in [0, \infty), |\phi| < 1\), and the innovations \(\{z_t\}\) follow Student's t-distribution \((z_t - \nu (0, 1, \nu))\). The conditional variance, \(h_t\), is positive with a probability of one, and is a measurable function of the variance–covariance matrix.

To examine the asymmetry and long memory in the conditional variance, Tse's (1998) FIAPARCH \((p, d, q)\) model is expressed as:

\[ h_t^{1/2} = \omega \left(1 - \beta (L)^{-1} + [1 - 1 - \beta (L)^{-1} \phi (L) (1 - L)^d] (|\varepsilon_t| - \lambda \varepsilon_t)^d, \]  

where \(\omega, \beta, \phi, \) and \(d\) are the parameters to be estimated; the parameter \(d\), where \(0 \leq d \leq 1\), measures the long memory in the conditional volatility; \(L\) denotes the lag operator; \(\delta\) is the power term of returns for the predictable structure in the volatility persistence; and \(\lambda > 0\) represents the asymmetry parameter, indicating that negative shocks give rise to higher volatility than positive shocks of equal size.

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