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Research Article

Connectedness between Gold and Cryptocurrencies in COVID-19 Pandemic: A Frequency-Dependent Asymmetric and Causality Analysis

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We employ a frequency-dependent asymmetric and causality analysis to investigate the connectedness between gold and cryptocurrencies during the COVID-19 pandemic. Hence, the variational mode decomposition-based quantile regression is utilised. Findings from the study divulge that the variational mode functions at the lower quantiles are mostly significant and negative indicating that gold acts as a safe haven, a diversifier at most market conditions with insignificant coefficients, and a hedge at normal market conditions for most cryptocurrencies at various investment horizons. Particularly, hedging benefits mostly occur in the short- and medium-term for Bitcoin and Ripple, as well as Bitcoin and Dogecoin in the long-term with gold. This implies that there is high persistence in the hedging properties of gold with Bitcoin, followed by Ripple. We notice more significant relationship between gold and some cryptocurrencies in the long-term of the COVID-19 pandemic relative to the medium-term emphasising the delayed responses of prices to information. Investors are recommended to be observant and mindful of investing in these markets due to the different dynamics.

1. Introduction

The onset of the coronavirus (COVID-19) pandemic that was first recorded in Wuhan, China, in the last quarter of 2019 and declared a pandemic on March 11, 2020 [1], by the World Health Organisation (WHO) has caused quite a several variations in the social, economic, and epidemiological sectors of different countries globally causing panic. The complexity of the social and economic system makes it quite vulnerable and frugal; thus any phenomenon that disrupts the system, disrupts human activity [2]. Empirical literature reports that pandemic(s) aftermaths totally affects economies and their financial system because it leads to unemployment (retrenchment), inflation, and interest rate spikes causing the standard of living of individuals to decrease and shift in precautionary savings [3–6]. Empirically, Correia et al. [7] find that firms whose names and brands are related to the coronavirus are recording negative share prices. This indicates that the effect the pandemic on the economy would sweep the economies of sustainability.

To control the effect of the swelling upsurge in the COVID-19 pandemic, governments closed down borders to countries; irrespective, that did not prevent businesses from operating particularly in the advanced economies, where new strategies to meeting targets were assumed. People capitalized on working at home and equally moonlighting—in that avenue, people indulged in peer-to-peer electronic cash systems among other things to make money as the future was uncertain consequently, increasing trade volume [8] as a result of following other investor's trading activities [9]. The electronic cash system served as a means for most financial activities during this pandemic because unlike most transactions that need financial intermediaries to render service, traders did not require any intermediaries

[10]. Literature reports that trade volume of bitcoin (and other cryptocurrencies) increased during the COVID-19, and this is attributable to the fact that investors became active, and to pass time, they traded to entertain themselves [8]. With increasing trade volume, the volatility of the cryptocurrency market is expected to fluctuate just as a financial asset would leading to a noisy market, posing as a threat to other traditional assets while making the market risky [11], and also changing the level of asymmetry in the markets [12]. As the cryptocurrency market becomes risky, investors start looking for mechanisms to diversify risk [8]. Irrespective of how secure the network maybe (as a result of the cryptography), portfolio investors must be wary of the risk and return trade-offs from investing in the cryptocurrencies during the COVID-19 pandemic due to its price spikes.

However, if the cryptocurrencies markets are efficient, fluctuations in the cryptocurrency prices may not persist for a very long time. The efficient market hypothesis (EMH) by Fama [13] states that "market price for stocks incorporates all available information–past, public and private–on the stock; financial markets are efficient." Literature reports that efficiency in the cryptocurrency market is time-varying and is most highly efficient because the market adjusts to unexpected news with speed [14, 15]. Despite the level of efficiency and volatility in the cryptocurrency market, the blockchain of cryptocurrencies keeps increasing with the introduction of new coins almost every day [16] as well as variations in its market capitalization [11, 17]. Investors need to maximize returns and minimize risk in such a volatile market is guided by the Modern Portfolio Theory (MPT) which provides a framework to constructing and selecting portfolios based on the performance of the investment and the risk aversion level of the investor; mean-variance analysis [18]. As the trade in cryptocurrency is gradually warming itself into the minds of investors; it has widened the scope for investors and their portfolio options [19, 20]. The MPT guides investors with different degrees of risk aversion and needs to make viable investment decisions.

Empirically, studies have been conducted to explore the interrelatedness of some of the cryptocurrencies especially bitcoin (most valued coin) and gold to see which one is a hedge, diversifier, or safe haven for other financial instruments in a portfolio. Though gold has been proven to be a better hedging instrument [21–24], this study seeks to explore if indeed the empirical property of gold as a safe haven and a hedge or diversifier for cryptocurrencies during bad market conditions is threatened with the aid of quantile regression. Gold is an asset that is more likely not to be correlated but otherwise, has low correlation with other assets on stock markets and oil and gas and its ability to withstand inflation makes it a more sought-after asset; when investors want to hedge against inflation. Thus, gold returns exhibit low level of heterogeneity relative to other assets returns [19].

Gold prices are more stable; demand is relatively low but has quite stable positive returns [25]. However, a recent study by Bentes et al. [26] avers that gold returns display reverse pattern during the COVID-19 pandemic. Contrarily, they found that gold volatility exhibit positive asymmetric effect. Notwithstanding, empirical literature has it that gold is a safe haven to equities [27]. Owusu Junior et al. [28] report that gold and cryptocurrencies can interrelatedly be used as a hedge or a diversifier against each other using data from the period of April 2013 to April 2019 and as well to assets like crude oil and fiat currencies. Akhtaruzzaman et al. [29]; find that in the first wave of the pandemic, gold was still a safe haven to equities but in the first quarter of 2020, it lost this property against the same equities: S&P 500, Euro Stoxx 50, Nikkei 225, and China FTSE A50 indices. This partly supports the outcome of Bentes et al. [26] on gold returns in the COVID-19 pandemic. Yousaf et al. [30]; report in their findings on thirteen Asian countries and their stock markets stating that gold exhibits properties of diversifier and safe haven (weak and strong) interchangeably between these markets during the coronavirus pandemic. It is for these contradictions in literature that this study seeks to test the empirical properties of gold against cryptocurrencies (Bitcoin, Dogecoin, Ethereum, Litecoin, Tether, and Ripple) as established by Baur and Lucey [31] be it that we are in a pandemic (COVID-19) and gold is reported to serve as a safe haven for stocks during extreme stock market conditions or in a turmoil.

However, unstable signals typically contain essential details [32] which investors can capitalize on in order to diversify or hedge against risk if they know the time-varying characteristics of the financial assets. The ubiquitous behaviour of unstable signals, financial time series are surrounded by noise and experience rapid changes of which cryptocurrencies and gold are no exception. Market players are viewed as heterogeneous by the heterogeneous market hypothesis (HMH), with a wide range of information, purposes, and investment horizons [19, 33]. Market participants respond to information at different times, resulting in very noisy market data. Consequently, cryptocurrency and gold price series exhibit nonlinearity and nonstationarity. Day traders of cryptocurrencies and gold trade short-term price movements to enter and exit a position in a matter of minutes or hours. Some noise traders try to profit from market turbulence by entering buy and sell orders without using fundamental data. As a result, this noise may influence the outcome of the study if not dealt with. We, therefore, decompose the data to illustrate market participants' numerous investment time scales which corroborates with the heterogeneous market hypothesis (HMH) as indicated by Müller et al. [34]. Again, the adaptive market hypothesis (AMH) engineered by Lo [35] indicates that market efficiency fluctuates in degrees of time [33, 36, 37]. Consequently, decomposition techniques reduce noise to maintain the true signals [19, 28, 38].

In this sense, the study employs the variational mode decomposition (VMD) method developed by Dragomiretskiy and Zosso [39], which is subsequently used for the quantile regression analysis. The VMD is a suitable method for sampling and dealing with the noise of signals to surpass EMD and EEMD developed by Huang et al. [40] and Wu and Huang [41], respectively. The VMD meticulously decomposes input signals into their major modes, known as variational mode functions (VMFs), which reproduce the input signal but with varying sparsity qualities [42]. Specifically, in the context of this study, the VMFs represent short-term, medium-term, and long-term periods. The quantile regression technique is specifically employed in this study to reveal the extent of asymmetric relationships between cryptocurrencies and gold within the COVID-19 pandemic period. As a result, various markets conditions (e.g., normal, crash, and boom conditions) come to bear [31, 43]. This is important because, information at diverse quantiles better provides a big picture about financial time series which mostly exhibit nonlinearity, asymmetry, and nonnormal relationships [43].

Therefore, the main contribution of this research is studying the degree of similarities/dissimilarities in cryptocurrencies returns concerning variations in the gold price returns. The sample period considers the COVID-19 pandemic period to reveal the extent of shocks in the cryptocurrencies and gold markets, from February 2020 to April 2021, which is ideal for the analysis of this study [33]. Furthermore, this study departs from extant literature by decomposing the sample data with the quest of minimising noise. The study investigates the asymmetric relationships between cryptocurrencies and gold returns depending on the varied market conditions. In addition, the nonparametric causality test proposed by Diks and Panchenko [44] is applied as robustness check to determine the extent to which gold is caused by cryptocurrencies. The study focuses on six coins (Bitcoin, Dogecoin, Ethereum, Litecoin, Tether, and Ripple) because they are the most dealt in coins and have the greater share of the market capitalization subject to other cryptocurrencies (Selfkey, Stellar, UMA, Mina, and Holo) and gold because it is the traditional asset used in Baur and Lucey [31].

The Diks and Panchenko [44] nonparametric causality test avoids the overrejection observed in the frequently used test as provided by Hiemstra and Jones [45]. Consequently, we are able to effectively estimate the directional influences of cryptocurrency on gold without any a prior hypothesis. It also permits a large number of lags with higher-order lags discounted as compared to other causality tests such as wavelets and transfer entropy [37, 46–52]. This would help to ascertain whether the behaviour of gold can be effectively predicted by cryptocurrencies. As a result, the degree of efficiency in the gold and cryptocurrencies markets can be revealed. These make our study differ significantly from the approach by Asafo-Adjei et al. [42] who employed the VMD-based entropy. However, we build on the VMD technique; the quantile regression is subsequently used to account for both diverse market conditions and investment horizons which Asafo-Adjei et al. did not consider. However, our quantile regression is not effective to establishing causality between financial assets. Consequently, in addition to our VMD-based quantile regression, the Diks and Panchenko [44], nonparametric causality test is used for all the VMFs to achieve the required outcome.

We find an asymmetric relationship between gold and most cryptocurrencies. Furthermore, the VMFs at the lower quantiles are mostly significant and negative indicating that gold acts as a safe haven, and as a diversifier at most quantiles with insignificant coefficient, and as a hedge at normal market conditions for most cryptocurrencies at various VMFs. Also, the Diks and Panchenko [44] nonparametric causality test indicates that most of the cryptocurrencies cause gold in the short-term. This implies that investors capitalize on the empirical properties of gold in the short-term to avoid losses during the coronavirus pandemic.

The rest of the paper is structured as follows: Section 2 is on literature review; Section 3 is the methodology data and data sources and description; Section 4 is the empirical analysis; and Section 5 summarizes the study.

