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RESEARCH PAPER

Hedge, Safe Haven, and Diversification for US and China Stock Markets during COVID-19 Outbreak: Volatile versus Stable Cryptocurrencies

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Abstract

This paper is designed to examine the volatile and stable cryptocurrencies' role in the US and Chinese stock market indexes. In this context, the TGARCH-ADCC modeling approach is used to determine the dynamic conditional correlation, to be implemented in the linear regression model to determine each of these instruments' specific behavioral effects on the US and China stock indices. The findings reveal well that TRUE Provesto stands as a strong safe-haven asset for US investors throughout the entire study period. However, it turns out to play a safe-haven role for Chinese investors in the pre-2020 period. As for Gold, it appears to have lost its safe-haven character before the global 2020 pandemic, to turn into a diversifier asset for US investors. The computed optimal hedge and hedging effectiveness reveal well that Gold proved to display the best hedging instrument for US investors during the pre-COVID-19 period, while Ethereum proved to represent the most optimal hedging tool for Chinese investors. It also turns out to stand as the most effective hedging instrument all over the COVID-19 pandemic period for both the US as well as Chinese investors.

Keywords: COVID-19, Diversification, Gold, Hedging, Safe Haven, US and China Stock Indices, Volatile and Stable Cryptocurrencies.
JEL Classification: C52, G11, G17.

1. Introduction

As the whole world heads towards tracking and facing a pandemic that has interrupted our daily lives, academic research continues to closely assess and monitor the coronavirus pandemic's financial and economic repercussions. The entirety of the world nations' economies have been significantly impacted and struck by this severe health crisis, while several nations have tried to adjust to new tight quarantine laws, demonstrating severely limited economic activities. COVID-19 has participated significantly in crumbling down the world stock markets, thereby, intensifying volatility. Moreover, it has further widened the USA and China prevailing conflicts, as the world's major Giant economies in 2021.

In effect, December 2019 marked the COVID-19 outbreak date. Initially emerging and originating in the Chinese city of Wuhan, it quickly spread to other parts of China and, therefrom, worldwide. The World Health Organization has declared it as a serious pandemic on March 11, 2020. Ever since, multiple variants of the virus have emerged, mainly, the Alpha, Beta, Gamma, and Delta ones. As of November 5, 2021, more than 256 million infections and five million death cases have been confirmed. As the COVID-19 disease epicenter moved from China to Europe and, subsequently, to the US, Trump told the United Nations to hold China accountable for the COVID-19 pandemic thus, further intensifying strategic competition between the US and China and sending bilateral relations into a tailspin. The Coronavirus pandemic first affected the Chinese stock markets and, therefore, the remaining stock markets worldwide. The COVID-19 ensuing global recession was triggered in February 2020. March 9, 2020, was the date marking the triggering of the circuit breakers on the US stock market for the first time since 1997. The 2020 global pandemic engendered an unprecedented surge in the global financial markets associated risk (Zhang et al., 2020).

On examining the digital and financial assets’ volatility, a large volume of literature appears to apply various GARCH model specifications (e.g., Katsiampa, 2017; Bouri et al., 2017; Caporale and Zekokh, 2019; Guesmi et al., 2019; Fakhfekh and Jeribi, 2020; Fakhfekh et al., 2021; Jeribi and Ghorbel, 2021; Jeribi et al., 2022). The non-observability of market volatility has traditionally been proxied by non-parametric measures, mainly squared returns, as well as GARCH modeling-based parametric measures (Engle, 1982; Bollerslev, 1986; Nelson, 1991), and stochastic volatility-associated models (Taylor, 1994; Ghysels et al., 1996). Owing to the significant importance of volatility, depicting the most appropriately effective predictors and model selections turns out to be a critical priority.

In this respect, financial market risks have been amplified throughout the 2020 global economic and financial crisis, resulting in new challenges for financial risk managers. Therefore, for the sake of defining their portfolio strategies and hedging risks, investors need to distinguish between three types of assets: diversifier, hedge, and safe-haven assets (Baur and Lucey, 2010). In this regard, the safe-haven assets, most widely discussed in the COVID-19 literature, involve gold (Belhassine and Karamti, 2021; Ghorbel and Jeribi, 2021a; 2021b; 2021c; Jeribi et al., 2021; Rubbaniyet al., 2021) and cryptocurrencies (Conlon and Mcgee, 2020; Mariana et al., 2020; Ghorbel and Jeribi, 2021a; 2021b; 2021c; Jeribi et al., 2021; Loukil et al., 2021). While cryptocurrencies can be considered as diversifier assets, their application as exchange mediums is limited by their price volatility

(Katsiampa, 2017; Fakhfekh and Jeribi, 2020; Lahiani et al., 2021; Jeribi and Masmoudi, 2021). Pegged to less volatile assets or currencies, Stablecoins can be used as alternatives to volatile cryptocurrencies. Recently, Stablecoins have received noticeable attention from the part of portfolio managers as well as academicians, beyond the realm of cryptocurrency markets (Wang et al., 2020; Ante et al., 2021a; 2021b; Baur and Hoang, 2021; Giudici et al., 2021; Grobys et al., 2021; Jalan et al., 2021; Kristoufek, 2021). In this context, the present study is intended to provide further contribution to the relevant literature by undertaking to evaluate the hedging and safe-haven characteristics of two volatile crypto-currencies, two Stablecoins and Gold applied by US and Chinese investors throughout the Coronavirus pandemic span.

The remainder of this paper is organized as follows. Section 2 encloses a general literature review, while Section 3 depicts a description of relevant data. Section 4 involves details of the applied methodology, and Section 5 is devoted to discussing the results. Finally, Section 6 bears the main concluding remarks.

2. Literature Review

It is hardly surprising that the impact has spread to other global commodity markets, given the global economic interdependence. Gold has not been immune to this pandemic, with changing and profound short and long-term consequences. As a store of value, it appears to have a significant impact on the evolution of budgetary policy imposed by central banks. Similarly, precious metals are viewed as a diversifier and hedging asset investment during times of calm economic conditions, as well as a safe-haven asset during times of economic distress and significant political instability (Baur and Lucey, 2010; Baur and McDermott, 2010). Furthermore, gold's significance as a hedge and a safe-haven against other financial assets during financial instability and global volatility is excessively examined in literature (for instance, Baur and McDermott, 2010; Baur and Lucey, 2010; Reboredo, 2013; Baur and McDermott, 2016; and Bouoiyour et al., 2019). The importance of gold as a hedging instrument has been the subject of two major theoretical mechanisms. Firstly, the seeking-for-security tendency of averse-to-risk investors, who leave other financial markets as their volatility, rises. In turn, this procedure causes a surge in gold demand, driving up its prices and boosting investors' wealth. Baur and McDermott (2016) argue that gold is preferable to other safe-haven assets owing to behavioral factors associated with gold's history as a currency, value store, and safe-haven. They also demonstrate that gold has always stood as a powerful refuge during financial and political shocks.

Ever since the 2008 Global Financial Crisis, commodities' behavior, typically considered safe-haven investments, has changed substantially (Bouri et al., 2020; Wu et al., 2020). According to Ji et al. (2020), their former function as safe-haven assets is being questioned, attracting much-needed attention to the investigation of these commodities in light of the underway global health crisis. Surprisingly, even gold as an asset (historically serving as a perfect safe-haven) is being questioned as to its potential to serve as a safe-haven commodity. In this regard, O'Connor et al. (2015) explain the erratic empirical evidence for gold's position as a safe-haven, by changing gold's price and holding mechanism based on behavioral economic concerns. According to Baur and Glover (2012), gold's safe-haven role has been weakened by an increase in holding gold for exclusively speculative objectives, making it prone to suffering in times of economic turmoil, like other financial assets. This viewpoint is highlighted by Ivanov (2013), who claims that traders in gold futures markets, rather than hedgers, are the primary long-run drivers of its price.

Previous research does not provide clear evidence of gold's safe-haven role during the current COVID-19 period, nor does it provide any clear spillover evidence between gold markets and stock markets. On comparing Bitcoin and foreign exchange currencies, Ji et al. (2020) discovered that gold remains robust as a safe-haven asset throughout the COVID-19 outbreak period. In turn, Kanamura (2021) stated that the speed of infection spread and the number of coronavirus pandemic deaths reduced the impact of the tendency to a high price volatility regime for gold futures, suggesting that, during the COVID-19 crisis, gold markets proved to act as safe risk-hedging assets compared to other financial assets. Corbet et al. (2020) showed that during the coronavirus fast spread in China, neither Gold nor Bitcoin appeared to demonstrate a substantial link with stock prices on the Shanghai and Shenzhen Stock Exchanges. According to Ali et al. (2020), when the coronavirus evolved from an epidemic to an extremely severe pandemic, the returns of gold became negative, though less volatile. Concerning Shahzad et al. (2019), gold stood as a weak safe-haven, even though such a behavior tends to vary over time, Cheema et al. (2020) found that gold was not able to protect the investors' belongings and assets during the COVID-19 outbreak. As regards Jeribi and Snene Manzli (2021) pointed out that gold did not seem to act as a hedge or a safe-haven for Tunisian investors during the coronavirus outbreak. Such challenging findings demonstrate well that the safe-haven feature is prudent for market selection, stressing the need for further studies regarding the spillover across the stock, oil, and gold markets.

In effect, several studies undertook to examine the presence of spillovers and growing cryptocurrency sector, specifically Bitcoin, with earlier research in a bid to establish contagion channels in various ways, as the product has continued to evolve ever since its inception in 2009 (Corbet et al., 2018; Yi et al., 2018; Guesmi et al., 2019; Akyildirim et al., 2019; Ji et al., 2019; Corbet et al., 2020; Dehbashia et al., 2022). According to an important number of researchers, Bitcoin and other cryptocurrencies are considered highly volatile financial assets (Bouoiyour et al., 2014; Brière et al., 2015; Sahoo, 2017; Selmi et al., 2018; Bouri et al., 2018; Symitsi and Chalvatzi, 2019; Hu et al., 2019; Pelster et al., 2019; Kostika and Laopodis, 2019; Miglietti et al., 2020; Sahoo, 2020; Baur and Hoang, 2020). They are also rated as displaying better hedging capabilities than equities and the American Dollar (Dyhrberg, 2016). In this respect, Yu et al. (2019) revealed that, due to volatility asymmetry, the Bitcoin market effectiveness turns out to be more important relative to the overall financial market. Similarly, Grobys and Sapkota (2019) concluded that the cryptocurrency market proves to be more adequate than previous research revealed (e.g., Sigaki et al., 2019; Vidal-Tomás et al., 2019). Therefore, investors attempted to diversify their portfolios by incorporating cryptocurrencies during the pandemic to draw benefits in the short run. By the start of the COVID-19 pandemic, however, Bitcoin and other cryptocurrencies' value has plummeted, resulting in noticeable panic among users (Chen et al., 2020b).

Dehbashia et al. (2022) use the VAR-BEKK-GARCH approach to investigate volatility spillovers among financial markets in Iran, including stock, foreign exchange, and gold markets pre and post-JCPOA. They found that the effect of volatility spillover from stock to foreign exchange markets was negative in the per-JCPOA period and positive in the post-JCPOA period, and volatility spillovers between financial markets significantly decreased in the post-JCPOA period.

Although Bitcoin and other cryptocurrencies provide quick and irreversible transactions, their use, as exchange means, remains severely constrained due to the related price volatility (Dyhrberg, 2016; Katsiampa, 2017). As an alternative to volatile cryptocurrencies, Stablecoins, are associated with less volatile assets or currencies (mainly gold and the US Dollar). In this regard, a great deal of the Stablecoins' price stability associated research has been conducted, whether theoretically (Mita et al., 2019; Usman and Chohan, 2020; Klages-Mundt and Minca, 2020), or empirically (Gee et al., 2019; Bullmann et al., 2019). According to Shipman and Samman (2018), one of the most important aspects of a Stablecoin system is how effectively a Stablecoin acts during financial crisis times. On using a DCC-GARCH modeling approach, Wang et al. (2020) examined the Stablecoins' diversification, hedging, and safe-haven properties concerning conventional cryptocurrencies. Their findings indicate that Stablecoins could well serve as safe havens in specific situations, but turn out to act predominantly as effective diversifiers in normal market conditions. They also discovered that gold-pegged Stablecoins appear to perform rather worse as safe havens than USD-pegged Stablecoins, but both perform better than their respective underlying assets and that the Stablecoins' safe-haven ability proves to vary depending on market conditions. In investigating Stablecoins' stability during the novel COVID-19 pandemic, Jeger et al. (2020) reached results revealed that the two examined largest capitalized and

fiat collateralized Stablecoins proved to offer liquidity and stability during the cryptocurrency market fall in 2020. More recently, Baur and Hoang (2021) advanced a special methodology useful for testing stable the coins' absolute and relative stability. According to the authors, Stablecoins turn out to be more stable than Bitcoin and the S&P500, though less stable than major national currencies.
On the other hand, using the ARMA-GARCH model, Wassiuzzaman and Abdul-Rahman (2021) examined the performance of gold-pegged Stablecoins during the novel COVID-19 pandemic. Their results revealed that Stablecoins witnessed an increase in volatility during this health, though insignificant. Grobys et al. (2021) examined the Stablecoins' volatility mechanisms and their possible interdependency with Bitcoin's volatility. Their findings revealed that Bitcoin's volatility is statistically well-behaved, with a limited theoretical variance. Surprisingly, however, they discovered that the Stablecoins' volatilities turn out to be statistically unstable, responding to the Bitcoin's volatility in real-time. They also concluded that Bitcoin's volatility proves to stand as a major factor driving the Stablecoins' volatility, a finding also corroborated by Lyons and Viswanath-Natraj (2020).