2. Literature Review

Baur et al. [31]; found that in normal market conditions, gold could serve as a safe haven for stocks; for about 15 trading days but not for bonds in any financial market. Their findings suggest that investors use gold to store value when the volatility in a market is high and sell it off when the stock market's volatility stabilizes. In normal or average market conditions, Shan et al. [53] report that neither Bitcoin nor gold could serve as a safe haven or hedge for economic policy uncertainty. Owusu Junior et al. [19] using data on gold and eight cryptocurrencies (Bitcoin, Ethereum, Dash, Litecoin, Ripple, Stellar, NEM, and Monero) from April 2013 to April 2019 and using the EEMD-based quantile-on-quantile regression to explore the hedging and diversification properties of these assets found that gold and cryptocurrencies can hedge and diversify against each other at varying times of their returns. They also found that gold and cryptocurrencies depict same properties towards traditional assets like crude oil and fiat currencies which is deflates findings from Klein, Thu, and Walther [54].

Emphatically, there has been empirical literature on gold and cryptocurrency trying to draw the relationship between bitcoin (in particular) and gold. Cryptocurrencies are not purely speculative assets contrary to findings from Baek and Elbeck [55] which says that Bitcoin is a highly speculative asset. Due to the increase in the volume of bitcoin, there have been questions as to if it is more efficient for investors to hold more bitcoin as opposed to gold. Klein et al. [54] report that gold and bitcoin are not similar in any way in an investor's world on the market. Studies from Jareño et al. [56] also sought to assess the relationship between bitcoin, gold prices, and other international risk factors. Importantly, bitcoin was found to be more sensitive in extreme market conditions and the VIX index was the most relevant international risk factor [56]. Nakagawa and Sakemoto [57] robustly find that investors' decision to holding cryptocurrencies are influenced by gold returns and both assets are unaffected by government monetary policies. However, during the COVID-19 pandemic, gold and cryptocurrencies have become interconnected where cryptocurrencies are asymmetrically responding to gold returns [58]. Also, gold backed cryptocurrencies are empirically acting as safe haven for investors because it reduces the fluctuations in cryptocurrency prices [59]. Empirically, there have been several studies that have been conducted on gold and cryptocurrencies being safe haven, diversifier, or serve as a hedge between stock markets and amongst each other during the corona period and before the pandemic due to the volatility in these markets.

Even though cryptocurrencies are digital assets, it should be noted that volatility among these currencies implies the need to hedge or diversify against risk if they are in a portfolio with other underlying assets or not though during the period of COVID-19, there was persistence in the Bitcoin and Ethereum market [60]. Stable coins could serve as safe haven for Bitcoins (highly volatile) though this property varies across market conditions mostly acting as diversifiers in a portfolio of cryptocurrencies. They further go on to report that gold pegged cryptocurrencies perform worse off than USD pegged stable coins in extreme volatility [61]. Hoang and Baur [62] opine that even though Bitcoin has properties of a safe haven, looking at its volatility, investors should look at building a portfolio where another asset would serve as a safe haven against Bitcoin. They report that stable coins could serve as a safe haven; however Tether is more suitable as a safe haven against Bitcoin.

Corbert et al. [63]; employing the GARCH (1, 1) model, to explore the effects of COVID-19 sentiments on cryptocurrency returns, using data from social media, analyze the relationships between cryptocurrencies and the economic shock centralized within the rapidly-escalating pandemic report that "cryptocurrencies are significantly influenced by negative sentiments relating to COVID-19." They also report that the cryptos acted as diversifiers and safe haven for investors as there was significant growth in both volumes traded and their respective returns. Kristoufek [64]; studied the safe haven property of bitcoin and gold against S&P 500 and VIX (index measure of uncertainty and future uncertainties) and adopting quantile correlation find that Bitcoin could be used to diversify against S&P 500 during the pandemic but making comparison to gold, Kristoufek found that gold is a better diversifier as it serves as a safe haven.

Corbet et al. [16]; conduct a study using dynamic conditional correlation and GARCH (1, 1) to investigate the effects coronavirus had on Chinese stock markets (Shanghai and Shenzhen) it been the epicenter of the pandemic. Using hourly and daily returns, comparing periods before and after the pandemic, "we observe some strong changes in dynamic behaviour," correlations (+0.889 to +0.967) between the stock markets was stronger as market conditions worsened, correlation between the markets and gold also increased, respectively (+0.335 and +0.347); however, the relationship between the cryptos and the markets depicted short-term dynamic interactions after the pandemic was identified, time-varying. Cryptocurrencies and gold depict high volatility compared to traditional financial markets but the crypto market recover quickly compared to traditional financial markets [65]; also find that cryptocurrencies can be used for diversification as well as when you add gold to a portfolio because the cryptos (Bitcoin, Dash, Zlato, Litecoin, XRP, and Monero) showed positive skewness; representation of good volatility to generate additional income [66].

Contrary to other studies Conlon and McGee [67], assess the safe haven property of Bitcoin's bear market by examining whether an investor could reduce downside risk if he includes Bitcoin in his portfolio relative to a portfolio of only equities during the COVID-19 pandemic and find that Bitcoin may increase a portfolio's risk instead of serving as a safe haven during the market stress using S&P 500 daily prices against Bitcoin. Vidal-Tomas [68] conducted a study to assess how the pandemic affected the crypto network and report that the pandemic did not have any significant effect on the network but the logical layout changed after the first wave probably as a result of the financial shock across all assets on the market however this did not affect the market conditions of cryptocurrencies [69].

Following the empirical literature and contradicting findings, this study would explore the empirical properties of Bitcoin, Dogecoin, Ethereum, Litecoin, Ripple, and Tether to gold in a portfolio during the COVID-19 pandemic. Consequently, it is likely that the COVID-19 pandemic may have altered the already existing relationships between gold and cryptocurrencies which may require further attention.

3. Methodology

We initially present the VMD technique followed by the quantile regression. Thus, the outcome generated from the VMD is used as input data for the quantile regression.

3.1. VMD. The intrinsic mode function (IMF) of the VMD is defined as an amplitude-modulated-frequency-modulated signal [39]. The k_{th} mode $u_k(t)$ is presented as

$$u_k(t) = A_k(t)\cos\left(\phi_k(t)\right), \quad (1)$$

where $A_k(t)$ is the immediate amplitude; $\phi_k(t)$ is the immediate phase; and its derivative $\omega_k(t) = \phi_k\ (t)$ is the immediate scale.

For each mode $u_k(t)$, VMD uses the Hilbert transform to produce the analytic signal and estimates the autonomous frequency spectrum. The spectrum of the mode is then moved to baseband using the Fourier transform's displacement property and subsequently, the bandwidth is projected via the H^1 Gaussian smoothness. The purpose of optimization is to reduce the sum of all mode functions' spectral widths to the smallest possible value:

$$\min_{\{u_k\},\{\omega_k\}} \left\{ \sum_{k=1}^{k} \partial_t \left\| \left[\left(\delta(t) + \frac{j}{\pi t} \right) * u_k(t) \right] e_2^{-j\omega_k t} \right\|_2^2 \right\}$$
$$\text{s.t.} \quad \sum_{k=1}^{k} u_k = f, \quad (2)$$

where $\{u_k\}$ is mode ensemble and $\{\omega_k\}$ is the analogous center frequency ensemble K is the mode observation. The original signal is equal to the total of the modes, which is the constraint.

A quadratic penalty term and a Lagrangian multiplier are introduced to change the preceding constrained optimization problem into an unconstrained issue as follows:

$$L(\{u_k\},\{\omega_k\},\lambda) = \alpha \sum_{k=1}^{k} \left\| \partial_t \left[\left(\delta(t) + \frac{j}{\pi t} \right) * u_k(t) \right] e_2^{-j\omega_k t} \right\|_2^2 + \left\| f(t) - \sum_{k=1}^{k} u_k(t) \right\|_2^2 + \lambda(t), f(t) - \sum_{k=1}^{k} u_k(t), \tag{3}$$

where α is the penalty parameter and λ is the Lagrangian multiplier.

The Alternating Direction Method of Multipliers (ADMM) is used by VMD to solve the above equation iteratively. Finally, the original signal is decomposed into K IMF constituents. The code of VMD is available in Hamilton and Ferry's [70] package "VMD."

3.2. Quantile Regression. A basic quantile regression technique was employed to specify the influence of cryptocurrencies on gold. The model employed in this study is

$$\begin{aligned} \mathrm{Gold}_t &= \beta_0(\theta) + \beta_1 \mathrm{BTC}_t(\theta) + \beta_2 \mathrm{LTC}_t(\theta) + \beta_3 \mathrm{ETH}_t(\theta) \\ &+ \beta_4 \mathrm{DOGE}_t(\theta) + \beta_5 \mathrm{XRP}_t(\theta) + \beta_6 \mathrm{TETH}_t(\theta) + \mu_t(\theta), \end{aligned} \tag{4}$$

where Gold_t, BTC_t, LTC_t, ETH_t, DOGE_t, XRP_t, and TETH_t denote gold, Bitcoin, Litecoin, Ethereum, Dogecoin, Ripple, and Tether, respectively, at time t, θ is the θth quantile of the regressors, β represents coefficients to be estimated at each quantile, and μ_t is the error term at period t without a specific distribution form.

Previous works such as Owusu Junior et al. [19]; Boako et al. [71]; Demir et al. [72]; Fousekis and Tzaferi [73]; and Xue and Zhang [74] employed the quantile regression approach confirming its usefulness over the Ordinary Least Square method. The quantile regression approach as popularly introduced by Koenker and Bassett [75] expresses the conditional quantile of a response variable as a linear function of the explanatory variables rather than just the conditional mean of the explained variable and as such estimates from quantile regression are more robust against outliers in the response measurement. Furthermore, quantile regression gives a more comprehensive depiction of the influence of the independent variables on the dependent variable. That is, it richly describes and characterizes the data by portraying the effects of the explanatory variable on the explained variable across the gamut of the dependent variable. Generally, the quantile regression model is described by the equation as

$$Y_t(\theta \mid X) = \beta(\theta) X_t' + \mu_t(\theta), \tag{5}$$

where β_θ represents the vector of unknown parameters associated with the θth quantile. The quantile regression minimizes $\sum_t \theta|\mu_t| + \sum_t (1-\theta)|\mu_t|$, thus the sum that offers the asymmetric penalties $\theta \mid \mu_t$ for underprediction and $(1-\theta)\ |\mu_t|$ for overprediction. To calculate the coefficient or the quantile estimator can be solved using the optimization problem stated as

$$\min \sum_{t\varepsilon\{Y_t \geq X_{t\theta}'\}}^{n} \theta \left| Y_t X_t' \beta \right| + \sum_{t\varepsilon\{Y_t \geq X_{t\theta}'\}}^{n} (1-\theta) \left| Y_t X_t' \beta \right| \min, \tag{6}$$

where Y_t is the dependent variable and X_t, a K by 1 vector of regressors. The relationships between gold and cryptocurrency returns were examined at 19 different quantiles, the 0.05^{th} quantile to 0.95^{th} quantile. These quantiles assess whether the variations in the cryptocurrency trade network market conditions would have an impact on gold return movements implicating its empirical properties [31]. Owing to this, the three market conditions, the crash market condition (lower quantiles; $\theta = 0.05$, 0.10, 0.15, 0.20, 0.25, 0.30), normal or stable market condition (intermediate quantiles; $\theta = 0.35$, 0.40, 0.45, 0.50, 0.55, 0.60, 0.65), and the boom market condition (higher quantiles; $\theta = 0.70$, 0.75, 0.80, 0.85, 0.90, 0.95) were specified in the study.