3. Methodology

To compare the five instruments' capacity to act as hedge, safe-haven, or diversifier mechanisms (namely, Bitcoin, Ethereum, True, Tether, and Gold) relative to S&P500 and SSE Stock markets, we initiate by determining the dynamic conditional correlation between two market return series using the ADCC modeling approach. The study's major objective lies in analyzing how the relationship between each of the five instruments and stock market index returns marks a change between two different periods: the post-COVID-19 period, and the COVID-19 actual meanwhile period, in a bid to help investors make the right appropriate decisions on drawing their proper portfolio.

Following Baur and Lucey (2010) as well as Reboredo (2013), an asset is dubbed a hedge if it exhibits a negative (or insignificant) correlation in normal states and, therefore, does not have the specific property of mitigating risks and losses during market anxiety or crash times. Similarly, an asset is recognized as a safe-haven if it is uncorrelated (or negatively correlated) with another asset or portfolio during market turmoil times. The specific property of a safe-haven asset is the non-positive correlation with a portfolio it displays during extreme market conditions. On average, this property does not require the persistence of a positive or a negative correlation, but there should be zero or a negative dependence between the two assets during well-specified periods. This denotes that in normal states, or bullish regimes, correlation can be positive or negative.

Like a hedger, the diversifier does not demonstrate the specific property of minimizing losses in extremely detrimental market conditions, as correlation holds only on average. An asset is considered as a diversifier if it is positively (but not perfectly) correlated with another asset on average.

Concerning our study context, the TGARCH-ADCC modeling specification is applied to estimate the dynamic conditional correlations, to be subsequently implemented to estimate the regression; following Baur and Lucey (2010) advanced formulation. To determine the five instruments' capacity to act as hedging, safe-haven, or diversifying instruments in stock market portfolio, we consider estimating the already cited regression regarding the two sub-periods: the post-COVID-19 period regression, as well as the actual COVID-19 span regression. The purpose is to check whether the instrument in question has changed in nature, or remained stable across both sub-periods.

3.1 TGARCH Modeling

It is important to note that the threshold GARCH (TGARCH) specification displays the advantage of enabling to modeling of any leverage effects, through the implementation of the following formula:

$$\sigma_t^2 = a_0 + \sum_{i=1}^{P} a_i\, \varepsilon_{t-i}^2 + \sum_{i=1}^{P} \gamma_i\, S_{t-i}\varepsilon_{t-i}^2 + \sum_{j=1}^{q} b_j \sigma_{t-j}^2 \quad (1)$$

where $S_{t-i} = \begin{cases} 1 & if\, \varepsilon_{t-i} < 0 \\ 0 & if\, \varepsilon_{t-i} \geq 0 \end{cases}$

It denotes well that, depending on whether ε_{t-i}lies above or below the threshold value of zero, ε_{t-i}^2 displays different effects on the conditional variance σ_t^2, i.e., onceε_{t-i} is positive, the total effects turn out to be provided by $a_i\varepsilon_{t-i}^2$. In case$\varepsilon_{t-i}$is negative, however, the total effects are given by $(a_i + \gamma_i)\varepsilon_{t-i}^2$. Hence, one would expect $\gamma_i$to be positive for bad news to have greater impacts. This approach is also known as the GJR model because Glosten et al. (1993) proposed essentially the same model.

3.2 ADCC Representation Model

Relying on the DCC model as well as the asymmetric GARCH modeling specification of Glosten et al. (1993) and Cappiello et al. (2006) set up a further modeling extension framework by incorporating an asymmetric term, thereby, establishing the Asymmetric DCC (ADCC) modeling method, such as:

$$h_{i,t} = \omega_i + \alpha_i {\varepsilon_{i,t-1}}^2 + \beta_i h_{ii,t-1} + d_i {\varepsilon_{i,t-1}}^2 I(\varepsilon_{i,t-1}) \quad (2)$$

$\omega > 0\,;, \alpha > 0\ \ and\, \beta > 0$

where h_t designates the conditional variance;ω_i is a constant;α_i and β_i are, respectively, the short-term and long-term volatilities' capturing parameters, while $\mathrm{d}_i$stands for the asymmetric parameter.

The indicator function $I(\varepsilon_{i,t-1})$ is equal to one if $\varepsilon_{i,t-1} < 0$, and to 0 otherwise. In terms of this specification, a positive value of d should denote that it is the negative residuals, rather than the positive ones, which tend to increase the variance. The asymmetric, or "leverage effect", is intended to capture an often observed feature of financial assets, namely, that an unexpected drop in asset prices tends to increase volatility more than an unexpected increase in asset prices of the same magnitude. This fact implies well that bad news tends to contribute to increasing volatility more than good news would do.

About the ADCC model, the Q dynamics are provided by:

$$Q_t = \left(\bar{Q} - A'\bar{Q}A - B'\bar{Q}B - G'\bar{Q}^{-}G\right) + A'z_{t-1}z'_{t-1}A + B'Q_{t-1}B + G'z_t^{-}z_t^{-\prime}G \qquad (3)$$

in the above equation,A,B, and G are $n \times n$ parameter matrices, and z_t^- are zero-threshold standardized errors that are equal to z_t once discovered to be inferior to zero, and zero otherwise. $\bar{Q}$ and $\bar{Q}^-$ are the unconditional matrices of z_t and z_t^-, respectively.

3.3 Regression Modeling

Following Baur and Mcdermott (2010), the regression model can be formulated as follows:

$$ADCC_{Instrument/Asset,t} = \beta_0 + \beta_1 D_1(r_{asset}q_{10}) + \beta_2 D_2(r_{asset}q_5) + \beta_3 D_3(r_{asset}q_1) + \varepsilon_t \qquad (4)$$

with:

$ADCC_{Instrument/Asset,t}$: is the dynamic conditional correlation from between a hedging instrument and a stock index in consideration within the ADCC modeling specification;

β_0: is the constant;

β_1, β_2, β_3: are the extreme movements associated coefficients;

$r_{asset}q_{10}$, $r_{asset}q_5$, $r_{asset}q_1$ are the percentiles of the asset return series at 10%, 5% and 1% respectively;

ε_t: stands for the error term.

should one of the parametersβ_1, β_2 or β_3 prove to be significantly different from zero, then there is evidence of a non-linear relationship between the instrument (whether Bitcoin, Ethereum, True, Tether, or gold) and the S&P500/SSE stock market indexes. If one of the parameters in Equation (4) proves to be non-positive (including β_0), it turns out to act as a weak safe-haven for the market considered. Should one of these parameters appear to be negative and statistically different from zero, the instrument turns out to function as a strong safe-haven. The instrument proves to be a hedge for a specific market if the parameter β_0 is zero (weak hedge) or negative (strong hedge), and the joint sum of the parameters β_1 to β_3 is not positive, exceeding the value of β_0.

3.4 Hedging Ratio and Effectiveness Hedging

At this stage, it consists in estimating the dynamic conditional correlation coefficient, useful for computing the Hedging ratio, as a necessary element for demonstrating how the US and Chinese price indexes related risks can be effectively hedged. As a thorough illustration of the scenario, let us consider an investor desiring to hedge his portfolio position against the US and Chinese price indexes' fluctuation. In such a case, the investor would encounter the problem of having to minimize his portfolio-associated risk without reducing its expected return. According to Kroner and Sultan (1993), for an investor desiring to determine his proper portfolio optimal hedge ratio, the hedge ratio needs to be calculated as follows:

$$\beta_t^{SO} = \frac{h_t^{SO}}{h_t^S} \tag{5}$$

To minimize the relevant risk, the considered hedging strategy consists of retrieving how much a long position (buy) of one Dollar in the US and Chinese indexes should be hedged by a short position (sell) of β dollar in gold and digital assets, where:

- β_t denotes the risk-minimizing hedge ratio for stock indexes;
- h_t^s represents the conditional variances of the stock market index;
- h_t^{so} refers to the conditional covariance between digital assets and gold on the one hand, and stock market returns, on the other hand, at time t.

The performance of different optimal hedge ratios, drawn from the different cryptocurrencies and Gold, is measured using the hedging effectiveness (HE) index (Chang et al., 2011; Ku et al, 2007) as follows:

$$HE = \frac{var_{unhedged} - var_{hedged}}{var_{unhedged}} \tag{6}$$

wherein, a high HE index would reflect a high hedging effectiveness.

4. Data and Descriptive Statistics

4.1 Data

Our study period includes both the pre-COVID-19 span (August 24, 2018, to December 31, 2019), and the COVID-19 actual period (January 1, 2020, to November 5, 2021), starting on the day when China reported the first COVID-19 infection case. To check whether each of the five instruments proved to behave as a diversifier, a safe-haven, or a hedge along both sub-periods, we consider examining two major stock market indexes, namely, the American S&P 500 and the Chinese SSE. The relevant data has been collected from the site: coindesk.com. All the return series are calculated on a compound continuous basis:

$$R_{i,t} = \log\left(\frac{P_{i,t}}{P_{i,t-1}}\right) * 100$$

where $P_{i,t}$ represents the closing price of asset i at time t.

4.2 Descriptive Statistics

Figure 1 displays the daily return dynamics of the entire sampling period financial series. The graphical evidence indicates well that all the return series turned out to display high volatility throughout the COVID-19 crisis span, except for the two stable crypto-currencies True and Tether, whose associated returns proved to remain stable.

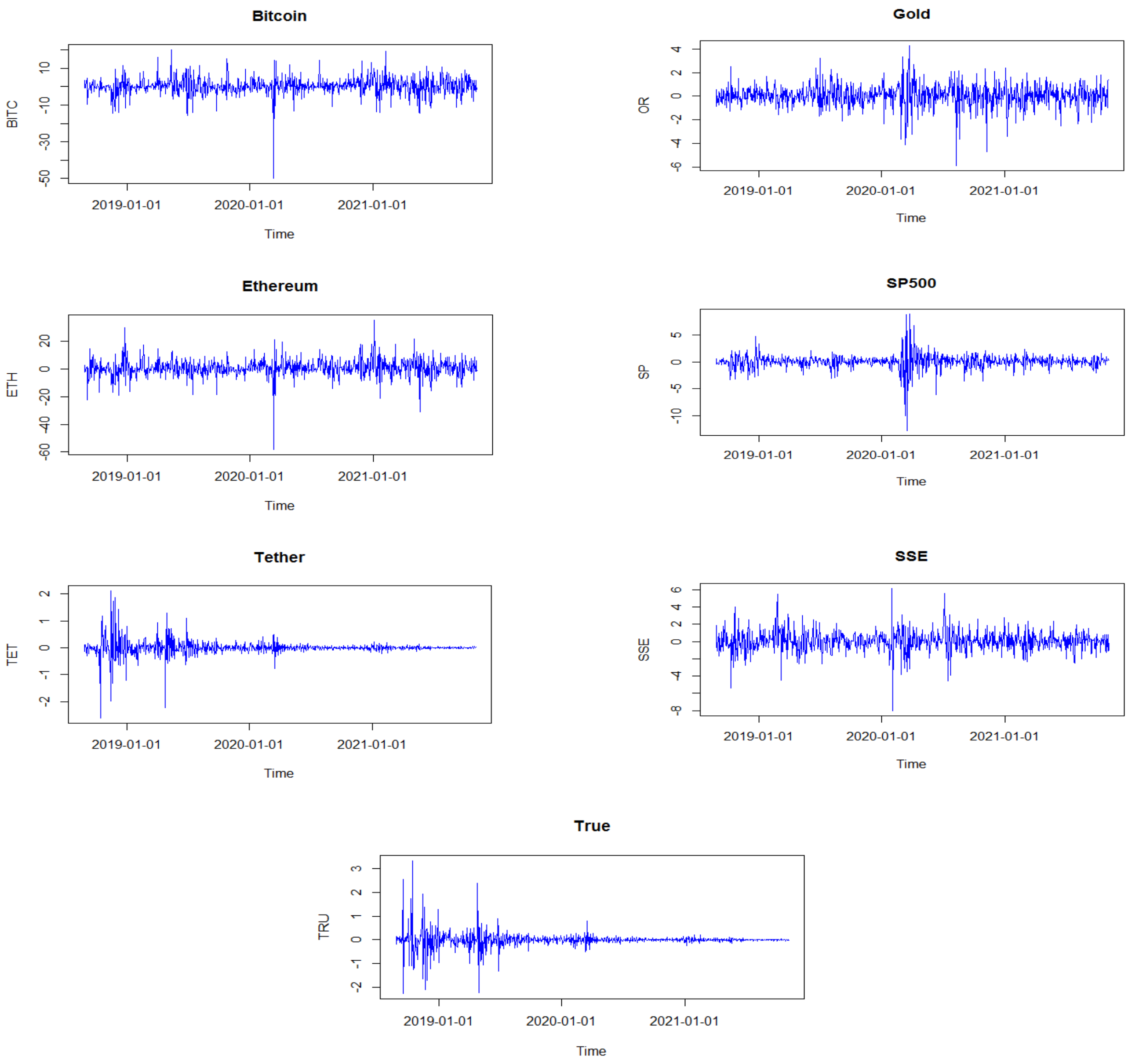

Figure 1. Daily Return Index Dynamics Regarding the Entire Period
Source: Research finding.