3.3. Data Sources and Descriptions. The study uses daily returns covering the period of February 2020 to April 2021 yielding a total of 307 observations after dealing with missing data. The duration is relatively a long period of the COVID-19 pandemic, which has caused havoc on markets [33, 76], providing better discernments about the diversification properties of gold and cryptocurrencies. We employ gold and six cryptocurrencies (Bitcoin, Litecoin, Ethereum, Dogecoin, Ripple, and Tether) during the COVID-19 pandemic to explore the interrelatedness between them. However, the inclusion of these cryptocurrencies is influenced by their market capitalization and the tendency for them to exhibit safe haven, hedge, and diversification benefits with gold [19, 54, 77]. The data for cryptocurrencies and gold are extracted from yahoo finance, both quoted in USD. The daily data from cryptocurrencies are matched with the trading days and time span for gold for the study [19]. As shown, the study was based on daily returns of $r_t = \ln P_t - lnP_{t-1}$, where r_t is the continuously compounded return and P_t and P_{t-1} are current and previous index correspondingly.

Figure 1 provides the time-varying prices and returns of cryptocurrencies and gold for both the original (signal) and the decomposed series (M1, M2, M3, and MAgg). It can be observed from the plots that in the early part of 2020, the price series for most markets trend upwards, after a downward spike. That is, the prices are experiencing a rapid increase which concurs with the assertion made by Zhang, Hu, and Ji [78] of markets rebound later in the COVID-19 periods since most businesses and economies have cultured how to survive. Generally, it can be observed from the plots that fluctuations in cryptocurrencies surpass gold. This supports the assertion made by extant literature on the riskiness of cryptocurrencies [79, 80]. On the other hand, the returns series of cryptocurrencies and gold exhibit volatility clustering, which is in line with the stylized facts of most financial assets [81].

Table 1 presents the descriptive statistics of the data at M1 (short-term), M2 and M3 (medium-term), and the MAgg (long-term) frequency levels as well as the signal. The standard deviations indicate the fluctuations in time series which can be used to explain volatility among the returns in the variables. In testing for normality of the data at the different decomposed levels, the Normtest W

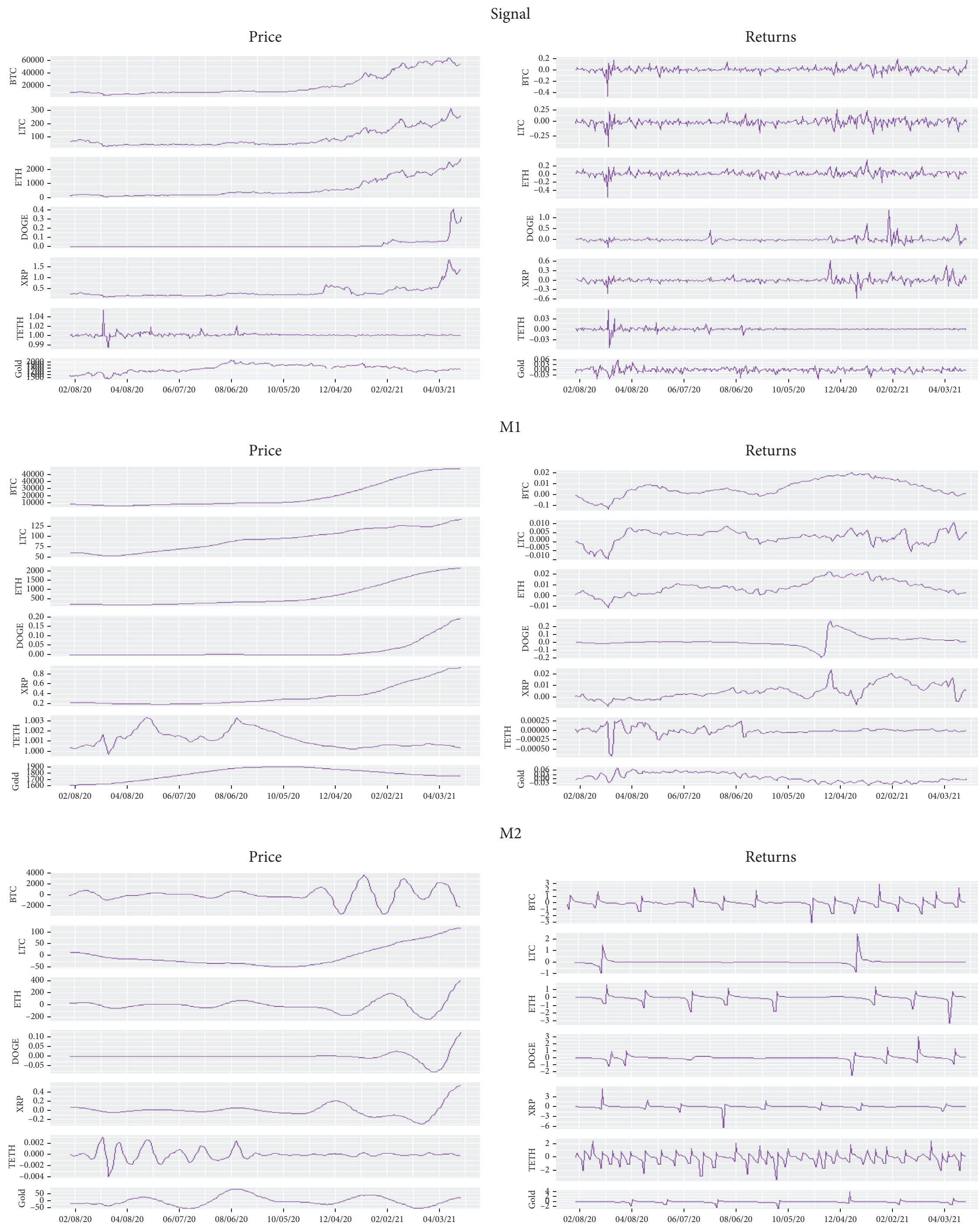

FIGURE 1: Continued.

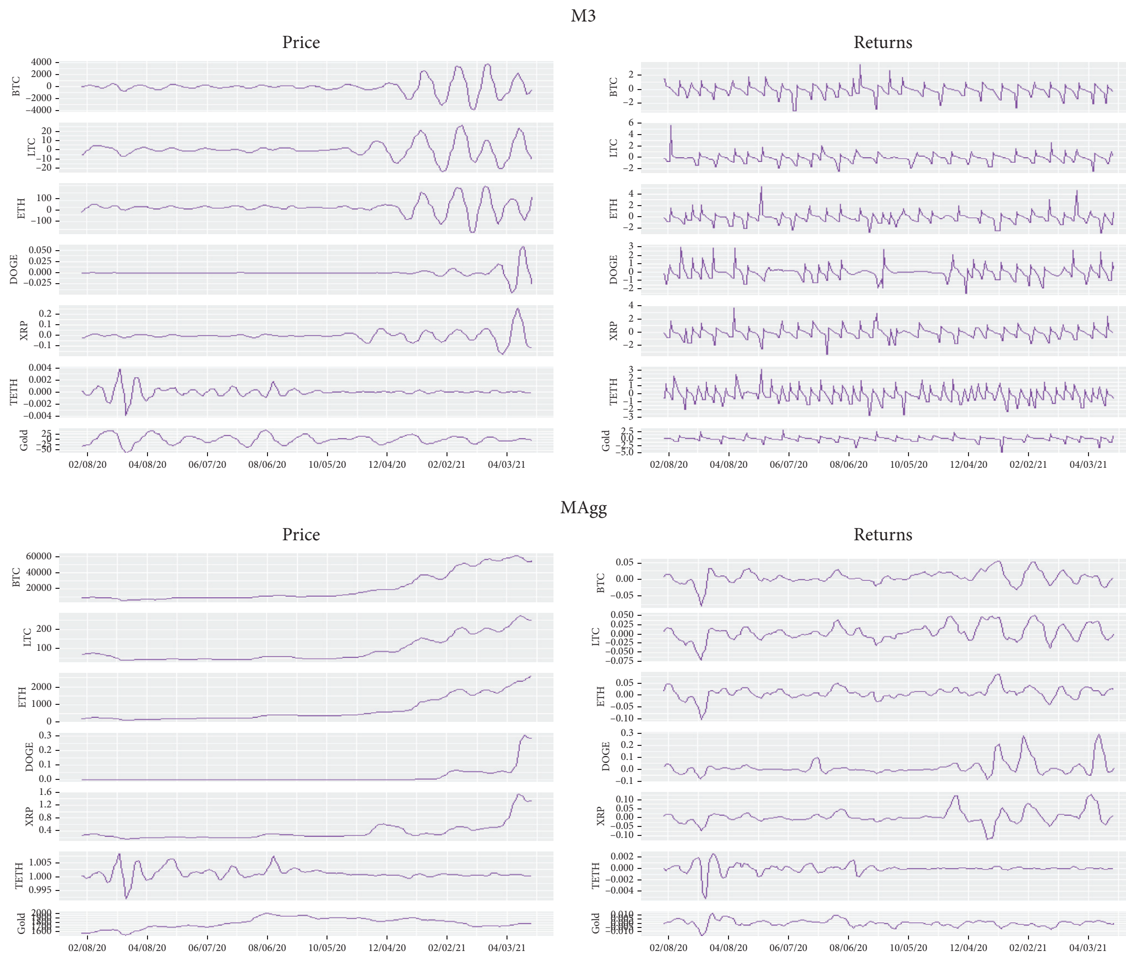

Figure 1: Plots of prices and returns series. Note: the time-varying prices and returns of cryptocurrencies and gold for both the original (signal) and the decomposed series (M1, M2, M3, and MAgg). The decomposed series reveal the investment horizons, where M1 indicates short-term; M2 and M3 depict medium-term, whereas MAgg shows long-term. At the early part of 2020, the price series for most markets trend upwards, after a downward spike. That is, the prices depict rapid increase.

(Shapiro–Wilk test) analysis reflects that the data is not normally distributed. This is in agreement with existing research on cryptocurrency returns distributions [82, 83]. We compare the augmented Dickey–Fuller (ADF) and Philips–Perron (PP) tests for robustness of stationarity. We found that all the returns series are stationary for all variables, but for M1.

We present the correlation matrix to assess the relationship between gold and cryptocurrencies in Table 2. We find that gold and cryptocurrencies depict significant relationship among themselves, especially, for the original (signal) and decomposed series, except M2 and M3 representing the medium-term. This may be an indication that in the medium-term investors may minimize their investing risk within these assets. The significant relationships in the short-term and long-term indicate short-lived market fluctuations and real economic growth for institutional investors. The negative relationship between some of the assets may suggest potential diversification benefits. Testing for potential multicollinearity from the data, we realise the absence of multicollinearity among the independent variables because generally, their coefficient estimates are below 0.8, and it would be worthwhile to include all the cryptocurrencies in a single model.

4. Results and Discussion

This section presents the results and discussion relating to the study. The frequency-dependent quantile regression is therefore presented in addition to the Diks and Panchenko [44] nonparametric causality test as robustness check. We utilise the VMD to meticulously decompose the input signals into VMFs, which reproduce the input signal but with varying sparsity qualities. Specifically, in the context of this study, the VMFs represent short-term (M1), medium-term (M2 and M3), and long-term (M4) periods, in addition to the signal (original series). To interpret the relationship between gold and cryptocurrencies, we present the quantile regression coefficients results at various significance levels for each VMFs, in addition to the signal.

Table 1: Summary descriptive.

Statistic	Gold	Bitcoin	Litecoin	Ethereum	Dogecoin	XRP	Tether
Signal							
Mean	0.0004	0.0058	0.0043	0.0087	0.0159	0.0055	0.0000
Std. dev.	0.0133	0.0510	0.0664	0.0685	0.1305	0.0914	0.0057
Skewness	−0.1938	−2.3976	−1.1472	−1.4269	4.7547	0.6776	0.3542
Kurtosis	3.5359	23.6870	8.1408	15.8533	38.1795	14.4548	49.1498
Normtest W	0.9385***	0.8161****	0.8987***	0.8552***	0.5777***	0.7802***	0.5181***
ADF	−8.9301***	−6.3731***	−6.6347***	−6.8754***	−7.0512***	−6.3193***	−10.1210***
PP	−289.200***	−369.700***	−353.420***	−357.180***	−264.340***	−317.630***	−344.750***
M1							
Mean	0.0003	0.0059	0.0027	0.0079	0.0149	0.0046	0.0000
Std. Dev.	0.0096	0.0075	0.0036	0.0066	0.0626	0.0060	0.0001
Skewness	0.2324	−0.0353	−0.9482	0.5366	0.7858	0.6507	−1.6855
Kurtosis	−1.2810	−0.5221	1.0177	−0.3690	3.8985	−0.0801	12.8349
Normtest W	0.9325***	0.9702***	0.9429***	0.9771***	0.8385***	0.9593***	0.7908***
ADF	−2.1822	−0.9913	−2.6555	−0.4637	−4.0556***	−3.4290**	−6.6380***
PP	−23.1370**	−1.7362	−17.7140	−3.4260	−20.1460*	−25.6620**	−71.2650***
M2							
Mean	−0.0372	−0.0404	0.0107	−0.0507	0.0156	−0.0332	−0.1653
Std. dev.	0.4622	0.5719	0.2083	0.4585	0.3852	0.6797	0.8116
Skewness	−0.1153	−0.2890	5.1496	−3.0141	−0.2456	−3.2187	−0.8538
Kurtosis	26.6510	9.0486	64.0178	18.5501	24.7125	54.0895	2.6925
Normtest W	0.5823***	0.7854***	0.3811***	0.6456***	0.6250***	0.4432***	0.9232***
ADF	−6.3697***	−7.3832***	−6.8617***	−6.6855***	−6.6165***	−6.5240***	−8.0789***
PP	−180.220***	−177.480***	−215.470***	−150.860***	−180.640***	−175.890***	−158.870***
M3							
Mean	−0.1477	−0.1574	−0.0864	−0.0916	−0.0410	−0.1019	−0.1641
Std. dev.	0.8209	0.8188	0.7491	0.8843	0.7350	0.8116	0.8610
Skewness	−1.6275	−0.4881	1.1143	0.9945	0.5367	−0.0346	0.0455
Kurtosis	9.0989	3.0606	11.6477	7.6663	3.7610	3.4546	1.2112
Normtest W	0.8173***	0.9182***	0.8598***	0.8770***	0.9039***	0.9313***	0.9801***
ADF	−7.5900***	−8.6145***	−8.6332***	−7.8387***	−8.2543***	−8.5140***	−6.4569***
PP	−159.080***	−161.260***	−185.970***	−192.410***	−183.300***	−170.680***	−161.950***
MAgg							
Mean	0.0004	0.0058	0.0042	0.0085	0.0158	0.0053	0.0000
Std. dev.	0.0036	0.0183	0.0208	0.0225	0.0580	0.0348	0.0007
Skewness	−0.1052	−0.5312	−0.1363	−0.7033	2.5196	0.6002	−2.0575
Kurtosis	1.7924	3.1348	0.7600	4.2604	7.4451	3.1871	16.4644
Normtest W	0.9690***	0.9449***	0.9756***	0.9296***	0.7193***	0.8948***	0.7286***
ADF	−4.5819***	−5.3421***	−5.7570***	−4.7763***	−5.7524***	−4.4650***	−10.0630***
PP	−44.4320***	−44.4080***	−42.0620***	−44.1140***	−55.7200***	−44.8660***	−83.0000***

NB: ***, **, and * denote significance at 1%, 5%, and 10%, respectively. The daily data observed are 307 for each variable sampled from 03/02/2020 to 30/04/2021. Descriptive statistics are presented for 7 tests for both cryptocurrencies and gold at various frequencies (short-, medium-, and long-term) in addition to the original series. The null hypothesis for ADF and PP tests is the presence of unit root. The return series for cryptocurrencies and gold depict nonnormal distribution at all frequencies, whereas most return series are stationary.

4.1. Frequency-Dependent Quantile Regression. We present the results of the frequency-dependent quantile regression for the original and decomposed series. We utilise 19 quantiles to reveal the extent of safe haven, hedge, and diversification benefits based on various markets conditions (crash, normal, and boom).

Table 3 presents the quantile regression coefficient estimates of the original return series. The estimates projected show that bitcoin is more dominating however, at 10% significance level, followed by Dogecoin. Gold provides diversification benefits for all the cryptocurrencies under study with less potential to act as an effective hedge against all the cryptocurrencies (normal market conditions) in a portfolio. At market boom (beyond quantile 0.65), gold provides safe haven benefits for all cryptocurrencies, except bitcoin. Looking at the analysis above, in this pandemic season, any investor who would want to use gold as a hedge, a diversifier or a safe haven should best use it to diversify risk in the cryptocurrency market due to the unstable empirical properties of gold in the market.

Table 4 presents the short trend decomposition of the gold and the six cryptocurrency data indicating significance at 1% at almost all the quantiles. From the table, Litecoin and Ripple are the most dominating variables in the short-term. This is followed by Bitcoin, Ethereum, and Dogecoin. The coefficients of Ripple and Litecoin at all quantiles are significant at 1%. Notwithstanding, gold acts as an effective hedge for variations in Ripple during normal market outcomes and as a safe haven at extreme market conditions.

Table 2: Correlation matrix.

	Gold	Bitcoin	Dogecoin	Ethereum	Litecoin	Tether	XRP
				Signal			
Gold	1.000						
Bitcoin	0.218***	1.000					
Dogecoin	0.025	0.369***	1.000				
Ethereum	0.143**	0.722***	0.379***	1.000			
Litecoin	0.192***	0.743***	0.364***	0.738***	1.000		
Tether	−0.022	−0.321***	−0.102*	−0.307***	−0.273***	1.000	
XRP	0.041	0.431***	0.266***	0.542***	0.535***	−0.162**	1.000
				M1			
Gold	1.000						
Bitcoin	−0.491***	1.000					
Dogecoin	−0.272***	0.361***	1.000				
Ethereum	−0.493***	0.796***	0.373***	1.000			
Litecoin	0.312***	0.398***	0.073	0.314***	1.000		
Tether	0.150***	−0.040	0.021	−0.073	0.059	1.000	
XRP	−0.551***	0.466***	0.281***	0.544***	0.100*	−0.029	1.000
				M2			
Gold	1.000						
Bitcoin	−0.013	1.000					
Dogecoin	−0.097*	−0.075	1.000				
Ethereum	0.067	0.006	0.032	1.000			
Litecoin	−0.020	0.020	0.049	−0.013	1.000		
Tether	−0.009	−0.097	−0.043	0.112	0.013	1.000	
XRP	−0.042	0.010	−0.021	0.021	−0.076	0.017	1.000
				M3			
Gold	1.000						
Bitcoin	0.015	1.000					
Dogecoin	−0.012	−0.026	1.000				
Ethereum	0.021	0.148**	0.045	1.000			
Litecoin	−0.012	0.161**	0.046	0.144**	1.000		
Tether	−0.069	−0.012	0.010	0.074	0.009	1.000	
XRP	0.082	0.147**	−0.009	0.121**	0.094	−0.053	1.000
				MAgg			
Gold	1.000						
Bitcoin	0.254***	1.000					
Dogecoin	0.005	0.313***	1.000				
Ethereum	0.364***	0.786***	0.422***	1.000			
Litecoin	0.266***	0.780***	0.348***	0.780***	1.000		
Tether	0.191***	0.141**	0.064	0.218***	0.079	1.000	
XRP	0.075	0.379***	0.425***	0.460***	0.489***	0.094	1.000

NB: correlation coefficients >0.8, show multicollinearity among independent variables [84].***, **, and * denote significance at 1%, 5%, and 10%, respectively. Gold and cryptocurrency returns show significant relationship among themselves, especially, for the original and decomposed series, except M2 and M3 representing the medium-term. That is, at most times, no significant relationship occurs in the medium-term suggesting high likelihoods for short-lived market fluctuations and real economic growth.

This is followed by Bitcoin, from 0.4 to 0.95 quantiles with significance at 1% suggesting both safe haven and effective hedge depending on the market outcomes. Just as González et al. [58] report, our analysis shows that gold and cryptocurrencies are more correlated in the coronavirus pandemic period confirming the connectedness between gold and cryptocurrency returns. Gold provides the safe haven and hedge properties for Ripple and Bitcoin at all market conditions. Also, Table 4 shows that gold diversifies against Dogecoin and Tether dominantly.

Empirically gold serves as a safe haven, a hedge and diversifier for the cryptocurrencies but for Litecoin just as it has been proven for most assets [12, 29, 30, 54, 85, 86] contrary to findings from the Indonesian market [87], the exchange rate [88] and for some commodities [86]. Also, gold is said to be highly effective in its property as a hedging instrument [85] and more so during the pandemic [30]. Inadvertently, gold can be used as a diversifier for Ethereum, Dogecoin, and Tether in the pandemic [30]. The outcome is in line with our study except that gold only act as a safe haven for Ethereum at stressed market outcome (below quantile 0.25). Conclusively, just as reported by Baur and Lucey [31]; gold acts as a safe haven and a hedge for Bitcoin and Ripple and as a diversifier for Dogecoin and Tether in short-term in the stress market condition of the coronavirus pandemic.

In Table 5, it is quite the contrary to what happened in the short-term. Unlike Ripple and Litecoin that were dominantly significant at all quantiles in the short-term, here

Table 3: Quantile regression results of signal.

Quantiles	Bitcoin	Litecoin	Ethereum	Dogecoin	Ripple	Tether
0.05	0.0440	0.0282	−0.0286	−0.0137	−0.0038	−0.1821
0.10	0.0454	0.0198	−0.0147	−0.0134*	−0.0042	−0.1647
0.15	0.0365	0.0171	−0.0066	−0.0113	−0.0047	−0.1551
0.20	0.0416	0.0139	−0.0036	−0.0115	−0.0046	−0.1855
0.25	0.0417	0.0110	−0.0009	−0.0112	−0.0044	−0.1900
0.30	0.0421	0.0120	0.0011	−0.0104	−0.0033	−0.2178
0.35	0.0424	0.0098	0.0016	−0.0085	−0.0036	−0.2181
0.40	0.0396	0.0114	0.0021	−0.0063	−0.0045	−0.2173
0.45	0.0439	0.0110	0.0006	−0.0033	−0.0040	−0.1744
0.50	0.0450	0.0112	0.0008	−0.0022	−0.0040	−0.1543
0.55	0.0526*	0.0058	0.0040	0.0019	−0.0031	−0.0661
0.60	0.0548**	0.0041	0.0061	0.0031	−0.0039	−0.0397
0.65	0.0558*	0.0033	0.0072	0.0059	−0.0060	−0.0227
0.70	0.0559*	0.0036	0.0069	0.0063	−0.0064	−0.0227
0.75	0.0565*	0.0013	0.0089	0.0077	−0.0070	−0.0116
0.80	0.0584	0.0005	0.0107	0.0079	−0.0074	0.0005
0.85	0.0720*	−0.0068	0.0139	0.0094	−0.0076	0.0167
0.90	0.0713*	−0.0082	0.0168	0.0096	−0.0077	0.0207
0.95	0.0829*	−0.0228	0.0246	0.0125	−0.0057	0.0395

NB: ***, **, and * denote significance at 1%, 5%, and 10%, respectively. At the extreme quantile levels (0.05 to 0.3 and 0.7 to 0.95), a negative and significant or uncorrelated relationship in stressed condition exhibits safe haven properties. On the other hand, a significant but negative relationship in a normal market condition has hedging properties. Averagely, any asset with a positive but insignificant relationship is a diversifier against the other (see [31]). The most dominating impact of cryptocurrency on gold is bitcoin, followed by Dogecoin. However, for Bitcoin, gold can only act as a safe haven during stressed market conditions.