Based on Table 1, one can note that the Ethereum proves to exhibit the highest return (0.3369), while the True cryptocurrency displays a negative return. Both of the Bitcoin and Ethereum were more volatile than the other return assets. The stable cryptocurrencies' mean returns are very close, demonstrating noticeable weakness relative to the return standard deviations, reflecting no significant trend in the data. The skewness coefficients reveal that the majority of the returns, except the True crypto-currency returns, are left skewed in view that their values are negative. All return series appear to exhibit significant leptokurtosis. These returns are non-normal, as indicated by the Jarque-Bera test, justifying an investigation of the dynamic conditional correlations via ADCC modeling specification.

The administered Lagrange multiplier test reveals the persistence of an ARCH effect for all return series, enabling the implementation of the ARCH family modeling to capture the entirety of the return series' volatility. The Box-Pierce Q-test strongly rejects the presence of insignificant autocorrelations within the initial twelve lags in all the variables 'return series except for the SSE index, while the Box-Pierce squared Q-test highlights the non-presence of any significant autocorrelations regarding the entirety of series.

Table 1. Descriptive Statistics

	BITC	ETH	TET	TRU	Gold	SP	SSE
Mean	0.2693	0.3369	0.0003	-0.0002	0.0492	0.0588	0.0299
sd	4.7373	6.3374	0.2777	0.3438	0.9413	1.4099	1.1513
Min.	-49.728	-57.987	-2.602	-2.246	-5.893	-12.765	-7.994
Max.	20.0785	34.9939	2.1149	3.3216	4.2968	8.9683	6.1299
Skew.	-1.4117	-0.8727	-0.6864	1.3139	-0.5949	-1.0471	-0.2640
Kurt.	16.3389	11.4652	28.33306	28.6828	4.5609	17.9014	5.9071
J.Bera	9470.2***	4634.6***	27707.82***	28567.06***	766.91***	11189.1***	1213.52***
Q(12)	24.614**	22.454**	92.837***	57.407***	25.013***	288.58***	15.375
Q^2(12)	24.729**	29.564***	258.93***	222.56***	125.48***	1181.8***	80.701***
LM(12)	24.339**	25.129**	115.45***	144.14***	65.87***	355.47***	61.203***

Source: Research finding.

Note: *, **, and *** are significant at 10%, 5%, and 1% levels, respectively. BITC, ETH, TET, TRU represents the Bitcoin, Ethereum, Tether, and True cryptocurrencies, respectively. SP and SSE design the US and China stock market indices. sd = standard deviation and J.Bera = Jarque-Bera normality test.

5. Empirical Results

5.1 Volatility and Dynamic Conditional Correlations Analysis

The TGARCH (1,1) model, applied to investigate asymmetries in positive and negative shocks on volatility, records regression coefficients «alpha1», «beta1» and «alpha1 +eta11» registered between the two sub-periods, as depicted in Table2, reflecting the effect of "good news", leverage, and "bad news", respectively. The table highlights well that all the selected series turned out to demonstrate a statistically significant ARCH effect throughout the actual COVID period, except for Ethereum. Accordingly, the null hypothesis proves to be rejected, confirming the alternative hypothesis and maintaining the persistence of an ARCH effect. Hence, the TGARCH test is administered to capture the effect of information asymmetry. The TGARCH tests reached results show that all returns series turnout to demonstrate a significant effect of the coefficient « eta11 » throughout the pre-COVID and actual COVID spans. The null hypothesis is therefore rejected, and the alternative hypothesis, maintaining the persistence of a leverage effect regarding all series, is accepted. In effect, the attained results appear to indicate that COVID-19 does have a significant effect on all return indexes. Additionally, the effect of information asymmetry seems well pronounced concerning all series during the actual COVID-19 period, as compared to the pre-COVID span, except for the stable cryptocurrencies (i.e., Tether and True) and Gold. Such a result has its explanation in the stable and non-volatile nature of these crypto-currencies. Furthermore, the coefficient «alpha1 +eta11» helps measure the continuous impact of shocks on these series. The relevant results indicate well that most series tend to display a higher COVID-period coefficient than a pre-COVID-period one, except for stable cryptocurrencies. For instance, Bitcoin proves to demonstrate a pre-COVID span value of 0.2015 and a value of 0.4401 throughout the actual COVID period, indicating a stronger effect of during-COVID shocks than pre-COVID ones.

Table 2. TGARCH Estimation Results throughout Both Periods

	BTC	ETH	TET	TRUE	GOLD	SP	SSE
Panel 1 : Pre-COVID Period							
mu	0.0326	-0.2574	-0.0099	0.0109	0.0609*	0.0636**	0.0288
ar1	0.0311	-0.0673	-0.1639***	-0.1430***	-0.0667	0.0045	-0.0073
omega	0.2946	1.5533*	0.0079*	0.0112	0.0163*	0.0383***	0.0274
alpha1	0.3338**	0.3158**	0.2135***	0.2544***	0.0371**	0.1348***	0.0734**
beta1	0.8006***	0.6843***	0.8484***	0.8422***	0.9489***	0.8527***	0.9233***
eta11	-0.1323*	-0.0954**	0.7752***	-0.1909***	-0.0236*	0.5370***	0.0364***
alpha1+ ta11	0.2015	0.2204	0.9887	0.0635	0.0135	0.6718	0.1098
shape	2.3363***	2.2819***	2.9129***	2.5794***	6.8145***	5.5041***	4.3213***
Panel 2 : COVIDperiod							
mu	0.4526***	0.8399***	0.0003	-0.0019	0.0961**	0.1234***	0.0429
ar1	-0.0969**	-0.1264***	-0.3299***	-0.2955***	0.0061	-0.1001**	-0.0550*
omega	0.0563	0.23716	0.0010*	0.0013*	0.0795*	0.0744***	0.1231*
alpha1	0.5823***	0.6614	0.1574***	0.1786***	0.0025***	0.2418***	0.1639***
beta1	0.9359***	0.9225***	0.8686***	0.8487***	0.8536***	0.7544***	0.7762***
eta11	-0.1422**	-0.2759***	0.2238**	-0.0748***	0.0101*	0.5681***	0.3710*
alpha1+ eta11	0.4401	0.3855	0.3812	0.1038	0.0126	0.8099	0.5349
shape	3.1293***	3.4525***	5.0019***	6.5629***	3.7599***	5.1566***	3.8973***

Source: Research finding.