Table 4: Quantile regression results of M1.

Quantiles	Bitcoin	Litecoin	Ethereum	Dogecoin	Ripple	Tether
0.05	0.0655**	0.0564***	−0.1290***	0.0001	−0.0251***	1.1208*
0.10	−0.0103	0.0543***	−0.0473	−0.0003	−0.0306***	1.2622*
0.15	−0.0181	0.0618***	−0.0382*	−0.0006	−0.0299***	0.9769
0.20	−0.0484**	0.0677***	−0.0005	−0.0012*	−0.0355***	1.6694**
0.25	−0.0519***	0.0702***	0.0094	−0.0012**	−0.0384***	1.8050***
0.30	−0.0765***	0.0958***	0.0282	−0.0007	−0.0364***	1.0532
0.35	−0.1148***	0.1398***	0.0556**	−0.0004	−0.0342***	0.7339
0.40	−0.1501***	0.1744***	0.0873***	0.0000	−0.0397***	0.7208
0.45	−0.1637***	0.1857***	0.1031***	0.0003	−0.0370***	0.6685
0.50	−0.1633***	0.1972***	0.1022***	0.0006	−0.0355***	0.5844
0.55	−0.1545***	0.2046***	0.1031***	−0.0001	−0.0389***	0.5287
0.60	−0.1517***	0.2008***	0.1159***	−0.0011	−0.0467***	0.6091
0.65	−0.1449***	0.1956***	0.1238***	−0.0023*	−0.0479***	0.7334
0.70	−0.1443***	0.1977***	0.1278***	−0.0025**	−0.0507***	0.8117
0.75	−0.1463***	0.1990***	0.1337***	−0.0029**	−0.0502***	0.7621
0.80	−0.1461***	0.1961***	0.1424***	−0.0036***	−0.0543***	0.7263
0.85	−0.1302***	0.1938***	0.1461***	−0.0042***	−0.0617***	0.5045
0.90	−0.1218***	0.1977***	0.1663***	−0.0053***	−0.0784***	0.2651
0.95	−0.1449***	0.1891***	0.2622***	−0.0067***	−0.1314***	1.1244

NB: ***, **, and * denote significance at 1%, 5%, and 10%, respectively. At the extreme quantile levels (0.05 to 0.3 and 0.7 to 0.95), a negative and significant or uncorrelated relationship in stressed condition exhibits safe haven properties. On the other hand, a significant but negative relationship in a normal market condition has hedging properties. Averagely, any asset with a positive but insignificant relationship is a diversifier against the other (see [31]). Litecoin and Ripple are the most dominating variables in the short-term. This is followed by Bitcoin, Ethereum, and Dogecoin. However, Bitcoin and Ripple act as a safe haven, diversifier, and hedge depending on the market outcomes. Litecoin becomes a complementary asset for gold at all market conditions which hinders portfolio diversification. Tether has the least impact on gold among all the cryptocurrencies in the short-term.

we find that Tether, Dogecoin and Bitcoin are more dominant at varying significant levels. We find that gold acts as an effective hedge for Bitcoin at normal market condition. At the lower and upper quantiles (extreme market outcomes), we notice safe haven potentials for all the cryptocurrencies, but Tether. Though, we notice more uncorrelated relationships other than negative significant relationships at extreme market conditions in the medium-term relative to the short-term, to reflect the assertion made by Baur and Lucey [31] that the safe haven property of gold is short-lived. In Table 5, the quantile regression coefficients in the medium-term indicate that indeed the safe haven property of the gold against the other cryptocurrencies is sparse with more uncorrelated outcomes relative to significant negative

Table 5: Quantile regression results of M2.

Quantiles	Bitcoin	Litecoin	Ethereum	Dogecoin	Ripple	Tether
0.05	−0.0005	−0.0898	0.0928	−0.0758**	−0.0278	0.0652**
0.10	−0.0058	−0.0466	0.0709	−0.0705*	−0.0203	0.0494**
0.15	−0.0077	−0.0317	0.0413	−0.0696*	−0.0205	0.0504**
0.20	−0.0051	−0.0163	0.0377	−0.0666*	−0.0160	0.0400**
0.25	−0.0027	−0.0009	0.0348	−0.0622	−0.0108	0.0254
0.30	0.0000	0.0088	0.0351	−0.0599*	−0.0215	0.0164
0.35	−0.0011	−0.0011	0.0075	−0.0580	−0.0280	0.0151
0.40	−0.0108	0.0265	0.0059	−0.0573	−0.0275	0.0130
0.45	−0.0109*	0.0487	0.0046	−0.0571	−0.0274	0.0108
0.50	−0.0107	0.0488	−0.0033	−0.0565	−0.0268	0.0100
0.55	−0.0110*	0.0486	−0.0015	−0.0556	−0.0269	0.0072
0.60	−0.0112*	0.0483	−0.0010	−0.0543	−0.0269*	0.0032
0.65	−0.0112*	0.0482	−0.0014	−0.0540	−0.0269	0.0023
0.70	−0.0112	0.0482	−0.0016	−0.0539	−0.0269	0.0021
0.75	−0.0122*	0.0486	−0.0013	−0.0627	−0.0269	0.0005
0.80	−0.0114	0.0483	−0.0051	−0.0552	−0.0266	−0.0028
0.85	−0.0120	0.0488	−0.0041	−0.0631	−0.0267	−0.0039
0.90	−0.0119	0.0481	−0.0073	−0.0564	−0.0264	−0.0072
0.95	−0.0130	0.0478	−0.0081	−0.0602	−0.0263	−0.0093

NB: ***, **, and * denote significance at 1%, 5%, and 10%, respectively. At the extreme quantile levels (0.05 to 0.3 and 0.7 to 0.95), a negative and significant or uncorrelated relationship in stressed condition exhibits safe haven properties. On the other hand, a significant but negative relationship in a normal market condition has hedging properties. Averagely, any asset with a positive but insignificant relationship is a diversifier against the other (see [31]). Tether, Dogecoin and Bitcoin have the most significant impact on gold. Litecoin and Ethereum have the least impact on gold.

result in addition, which partly confirms the outcome of Yousaf et al. [30]. However, gold could averagely be used to diversify against the cryptocurrencies in a portfolio theoretically.

Contrary to Ripple dominating in the M1 short-term and M2 medium-term, it does not dominant in the M3 medium but Bitcoin, Litecoin, and Tether. Following from Table 6, it has been proven that gold serves as a safe haven dominantly the cryptocurrencies except Bitcoin and Litecoin at the crash market condition in the medium-term but can be used to make diversifiable investment decisions. It could be seen that at this level, the results are quite similar to M2, they communicate the same information that gold could be used to diversify at normal market outcomes, and serve as a safe haven for the cryptocurrencies during stressed conditions [54], however, it would be best for an investor not to capitalize on it because it may not last for a long period. This is due to the more uncorrelated outcomes between the variables.

Table 7 presents the long run trend in the gold and cryptocurrencies markets. In the long run, Litecoin dominates at the extremes, and it is significant as compared to Bitcoin, Litecoin, and Dogecoin at varying quantiles. In normal market conditions, Ozturk [89] reports that investors do benefit from diversification in the long run, which is broadly in consensus with our study. The analysis shows that gold maintains its diversification property for all the cryptocurrencies even under stress market conditions (except Litecoin), as well, averagely providing safe haven properties for most cryptocurrencies both in the crash (except Litecoin) and boom market (except Ethereum) conditions. The hedge property of course has been empirically proven to exist for Bitcoin and Dogecoin, but for few quantiles, which is short-lived [31, 54]. The more negative relationship between gold and most cryptocurrencies in the long-term during the COVID-19 pandemic partly reveals the delayed volatility of market competitiveness and external shocks (DVMCES) hypothesis proposed by Asafo-Adjei et al. [90]. We find from our study that diversification potentials heightened from the short-to-long-term for most cryptocurrencies (delay in market dynamics) in times of stressed conditions of the COVID-19 pandemic period. This is as a result of the delayed responses of price to information and the extent of saturation gold and cryptocurrencies markets become in the long-term during stressed market outcome of the COVID-19 pandemic. Table 8 presents summary of findings to the frequency-dependent quantile regression.

4.2. Validation of Stationarity of Quantile Residuals. We found from the stationarity outcome that the return series for most variables at frequency M1 are not stationary. This may lead to a bias in the regression estimates which requires that stationarity at various quantiles be examined, although there is a general assumption for local stationarity in quantile regression estimates. For this reason, we confirm the stationarity of the quantile regression to ensure reliable estimates. Table 9 shows the stationarity of quantiles residuals for both augmented Dickey–Fuller (ADF) and Philips–Perron (PP) tests. The outcome from Table 9 provides that all the quantile residuals are stationary for the PP test. On the other hand, the ADF test indicates that all but four extreme lower quantiles are stationary. This provides some justification for the robustness of the quantile regression model in addition to the general assumption of local stationarity.

Table 6: Quantile regression results of M3.

Quantiles	Bitcoin	Litecoin	Ethereum	Dogecoin	Ripple	Tether
0.05	0.0764	0.1218	0.0359	0.0330	0.0578	0.0352
0.10	0.0777	0.1203*	0.0359	0.0328	0.0564	0.0336
0.15	0.0788*	0.1228*	0.0359	0.0263	0.0476	0.0333
0.20	0.0792**	0.1131*	0.0392	0.0197	0.0326	0.0322
0.25	0.0717**	0.0982*	0.0389	0.0199	0.0265	0.0336
0.30	0.0687*	0.0898	0.0369	0.0257	0.0249	0.0187
0.35	0.0697**	0.0891	0.0384	0.0230	0.0233	0.0166
0.40	0.0711**	0.0967*	0.0466	0.0170	0.0045	0.0042
0.45	0.0396	0.1034*	0.0392	0.0093	0.0075	−0.0052
0.50	0.0595*	0.0827	0.0196	0.0109	0.0006	−0.0273
0.55	0.0528	0.0714	0.0282	0.0068	−0.0044	−0.0323
0.60	0.0357	0.0804	0.0175	0.0039	0.0004	−0.0393
0.65	0.0097	0.0823	0.0115	0.0006	0.0047	−0.0408
0.70	−0.0084	0.0676	0.0223	−0.0062	−0.0011	−0.0491
0.75	−0.0037	0.0562	0.0112	−0.0117	−0.0068	−0.0651
0.80	−0.0146	0.0640	−0.0006	−0.0120	−0.0094	−0.0684**
0.85	−0.0134	0.0368	−0.0209	0.0032	−0.0190	−0.0677**
0.90	−0.0260	0.0442	−0.0236	−0.0026	−0.0185	−0.0722
0.95	−0.0334	0.0407	−0.0200	−0.0047	−0.0176	−0.0800

NB: ***, **, and * denote significance at 1%, 5%, and 10%, respectively. At the extreme quantile levels (0.05 to 0.3 and 0.7 to 0.95), a negative and significant or uncorrelated relationship in stressed condition exhibits safe haven properties. On the other hand, a significant but negative relationship in a normal market condition has hedging properties. Averagely, any asset with a positive but insignificant relationship is a diversifier against the other (see [31]). Gold serves as a safe haven most cryptocurrencies at the crash market condition in the medium-term (M3) as well as a diversifier at normal market conditions.

Table 7: Quantile regression results of MAgg.

Quantiles	Bitcoin	Litecoin	Ethereum	Dogecoin	Ripple	Tether
0.05	−0.1044***	0.0937***	−0.0084	−0.0129	−0.0071	0.8416
0.10	−0.1038***	0.0972***	−0.0097	−0.0070	−0.0104	0.8993
0.15	−0.0997***	0.0944***	−0.0036	−0.0097	−0.0074	0.9182
0.20	−0.0936**	0.0918***	−0.0010	−0.0064	−0.0089	0.9542
0.25	−0.0938***	0.0896***	0.0089	−0.0073	−0.0092	0.9994
0.30	−0.0861**	0.0864**	0.0121	−0.0090*	−0.0060	1.0818
0.35	−0.0722**	0.0769**	0.0191	−0.0075	−0.0054	0.9141
0.40	−0.0564*	0.0559*	0.0292	−0.0088*	−0.0054	0.8026
0.45	−0.0454	0.0368	0.0407**	−0.0106**	−0.0026	0.7820
0.50	−0.0334	0.0278	0.0445**	−0.0097*	−0.0016	0.8083
0.55	−0.0296	0.0218	0.0483**	−0.0099	−0.0014	0.8057
0.60	−0.0129	0.0133	0.0491**	−0.0088	0.0000	0.8660
0.65	0.0095	−0.0046	0.0530*	−0.0077	0.0008	0.8081
0.70	0.0187	−0.0171	0.0777**	0.0074	−0.0026	0.6074
0.75	0.0345	−0.0425	0.1075***	0.0070	−0.0002	0.3758
0.80	0.0652	−0.0811**	0.1300***	0.0101	−0.0016	0.2229
0.85	0.0746*	−0.1023**	0.1405***	0.0120	−0.0015	0.1784
0.90	0.0699	−0.1045***	0.1539***	0.0125*	−0.0041	0.0930
0.95	0.0810	−0.1186***	0.1592***	0.0129*	−0.0017	0.0421

NB: ***, **, and * denote significance at 1%, 5%, and 10%, respectively. At the extreme quantile levels (0.05 to 0.3 and 0.7 to 0.95), a negative and significant or uncorrelated relationship in stressed conditions exhibits safe haven properties. On the other hand, a significant but negative relationship in a normal market condition has hedging properties. Averagely, any asset with a positive but insignificant relationship is a diversifier against the other (see [31]). Litecoin dominates at the extremes, and it is significant as compared to Bitcoin, Ethereum, and Dogecoin. On the other hand, Ethereum has less likelihood of portfolio diversification, except for stressed market outcomes. That is, Ethereum most often becomes a complementary asset with gold at most quantiles. This is followed by Litecoin at market crash.

4.3. Robustness Causality Check. The outcome of the nonparametric Diks and Pachenko [44] causality test between gold and cryptocurrencies is presented in Table 10. We investigate the extent of uni-directional causality between the variables to ascertain whether the behaviour of gold can be effectively predicted by cryptocurrencies. The analysis from this study would reveal the extent of efficiency in the gold and cryptocurrencies markets. With reference to the behaviour of the data, we present five series of data to illustrate the extent of causality.

Table 10 presents the output of the Diks and Panchenko [44] nonparametric causality analysis between gold and the respective cryptocurrencies at decomposed frequencies and signal. The most dominant decomposed frequency is M1

Table 8: Summary of frequency-dependent quantile regression result.

	Signal	Short-term (M1)	Medium-term (M2 & M3)	Long-term (MAgg)
Hedge	Bitcoin ($Q = 0.55–0.70$) Dogecoin ($Q = 0.10$)	Bitcoin ($Q = 0.40–0.70$) Litecoin ($Q = 0.40–0.70$) Ethereum ($Q = 0.40–0.70$) Dogecoin ($Q = 0.65–0.70$) Ripple ($Q = 0.40–0.70$)	Bitcoin (0.40–0.70) Litecoin ($Q = 0.40–0.45$) Ripple ($Q = 0.60$)	Bitcoin ($Q = 0.40$) Litecoin ($Q = 0.40$) Ethereum ($Q = 0.40–0.70$) Dogecoin ($Q = 0.40–0.50$)
Safe haven	Bitcoin ($Q = 0.75$, 0.85–0.95)	Bitcoin ($Q = 0.05$, 0.20–0.35 & 0.75–0.95) Litecoin ($Q = 0.05–0.35$ & 0.75–0.95) Ethereum ($Q = 0.05$, 0.15 & 0.75–0.95) Dogecoin ($Q = 0.20$, 0.25 & 0.75–0.95) Ripple ($Q = 0.05–0.35$ & 0.75–0.95) Tether ($Q = 0.05$, 0.10, 0.20 & 0.25)	Bitcoin ($Q = 0.15–0.35$ & 0.75) Litecoin ($Q = 0.10–0.25$) Dogecoin ($Q = 0.05–0.20$ & 0.30) Litecoin ($Q = 0.05–0.35$ & 0.75–0.95) Tether ($Q = 0.05–0.20$ & 0.80–0.85)	Bitcoin ($Q = 0.05–0.35$ & 0.85) Litecoin ($Q = 0.05–0.35$ & 0.80, 0.95) Ethereum ($Q = 0.75–0.95$) Dogecoin ($Q = 0.30$)
Diversification (almost all quantiles)	Bitcoin Ethereum Dogecoin Litecoin Ripple Tether	Bitcoin Ethereum Dogecoin Litecoin Ripple Tether	Bitcoin Ethereum Dogecoin Litecoin Ripple Tether	Bitcoin Ethereum Dogecoin Litecoin Ripple Tether

NB: Q denotes quantiles.

Table 9: Stationarity of quantile residuals.

Quantiles	ADF	PP
0.05	−2.2296	-26.0020^{**}
0.10	−2.3779	-28.7460^{***}
0.15	−2.5097	-30.1900^{***}
0.20	−2.6914	-30.4550^{***}
0.25	3.3159^{*}	-36.1560^{***}
0.30	-3.7425^{**}	-41.6150^{***}
0.35	-3.7850^{**}	-40.8460^{***}
0.40	-3.7998^{**}	-39.484^{***}
0.45	-3.6681^{**}	-36.1860^{***}
0.50	-3.7431^{**}	-37.4810^{***}
0.55	-3.9178^{**}	-39.6880^{***}
0.60	-3.9746^{**}	-40.7780^{***}
0.65	-4.0389^{***}	-40.8560^{***}
0.70	-4.0383^{***}	-40.8860^{***}
0.75	-4.1474^{***}	-42.4200^{***}
0.80	-4.1967^{***}	-42.532^{***}
0.85	-4.2204^{***}	-42.8520^{***}
0.90	-4.2582^{***}	-42.0080^{***}
0.95	-4.2435^{***}	-38.9630^{***}

NB: ***, **, and *denote significance at 1%, 5%, and 10%, respectively. The residuals stationarity outcome presented in Table 9 at all quantiles are similar for the signal and all the decomposed series. This is not surprising because each of the VMFs has a cosine function wave shape, and that is sparsely varying, positive envelopes, and an instantaneous frequency that fluctuates sluggishly. The outcome for PP depicts that all the quantiles are stationary, whereas ADF test indicates that all but four lower quantiles are stationary.

(short-term). We find that Bitcoin, Litecoin, Dogecoin, Tether, and Ethereum cause gold in the short-term. This implies that short-term fluctuations in cryptocurrencies on gold are eminent relative to the medium-term and long-term. This is similar to the study of Malladi and Dheeriya [91] and Nakagawa and Sakemoto [57] who found causality from bitcoin returns to gold returns. , the causality test has showed the connectedness of gold and cryptocurrencies in the sense of safe haven and hedge reflected in the causality attributes of the cryptocurrencies on gold in the short-term. Just as the safe haven and hedge properties are short-lived, in the medium-term (M2 and M3), we notice no causality between gold and the cryptocurrencies. This affirms that averagely, gold can be used as a diversifier for the six cryptocurrencies under study

Table 10: Diks and Panchenko nonparametric causality between gold and six cryptocurrencies.

GC <≠ BTC	GC <≠ DOGE	GC <≠ ETH	GC <≠ LTC	GC <≠ TETH	GC <≠ XRP
		Signal			
1.8400**	0.8430	1.3420*	1.0810	1.3800**	0.4100
		M1			
2.1360**	2.1800**	3.7490***	2.9990***	2.6450***	1.2140
		M2			
−3.1390	−0.3370	0.0250	−0.9530	−0.2440	−0.6100
		M3			
0.8290	−1.3620	−0.2270	2.0390	−0.0730	1.2860*
		MAgg			
1.2080	0.3200	1.6020	2.0570	1.6580**	0.7630

Note. The arrow "<≠" denotes the causality null hypothesis that cryptocurrency does not cause gold; embedding dimension = 2, and bandwidth = 0.5000 [44]. ***, **, and * indicate statistical significance levels of 1%, 5%, and 10%, respectively. The most dominant decomposed frequency is M1 (short-term). Bitcoin, Litecoin, Dogecoin, Tether, and Ethereum cause gold in the short-term. We notice no causality between gold and the cryptocurrencies in the medium-term.

because we fail to account for causality in both frequencies; however, investors need to be wary. The MAgg series reflect that Tether only causes gold, where their empirical relationship could pass as a safe haven implying some real economic growth for institutional investors.

The rate at which cryptocurrency prices are volatile raises the concern for investors as to when to hold or sell these coins to be able to maintain value and make stable returns [61] and with the findings from this study, investors would be able to develop profitable portfolios using gold and the cryptocurrencies under consideration. For instance, the more negative significant relationship between gold and Bitcoin at most market conditions and investment horizons is not daunting because as provided by Klein et al. [54]; Bitcoin positively correlates with downward markets relative to gold. Moreover, as posited by Jareño et al. [56]; investor fear and expectations (VIX) have an adverse impact on Bitcoin relative to gold contributing to their asymmetric behaviour. Analogously, Nakagawa and Sakemoto [57] aver that network factors have a greater impact on gold returns than on Bitcoin returns. It is necessary that an investor knows the empirical properties of the asset he or she ought to invest in so that he or she could diversify or hedge against some of the market risks to avoid losses caused by plunges in the gold and cryptocurrency markets. Thus, this study contributes to literature by informing investors interested in gold and cryptocurrencies to make effective portfolio decisions depending on diverse market conditions and investment horizons.

5. Conclusion

To explore the connectedness of gold and cryptocurrencies, we adopt a frequency-dependent asymmetric analysis. That is, the variational mode decomposition-based quantile regression and nonparametric causality techniques are utilised for daily returns of gold, Bitcoin, Dogecoin, Litecoin, Ethereum, Tether, and Ripple.