Note: *, **, and *** denote significance at 10%, 5%, and 1% levels, respectively.

Table 3 depicts the ADCCs between S&P500/SSE and the major financial digital classes of cryptocurrencies (Bitcoin, Ethereum, Tether and True) and Gold. Regarding the DCC modeling, the estimated coefficients on dcca1, dccb1 and dccg1 are all positive and statistically significant. These estimated coefficients sum to a value inferior to one, indicating that the asymmetric dynamic conditional correlations are mean reverting.

The Shape parameter (mshape) equates to the freedom degrees. In effect, the more the number of freedom degrees tends to approach infinity, the more the t distribution's shape tends towards the normal.

Gold and S & P500 prove to bear the highest estimated shaper parameters (over 5), indicating that each of the other data series' distributions (True, Bitcoin, Ethereum, Tether, and SSE) each have heavier tails than the distributions of Gold and S&P500.

The estimated asymmetric term (shape) is positive and statistically significant concerning all series. This finding indicates that for all series, negative residuals tend to increase the variance (conditional volatility) more than positive shocks of the same magnitude would. The different leverage effects may well emanate from different arbitrage activities, heterogeneity, asymmetric information, and/or contract liquidity.

Table 3. ADCC Estimation Results Regarding the Whole Period

	Estimate		Estimate		Estimate
[SP].mu	0.088996***	[SSE].mu	0.036063	[ETH].mu	0.298413**
[SP].ar1	-0.036287	[SSE].ar1	-0.029601	[ETH].ar1	-0.074851**
[SP].omega	0.047346***	[SSE].omega	0.079598**	[ETH].omega	0.746620
[SP].alpha1	0.173723***	[SSE].alpha1	0.117965***	[ETH].alpha1	0.143636***
[SP].beta1	0.823386***	[SSE].beta1	0.847838***	[ETH].beta1	0.803424***
[SP].eta11	0.790897***	[SSE].eta11	0.294739	[ETH].eta11	0.032690
[SP].shape	5.253363***	[SSE].shape	3.901345***	[ETH].shape	2.897042***
[BITC].mu	0.188542*	[TET].mu	-0.001438	[TRU].mu	0.000876
			-		-
[BITC].ar1	-0.031267	[TET].ar1	0.268320***	[TRU].ar1	0.244547***
[BITC].omega	0.122103*	[TET].omega	0.001087**	[TRU].omega	0.000997**
[BITC].alpha1	0.164188***	[TET].alpha1	0.186952***	[TRU].alpha1	0.188984***
[BITC].beta1	0.888811***	[TET].beta1	0.866718***	[TRU].beta1	0.865190***
[BITC].eta11	-0.113741	[TET].eta11	0.398973**	[TRU].eta11	-0.306896*
[BITC].shape	2.599218***	[TET].shape	3.456121***	[TRU].shape	3.488538***
[GOLD].mu	0.072589**				
[GOLD].ar1	-0.015008				
[GOLD].omega	0.022504				
[GOLD].alpha1	0.072368***				
[GOLD].beta1	0.925441***				
[GOLD].eta11	-0.271594				
[GOLD].shape	4.140991***				
[BITC/SP]dcca1	0.009117	[BITC/SSE]dcca1	0.026926	[ETH/SP]dcca1	0.017018
[BITC/SP]dccb1	0.987664***	[BITC/SSE]dccb1	0.933130***	[ETH/SP]dccb1	0.969977***
[BITC/SP]dccg1	0.001015	[BITC/SSE]dccg1	0.000000	[ETH/SP]dccg1	0.004910
[BITC/SP]mshape	4.000001***	[BITC/SSE]mshape	4.000000***	[ETH/SP]mshape	4.202750***
[ETH/SSE]dcca1	0.005941	[TET/SP]dcca1	0.000000	[TET/SSE]dcca1	0.003622
[ETH/SSE]dccb1	0.957015***	[TET/SP]dccb1	0.933797***	[TET/SSE]dccb1	0.989871***
[ETH/SSE]dccg1	0.000000	[TET/SP]dccg1	0.014482	[TET/SSE]dccg1	0.000000
[ETH/SSE]mshape	4.000000***	[TET/SP]mshape	4.535703***	[TET/SSE]mshape	4.105718***
[TRU/SP]dcca1	0.007851	[TRU/SSE]dcca1	0.012489	[GOLD/SP]dcca1	0.030257***
[TRU/SP]dccb1	0.992149***	[TRU/SSE]dccb1	0.930762***	[GOLD/SP]dccb1	0.963613
[TRU/SP]dccg1	0.000000	[TRU/SSE]dccg1	0.071183	[GOLD/SP]dccg1	0.000671
[TRU/SP]mshape	4.502127***	[TRU/SSE]mshape	4.064861***	[GOLD/SP]mshape	5.014826***
[GOLD/SSE]dcca1	0.011376				
[GOLD/SSE]dccb1	0.928597***				
[GOLD/SSE]dccg1	0.000000				
[GOLD/SSE]mshape	4.375876***				

Source: Research finding.

Note: 'mu' refers to the constant and 'ar(1)' refers to the AR(1) term in the mean equation. 'omega' refers to the constant in the variance equation, 'alpha1' refers to the ARCH term, 'beta1' refers to the GARCH term, 'etat11' refers to the asymmetry term while 'shape' refers to the shape term. ***, ** and * indicate significance at the 1%, 5% and 10% respectively.

Counting on the ADCC-GARCH modeling procedure, we have been able to estimate the time-varying conditional correlations between the US as well as the Chinese indexes and the other considered financial assets, as depicted in Figure 3. In this regard, one can identify the persistence of a significantly increasing correlation between the S&P500 and the other assets in absolute value, indicating that global economic integration, along with a rather open market environment has led to the prevalence of close relationships among stock markets. Before the 2020 global crisis, one could observe that the US index and the two volatile digital assets binding correlation proved to be decreasing in trend, turning negative by the second half of 2019. Based on this finding, and on applying the Baur and Lucey (2010) categorization procedures, we consider that Bitcoin and Ethereum do stand as a Hedge. This result is consistent with that published by Charfeddine et al. (2020), Ghorbel and Jeribi (2021a; b; c), Jeribi et al. (2021) and Jeribi and Masmoudi (2021). By the beginning of 2020, we could note that the correlation between the volatile cryptocurrencies and the American index appeared to increase, confirming well the coronavirus-associated contagion effect influencing them. In effect, these cryptocurrencies could not be considered safe-haven assets during the COVID-19 pandemic span. Contrary to the S&P500, Fig. 3 indicates well that the Chinese index and volatile cryptocurrencies binding correlation proved to decrease, getting closer and closer to zero. Thus, cryptocurrencies might be considered to play just a weak-hedge role for Chinese investors throughout the 2020 global pandemic. Such a result seems to be consistent with those released by Ghorbel and Jeribi (2021b; c) and Belhassine and Karamti (2021).

Concerning the conditional financial indexes and Stablecoins binding correlation, one may notice that the correlation between the US and Chinese indexes on the one hand, and Tether, on the other hand, turns out to be weak, drawing too close to zero. The results denote well that True could be considered as a hedge and strong safe-haven instrument for US and Chinese financial investors. This finding seems consistent with Wanget (2020), yet, inconsistent with Jalan et al. (2021) results. To sum it up, on investigating the relationship between Gold and stock market indices, our attained results appear to reveal that Gold could have been used as a hedge and a strong safe-haven for US investors until June 2020. This result sounds consistent with that documented by Ghorbel and Jeribi (2021; b; c) and Belhassine and Karamti (2021). Beyond that, it tends to lose its safe-haven character, thereby, becoming a diversifier asset, while being considered as a diversifier asset for Chinese investors. This result confirms that documented by Shahzad et al. (2019) as well as Cheema et al. (2020).

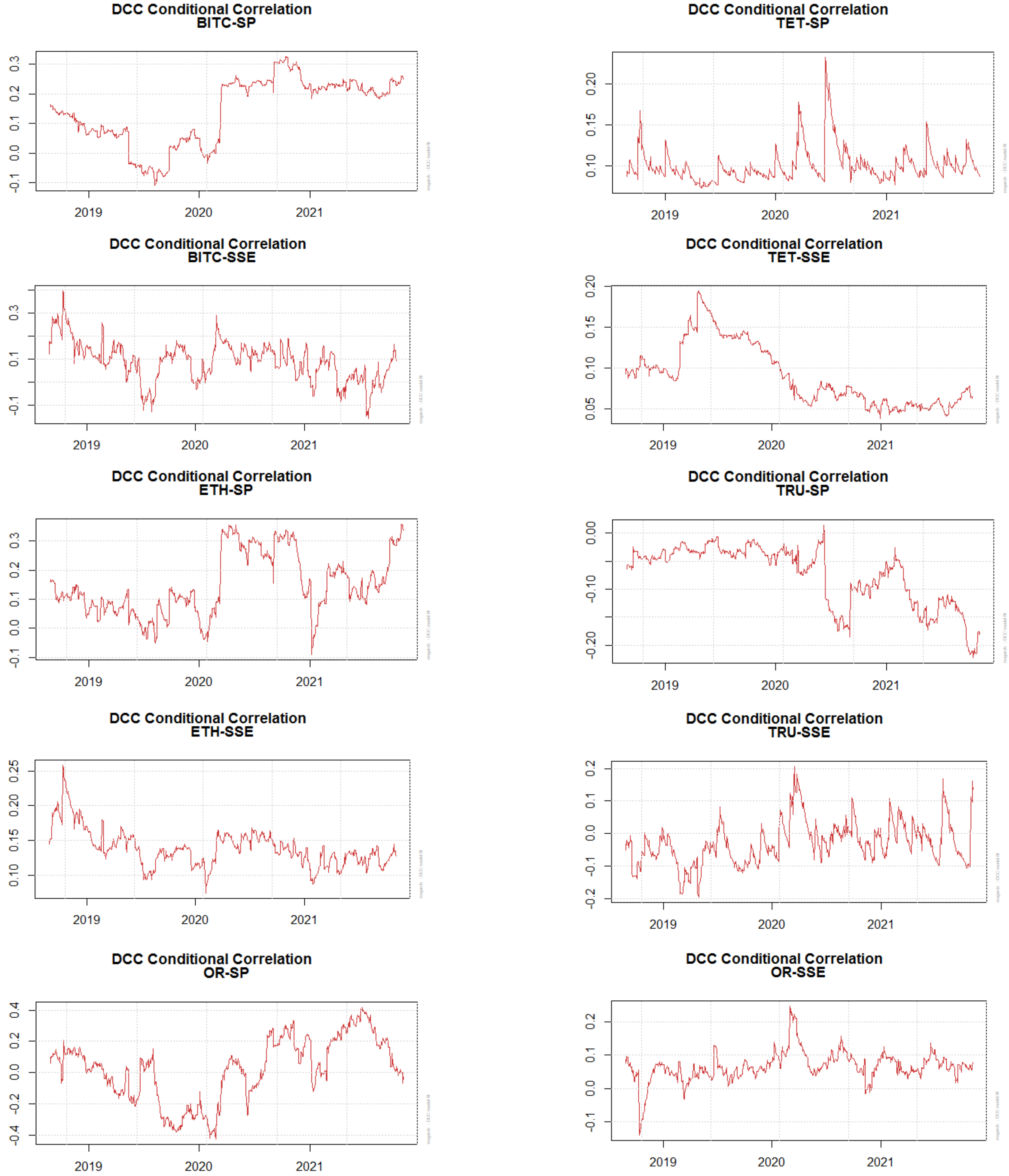

Figure 3. DCC Conditional Correlation between each Instrument and SP/SSE Index
Source: Research finding.

5.2 Safe-Haven, Diversification and Hedging Analysis

On implementing the Baur and McDermott (2010) advanced approach, as defined in Equation (4), the regression model emanating result is displayed in Table 4. The table illustrates the safe-haven, diversification, and hedging function relevant results, concerning cryptocurrencies and Gold for S&P500 and SSE indexes, regarding the two COVID-19 pre- and during sub-periods. These results do confirm the Figure 3 displayed results. Accordingly, True is considered a strong safe-haven asset for US investors, throughout the study period. However, it proved to play a safe-haven role for Chinese investors before 2020. Our results also reveal that Gold appeared to lose its safe-haven character before the 2020 global pandemic, to turn into a diversifier asset for US investors.