Findings are explained with respect to market conditions revealed by various quantiles at various frequencies as indicated by the VMFs. Specifically, in the context of this study, the VMFs represent short-term, medium-term, and long-term periods. The outcomes from the original series (Signal) divulge that gold offers safe haven and diversification benefits, but not hedge, for most cryptocurrencies. The outcome from the original series does not significantly differ from the studies of Ozturk [89] and Su and Li [19, 92]. We find specifically that the VMFs at the lower quantiles are mostly significant and negative indicating that gold acts as a safe haven, as a diversifier at all market conditions with insignificant coefficient, and as a hedge at normal market conditions with most cryptocurrencies for the various frequencies in the short- and long-terms. Specifically, gold serves as a hedge at M1 and M2 for Bitcoin and Ripple and as a safe haven and diversifier for most cryptocurrencies across diverse investment horizons. This partly corroborates the assertion made in [19] that gold and cryptocurrencies are driven by medium- and long-term fundamentals, but contrary to their short-term dynamics where insignificant relationships were dominant.

In addition, the causality test indicates that most cryptocurrencies cause gold in the short-term. This implies that investors can efficiently capitalize on the empirical properties of gold to avoid losses in the short-term during the coronavirus pandemic due to the presence of short-lived market dynamics within these markets. As a result, trading in gold and cryptocurrency markets portrays market inefficiency in the short-term. As a result, institutional investors may not find portfolio diversification worthwhile for these assets regarding the tendency for cryptocurrency returns to drive gold returns.

The asymmetric relationship between gold and cryptocurrencies and the tendency for gold to either hedge, diversify, or being a safe haven for cryptocurrencies and the degree of causality reveal the heterogeneous nature of market participants and adaptive behaviour of markets. The long-term negative impact of most cryptocurrencies on gold at stressed market conditions of the COVID-19 pandemic relative to the medium-term accentuates the DVMCES hypothesis of Asafo-Adjei et al. [90]. However, investors may not reduce their investment losses by forming a portfolio including gold, Ethereum, and Litecoin at most of the market conditions and investment horizons. Investors are recommended to be observant and mindful of investing in these markets due to different dynamics empirically detected in the markets.

Further studies can assess the bidirectional relationships between gold and cryptocurrencies to illustrate the diversification and hedge potentials for each other. Other techniques such as transfer entropy could be employed to assess the information flow between gold and cryptocurrencies during the COVID-19 pandemic. This study was limited to the use of six cryptocurrencies, other studies can concentrate on the remaining cryptocurrencies with a mixture of high and low market capitalisations to assess their diversification potentials with gold.

Data Availability

The data in relation to the findings of this study are available upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

References

[1] I. Zorgati and R. Garfatta, "Spatial financial contagion during the COVID-19 outbreak: local correlation approach," *The Journal of Economic Asymmetries*, vol. 24, Article ID e00223, 2021.

[2] S. Drozdz, J. Kwapien, P. Oswiecimka, T. Stanisz, and M. Watorek, "Complexity in economic and social systems: cryptocurrency market at around COVID-19," *Entropy*, vol. 20, no. 22, p. 25, 2020.

[3] A. Atkeson, "What will be the economic impact of COVID-19 in the US? Rough estimates of disease scenarios," Technical Report, vol. 26, pp. 867–892, National Bureau of Economic Research, Cambridge, MA, USA, 2020.

[4] M. Chaudhary, P. R. Sodani, and S. Das, "Effect of COVID-19 on economy in India: some reflections for policy and programme," *Journal of Health Management*, vol. 22, no. 2, pp. 169–180, 2020.

[5] Ò. Jordà, S. R. Singh, and A. M. Taylor, "The long economic hangover of pandemics: history shows COVID-19's economic fallout may be with us for decades," *Finance & Development*, vol. 57, no. 2, 2020.

[6] A. Sayed and B. Peng, "Pandemics and income inequality: a historical review," *SN Business & Economics*, vol. 1, no. 4, pp. 54–71, 2021.

[7] S. Correia, S. Luck, and E. Verner, "Pandemics depress the economy, public health interventions do not: evidence from the 1918 flu," *SSRN Electronic Journal*, 2020, https://ssrn.com/abstract=3561560.

[8] A. Guzmán, C. Pinto-Gutiérrez, and M. A. Trujillo, "Trading cryptocurrencies as a pandemic pastime: COVID-19 lockdowns and bitcoin volume," *Mathematics*, vol. 15, no. 9, 2021.

[9] G. Rubbaniy, S. Polyzos, S. K. A. Rizvi, and A. Tessema, "COVID-19, Lockdowns and herding towards a cryptocurrencymmarket-specific implied volatility index," *Economics Letters*, vol. 207, 2021.

[10] S. Nakamoto, "A peer-to-peer electronic cash system," 2008, http://www.KlausNordby.com/bitcoin.

[11] J. Liu and A. Serletis, "Volatility in the cryptocurrency market," *Open Economies Review*, vol. 30, no. 4, pp. 779–811, 2019.

[12] S. Kakinaka and K. Umeno, "Cryptocurrency market efficiency in short- and long-term horizons during COVID-19: an asymmetric multifractal analysis approach," *Finance Research Letters*, 2021.

[13] E. F. Fama, "The behavior of stock-market prices," *Journal of Business*, vol. 38, no. 1, pp. 34–105, 1965.

[14] M. A. Naeem, E. Bouri, Z. Peng, S. J. H. Shahzad, and X. V. Vo, "Asymmetric efficiency of cryptocurrencies during COVID19," *Physica A: Statistical Mechanics and Its Applications*, vol. 565, Article ID 125562, 2021.

[15] V. L. Tran and T. Leirvik, "Efficiency in the markets of crypto-currencies," *Finance Research Letters*, vol. 35, Article ID 101382, 2020.

[16] S. Corbet, Y. Hou, Y. Hu, C. Larkin, and L. Oxley, "Any port in a storm: cryptocurrency safe-havens during the COVID-19 pandemic," *Economics Letters*, vol. 194, Article ID 109377, 2020.

[17] A. ElBahrawy, L. Alessandretti, A. Kandler, R. Pastor-Satorras, and A. Baronchelli, "Evolutionary dynamics of the cryptocurrency market," *Royal Society Open Science*, vol. 4, Article ID 170623, 2017.

[18] H. Markowitz, "Portfolio selection," *The Journal of Finance*, vol. 7, no. 1, pp. 77–91, 1952.

[19] P. Owusu Junior, M. A. Adam, and G. Tweneboah, "Connectedness of cryptocurrencies and gold returns: evidence from frequency-dependent quantile regressions," *Cogent Economics & Finance*, vol. 8, no. 1, 2020a.

[20] Y. Liu and A. Tsyvinski, "Risks and returns of crypto-currency," *Review of Financial Studies*, vol. 34, no. 6, pp. 2689–2727, 2018.

[21] M. Aftab, S. Z. A. Shah, and I. Ismail, "Does gold act as a hedge or a safe haven against equity and currency in asia?" *Global Business Review*, vol. 20, no. 1, pp. 105–118, 2019.

[22] R. Regaieg, W. Moussa, and N. Mgadmi, "Can we reckon bitcoin as a hedge, a safe haven or a diversifier for US dollars?" *Global Business Review*, Article ID 0972150920968168, 2020.

[23] A. K. Pradhan, I. Mittal, and A. K. Tiwari, "Optimizing the market-risk of major cryptocurrencies using CVaR measure and copula simulation," *Macroeconomics and Finance in Emerging Market Economies*, vol. 14, pp. 1–17, 2021.

[24] U. Koumba, C. Mudzingiri, and J. Mba, "Does uncertainty predict cryptocurrency returns? A copula-based approach," *Macroeconomics and Finance in Emerging Market Economies*, vol. 13, no. 1, pp. 67–88, 2020.

[25] P. Owusu Junior, A. K. Tiwari, G. Tweneboah, and E. Asafo-Adjei, "GAS and GARCH based value-at-risk modeling of precious metals," *Resources Policy*, vol. 75, Article ID 102456, 2022.

[26] S. Bentes, M. Gubareva, and T. Teplova, "The impact of COVID-19 on gold seasonality," *Applied Economics*, pp. 1–11, 2022.

[27] G. Gorton and K. G. Rouwenhorst, "Facts and fantasies about commodity futures," *Financial Analysts Journal*, vol. 62, no. 2, pp. 47–68, 2006.

[28] P. Owusu Junior, A. K. Tiwari, H. Padhan, and I. Alagidede, "Analysis of EEMD-based quantile-in-quantile approach on spot- futures prices of energy and precious metals in India," *Resources Policy*, vol. 68, Article ID 101731, 2020b.

[29] M. D Akhtaruzzaman, S. Boubaker, B. M. Lucey, and A. Sensoy, "Is gold a hedge or safe haven asset during COVID–19 crisis?" 2020, https://ssrn.com/abstract=3621358.

[30] I. Yousaf, E. Bouri, S. Ali, and N. Azoury, "Gold against asian stock markets during the COVID-19 outbreak," *Journal of Risk and Financial Management*, vol. 14, no. 4, p. 186, 2021.

[31] D. G. Baur and B. M. Lucey, "Is gold a hedge or a safe haven? an analysis of stocks, bonds and gold," *Financial Review*, vol. 45, no. 2, pp. 217–229, 2010.

[32] J. Lian, Z. Liu, H. Wang, and X. Dong, "Adaptive variational mode decomposition method for signal processing based on mode characteristic," *Mechanical Systems and Signal Processing*, vol. 107, pp. 53–77, 2018.

[33] P. Owusu Junior, S. Frimpong, A. M. Adam et al., "COVID-19 as information transmitter to global equity markets: evidence from CEEMDAN-based transfer entropy approach," *Mathematical Problems in Engineering*, vol. 2021, Article ID 8258778, 19 pages, 2021.

[34] U. A. Müller, M. M. Dacorogna, R. D. Davé, R. B. Olsen, O. V. Pictet, and J. E. Von Weizsäcker, "Volatilities of different time resolutions-analyzing the dynamics of market components," *Journal of Empirical Finance*, vol. 4, no. 2-3, pp. 213–239, 1997.

[35] A. W. Lo, "The adaptive markets hypothesis," *Journal of Portfolio Management*, vol. 30, no. 5, pp. 15–29, 2004.

[36] E. Asafo-Adjei, A. M. Adam, and P. Darkwa, "Can crude oil price returns drive stock returns of oil producing countries in Africa? evidence from bivariate and multiple wavelet," *Macroeconomics and Finance in Emerging Market Economies*, pp. 1–19, 2021c.

[37] E. Asafo-Adjei, E. Boateng, Z. Isshaq, A. A.-A. Idun, P. Owusu Junior, and A. M. Adam, "Financial sector and economic growth amid external uncertainty shocks: insights into emerging economies," *PLoS One*, vol. 16, no. 11, Article ID e0259303, 2021.

[38] A. Bossman, "Information flow from COVID-19 pandemic to islamic and conventional equities: an ICEEMDAN-induced transfer entropy analysis," *Complexity*, vol. 2021, Article ID 4917051, 20 pages, 2021.

[39] K. Dragomiretskiy and D. Zosso, "Variational mode decomposition," *IEEE Transactions on Signal Processing*, vol. 62, no. 3, pp. 531–544, 2013.

[40] N. E. Huang, Z. Shen, S. R. Long et al., "The empirical mode decomposition and the Hilbert spectrum for nonlinear and non-stationary time series analysis," *Proceedings of the Royal Society of London. Series A: Mathematical, Physical and Engineering Sciences*, vol. 454, no. 1971, pp. 903–995, 1998.