Table 4. Instrument Status for the US and Chinese Stock Market Indexes over Both Periods

Before COVID-10 period				
	β_0	**β_1**	**β_2**	**β_3**
BTC/SP	0.03988***	0.00437	0.00600	-0.01386
BTC/SSE	0.11460***	-0.00586	-0.01564	0.00568
ETH/SP	0.07447***	0.00632	0.01096	-0.01515**
ETH/SSE	0.14833***	-0.00845	-0.00817	-0.00119
TET/SP	0.09308***	0.00539	-0.00167	-0.00102
TET/SSE	0.12654***	-0.00516	0.00382	-0.00603
TRU/SP	-0.03389***	-0.00487	0.00189	0.00046
TRU/SSE	-0.06583***	0.00679	0.00150	0.00476
GOLD/SP	-0.08349***	-0.00265	-0.01104	-0.03921
GOLD/SSE	0.04548***	-0.01385*	0.00888	0.00575
During COVID-19 period				
	β_0	**β_1**	**β_2**	**β_3**
BTC/SP	0.21553***	-0.00300	0.01296	-0.00273
BTC/SSE	0.07045***	-0.00585	0.02264	-0.02503**
ETH/SP	0.19813***	0.00079	0.01438	-0.02035
ETH/SSE	0.13088***	-0.00106	0.00115	-0.00077
TET/SP	0.10609***	0.00029	-0.00407	0.00129
TET/SSE	0.06283***	-0.00286	0.00189	-0.00288
TRU/SP	-0.10856***	0.00112	0.00099	-0.00959
TRU/SSE	-0.00240	0.00026	-0.00733	-0.00428
GOLD/SP	0.10388***	-0.01045	0.04259	0.00228
GOLD/SSE	0.07934***	-0.01123**	0.01425*	-0.01504**

Source: Research finding.

Note: *, ** and *** designate significant at 10%, 5% and 1% levels, respectively.

5.3 Hedging Effectiveness Analysis

Table 5 illustrates the hedge ratios and hedge effectiveness (HE) results regarding the SP500 and SSE stock-market indexes. The average hedge-ratio values turn out to be negative concerning TRUE for both stock markets and gold for the US market, throughout the pre-COVID-19 period. The negative values, emanating from the inverse relationship between the Stablecoin TRUE and stock indices, suggest well that the hedging process ensues from taking either long or short positions for both asset types (i.e., TRUE and stock indices). For instance, a $1000 long-position American stock is hedged for by taking another long position for $264 in the TRUE cryptocurrency market. Regarding the COVID-19 actual period, the picture is quite similar, except for Gold for the US stock market, which proves to be positive. Another equally important result highlights that the stable cryptocurrencies' average hedge-ratio value (i.e., Tether and TRUE) has been discovered to decrease from the pre-COVID period to the actual Covid period. This finding suggests well that a much smaller amount of US dollars is required for these cryptocurrencies to be able to effectively hedge the US and Chinese equity investments. A striking instance of this is the 0.004 (positive) average value of the hedge ratio between Tether and SSE, which indicates that a $1000 long position in the Chinese stocks is hedged by taking a short position of $4 in the Tether market.

As to the HE results, the best hedging instrument marking the pre-covid-19 period is Gold for SP500, and Ethereum for the SSE index, clearly noticeable as Ethereum proves to demonstrate the best-fit hedging instrument for the SP500 and the Chinese SSE indexes throughout the actual Covid period.

Table 5. The Hedge Ratio and Hedging Effectiveness (HE) Estimation Results

	Before COVID-10 period		**During COVID-19 period**	
	B	**HE**	**β**	**HE**
BTC/SP	0.01213942	0.006671373	0.04679028	0.05118572
BTC/SSE	0.03532751	0.02205891	0.01755002	0.01093294
ETH/SP	0.01159007	0.00790484	0.04053965	0.051987
ETH/SSE	0.02745005	0.02326986	0.02180501	0.01750934
TET/SP	0.3745426	0.0089227	1.928094	0.01193802
TET/SSE	0.6734436	0.01692952	1.172585	0.004216786
TRU/SP	-0.1186702	0.001317996	-1.995711	0.01385028
TRU/SSE	-0.3113728	0.007040227	-0.04437283	0.003808438
GOLD/SP	-0.04950335	0.03308114	0.07196187	0.04657365
GOLD/SSE	0.05822873	0.003395099	0.09574136	0.008159495

Source: Research finding.

6. Conclusion

The present work is conducted to investigate the hedging and safe-haven characteristics of two volatile crypto-currencies (bitcoin and Ethereum), two Stablecoins (Tether and True), and Gold for the US and Chinese investors, marking the Coronavirus pandemic prevailing period. In the first place, we considered determining the dynamic conditional correlation between the S&P500 and SSE Stock markets on the one hand, and the five potential hedging instruments on the other hand, using the ADCC modeling methodology.

The results turn out to reveal a significant increase in the correlation between the S&P500 and the other assets in absolute value. This finding reflects well that the global economic integration, along with the open market environment has brought about closer ties and relationships among stock markets. In the 2020 global crisis preceding period, the correlation between the US index and the two volatile digital assets tends to decrease, becoming rather negative throughout the second half of the year 2019. Based on this result, and on applying the Baur and Lucey (2010) categorization techniques, we end up concluding that Bitcoin and Ethereum turn out to stand as noticeable Hedge instruments. At the beginning of 2020, however, the correlation between volatile cryptocurrencies and the American index tended to increase, highlighting the persistence of a significant Coronavirus contagion effect binding them, which makes these cryptocurrencies inapt to stand as safe-haven assets throughout the COVID-19 pandemic span. Contrary to the S&P500, however, the Chinese index and volatile cryptocurrencies binding correlation tended to decrease, getting too close to zero. These cryptocurrencies proved to play a weak hedging role for Chinese investors, over the 2020 conditional global pandemic.

On examining the financial indexes and Stablecoins binding correlation, one may well argue that True can be considered as a hedge and strong safe-haven instrument for US and Chinese financial investors alike. Additionally, our attained results appear to indicate that Gold could have been used as a hedge and strong safe-haven for US investors up until June 2020. Beyond that, it tended to lose its safe-haven character to become a diversifier asset. Indeed, it proved to stand as a diversifier asset to Chinese investors. On implementing the Baur and McDermott (2010) proposed framework, however, the results appeared to confirm well the ADCC model's ensuing results. In effect, True is considered to stand as a strong safe-haven asset for the US investors, throughout the study period. However, it tends to assume a safe-haven role for Chinese investors before 2020. Similarly, the achieved results also indicate that Gold proved to lose its safe-haven character before the 2020 global pandemic, shifting towards a diversifier asset concerning US investors. The computed optimal-hedge and hedging-effectiveness values turn out to reveal well that Gold proves to stand as the best optimal hedging instrument for SP500 regarding the pre-COVID-19 period, while Ethereum tends to best fit hedger for the Chinese investors, whereas Ethereum proves to exhibit the most effective hedging instrument, throughout the actual COVID-19lapse, for both of the US as well as Chinese investors.

The findings in terms of determining the nature of all instruments in US and Chinese investors also have major implications for risk and portfolio management, and investigating the status of the stock market and the effect of other financial markets on this market constitutes a major component in investment management analyses. These investors should carefully choose the best instrument that provides the opportunity to minimize the portfolio risk and maximize their profit.

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