[41] Z. Wu and N. E. Huang, "Ensemble empirical mode decomposition: a noise-assisted data analysis method," *Advances in Adaptive Data Analysis*, vol. 1, no. 1, pp. 1–41, 2009.

[42] E. Asafo-Adjei, P. Owusu Junior, and A. M. Adam, "Information flow between global equities and cryptocurrencies: a VMD-based entropy evaluating shocks from COVID-19 pandemic," *Complexity*, vol. 2021, Article ID 4753753, 25 pages, 2021.

[43] E. Boateng, A. M. Adam, and P. O. Junior, "Modelling the heterogeneous relationship between the crude oil implied volatility index and African stocks in the coronavirus pandemic," *Resources Policy*, vol. 74, Article ID 102389, 2021.

[44] C. Diks and V. Panchenko, "A new statistic and practical guidelines for nonparametric Granger causality testing," *Journal of Economic Dynamics and Control*, vol. 30, no. 9-10, pp. 1647–1669, 2006.

[45] C. Hiemstra and J. D. Jones, "Testing for linear and nonlinear granger causality in the stock price-volume relation," *The Journal of Finance*, vol. 49, no. 5, pp. 1639–1664, 1994.

[46] P. Owusu Junior, A. M. Adam, and G. Tweneboah, "Co-movement of real exchange rates in the west african monetary zone," *Cogent Economics & Finance*, vol. 5, no. 1, Article ID 1351807, 2017.

[47] P. Owusu Junior, B. Kwaku Boafo, B. Kwesi Awuye, K. Bonsu, and H. Obeng-Tawiah, "Co-movement of stock exchange indices and exchange rates in Ghana: a wavelet coherence analysis," *Cogent Business & Management*, vol. 5, no. 1, Article ID 1481559, 2018.

[48] P. O. Junior, G. Tweneboah, and A. M. Adam, "Interdependence of major exchange rates in Ghana: a wavelet coherence analysis," *Journal of African Business*, vol. 20, no. 3, pp. 407–430, 2019.

[49] E. Asafo-Adjei, D. Agyapong, S. K. Agyei, S. Frimpong, R. Djimatey, and A. M. Adam, "Economic policy uncertainty and stock returns of Africa: a wavelet coherence analysis," *Discrete Dynamics in Nature and Society*, vol. 2020, Article ID 8846507, 8 pages, 2020.

[50] P. Owusu Junior, A. M. Adam, E. Asafo-Adjei, E. Boateng, Z. Hamidu, and E. Awotwe, "Time-frequency domain analysis of investor fear and expectations in stock markets of BRIC economies," *Heliyon*, vol. 7, no. 10, Article ID e08211, 2021.

[51] E. Boateng, E. Asafo-Adjei, A. Addison et al., "Interconnectedness among commodities, the real sector of Ghana and external shocks," *Resources Policy*, vol. 75, Article ID 102511, 2022.

[52] A. Bossman, S. K. Agyei, P. Owusu Junior et al., "Flights-to-and-from-Quality with islamic and conventional bonds in the COVID-19 pandemic era: ICEEMDAN-based transfer entropy," *Complexity*, vol. 2022, Article ID 1027495, 25 pages, 2022.

[53] W. Shan, M. Tong, Y. Zhongyi, and D. Abdelkader, "Does gold or bitcoin hedge economic policy uncertainty?" *Finance Research Letters*, vol. 31, pp. 171–178, 2019.

[54] T. Klein, H. Pham Thu, and T. Walther, "Bitcoin is not the new gold - a comparison of volatility, correlation, and portfolio performance," *International Review of Financial Analysis*, vol. 59, pp. 105–116, 2018.

[55] C. Baek and M. Elbeck, "Bitcoins as an investment or speculative vehicle? a first look," *Applied Economics Letters*, vol. 22, no. 1, pp. 30–34, 2015.

[56] F. Jareño, M. de la O González, M. Tolentino, and K. Sierra, "Bitcoin and gold price returns: a quantile regression and NARDL analysis," *Resources Policy*, vol. 67, 2020 https://www.sciencedirect.com/science/article/abs/pii/S0301420719309985, Article ID 101666.

[57] K. Nakagawa and R. Sakemoto, "Cryptocurrency network factors and gold," *Finance Research Letters*, 2021, https://www.sciencedirect.com/science/article/abs/pii/S1544612321003779, Article ID 102375.

[58] M. D. L. O. González, F. Jareño, and F. S. Skinner, "Asymmetric interdependencies between large capital cryptocurrency and Gold returns during the COVID-19 pandemic crisis," *International Review of Financial Analysis*, vol. 76, 2021.

[59] S. Wasiuzzaman and H. S. W. Haji Abdul Rahman, "Performance of gold-backed cryptocurrencies during the COVID-19 crisis," *Finance Research Letters*, vol. 43, Article ID 101958, 2021.

[60] N. Usman and K. N. Nduka, "Announcement effect of COVID-19 on cryptocurrencies," *Asian Economics Letters*, vol. 3, Article ID 29953, 2022.

[61] G.-J. Wang, X.-y. Ma, and H.-y. Wu, "Are stablecoins truly diversifiers, hedges, or safe havens against traditional cryptocurrencies as their name suggests?" *Research in International Business and Finance*, vol. 54, Article ID 101225, 2020.

[62] L. T. Hoang and D. G. Baur, "How stable are stablecoins?" *The European Journal of Finance*, 2021.

[63] S. Corbet, C. Larkin, and B. Lucey, "The contagion effects of the COVID-19 pandemic: evidence from gold and cryptocurrencies," *Finance Research Letters*, vol. 35, 2020.

[64] L. Kristoufek, "Grandpa, grandpa, tell me the one about bitcoin being a safe haven: evidence from the covid-19 pandemics," 2020, https://arxiv.org/abs/2004.00047.

[65] A. Omanović, A. Arnaut-Berilo, and A. Zaimović, "Effectiveness of cryptocurrency portfolio management before and during covid-19 pandemic," *International May Conference on Strategic Management*, vol. 16, no. 1, pp. 319–331, 2020.

[66] D. K. C. Lee, L. Guo, and Y. Wang, "Cryptocurrency: a new investment opportunity?" *Journal of Alternative Investments*, vol. 20, pp. 16–40, 2017.

[67] T. Conlon and R. McGee, "Safe haven or risky hazard? bitcoin during the COVID-19 bear market," *Finance Research Letters*, vol. 35, 2020.

[68] D. Vidal-Tomas, "Transitions in the cryptocurrency market during the COVID-19 pandemic: a network analysis," *Finance letter*, vol. 35, 2021.

[69] S. A. Sarkodie, M. A. Ahmed, and P. A. Owusu, "COVID-19 pandemic improves market signals of cryptocurrencies–evidence from bitcoin, bitcoin cash, Ethereum, and litecoin. finance research letters," , 2021.

[70] N. Hamilton and M. Ferry, "CRAN package: variational mode decomposition," 2017, https://CRAN.R-project.org/package=vmd.

[71] G. Boako, M. Omane-Adjepong, and J. M. Frimpong, "Stock returns and exchange rate nexus in Ghana: a bayesian quantile regression approach," *South African Journal of Economics*, vol. 84, no. 1, pp. 149–179, 2016.

[72] A. Demir, V. Pesqué-Cela, Y. Altunbas, and V. Murinde, "Fintech, financial inclusion and income inequality: a quantile regression approach," *The European Journal of Finance*, pp. 1–22, 2020.

[73] P. Fousekis and D. Tzaferi, "Price returns and trading volume changes in agricultural futures markets: an empirical analysis with quantile regressions," *The Journal of Economic Asymmetries*, vol. 19, 2019.

[74] W. Xue and L. Zhang, "Revisiting the asymmetric effects of bank credit on the business cycle: a panel quantile regression approach," *The Journal of Economic Asymmetries*, vol. 20, 2019.

[75] R. Koenker and G. Bassett, "Regression quantiles," *Econometrica*, vol. 46, no. 1, pp. 33–50, 1978.

[76] S. Cevik and B. Öztürkkal, "Contagion of fear: is the impact of COVID-19 on sovereign risk really indiscriminate?" *International Finance*, vol. 24, no. 2, pp. 134–154, 2021.

[77] L. A. Gil-Alana, E. J. A. Abakah, and M. F. R. Rojo, "Cryptocurrencies and stock market indices. Are they related?" *Research in International Business and Finance*, vol. 51, Article ID 101063, 2020.

[78] D. Zhang, M. Hu, and Q. Ji, "Financial markets under the global pandemic of COVID-19," *Finance Research Letters*, vol. 36, Article ID 101528, 2020.

[79] D. Das and M. Kannadhasan, "Do global factors impact bitcoin prices? evidence from wavelet approach," *Journal of Economic Research*, vol. 23, pp. 227–264, 2018.

[80] Z. Umar, F. Jareño, and M. D. L. O. González, "The impact of COVID-19-related media coverage on the return and volatility connectedness of cryptocurrencies and fiat currencies," *Technological Forecasting and Social Change*, vol. 172, Article ID 121025, 2021.

[81] A. M. Adam and P. Owusu Junior, *Financial Econometrics: An Example-Based Handbook*, Nova Science Publisher's, Incorporated, Hauppauge, NY, USA, 2017.

[82] J. J. Szczygielski, A. Karathanasopoulos, and A. Zaremba, "One shape fits all? a comprehensive examination of cryptocurrency return distributions," *Applied Economics Letters*, vol. 27, no. 19, pp. 1567–1573, 2020.

[83] S. Shanaev and B. Ghimire, "A fitting return to fitting returns: cryptocurrency distributions revisited," *SSRN Electronic Journal*, 2021.

[84] N. Shrestha, "Detecting multicollinearity in regression analysis," *American Journal of Applied Mathematics and Statistics*, vol. 8, no. 2, pp. 39–42, 2020.

[85] S. J. H. Shahzad, E. Bouri, D. Roubaud, and L. Kristoufek, "Safe haven, hedge and diversification for G7 stock markets: gold versus bitcoin," *Economic Modelling*, vol. 87, pp. 2112–2224, 2020.

[86] Q. Ji, D. Zhang, and Y. Zhao, "Searching for safe-haven assets during the COVID-19 pandemic," *International Review of Financial Analysis*, vol. 71, 2020.

[87] S. Puryandani and R. Robiyanto, "Gold: hedge, safe haven or diversifier for Indonesian capital market," *Fokus Ekonomi: Jurnal Ilmiah Ekonomi*, vol. 14, no. 2, pp. 226–239, 2019.

[88] C. Ciner, C. Gurdgiev, and B. M. Lucey, "Hedges and safe havens: an examination of stocks, bonds, gold, oil and exchange rates," *International Review of Financial Analysis*, vol. 29, pp. 202–211, 2013.

[89] S. S. Ozturk, "Dynamic connectedness between bitcoin, gold, and crude oil volatilities and returns," *Journal of Risk and Financial Management*, vol. 13, no. 11, p. 275, 2020.

[90] E. Asafo-Adjei, S. Frimpong, P. Owusu Junior, A. M. Adam, E. Boateng, and R. O. Abosompim, "Multi-frequency information flow between global commodities and uncertainties: evidence from COVID-19 pandemic," *Complexity*, 2022.

[91] R. K. Malladi and P. Dheeriya, "Time series of cryptocurrency returns and volatilities," 2020, https://www.researchgate.net/publication/344120233.

[92] X. Su and Y. Li, "Dynamic sentiment spillovers among crude oil, gold, and bitcoin markets: evidence from time and frequency domain analyses," *PLoS One*, vol. 15, no. 12, Article ID e0242515, 2020.