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COVID-19 government interventions and cryptocurrency market: Is there any optimum portfolio diversification?

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ABSTRACT

This study attempts to find the impact of the COVID-19 government interventions on the cryptocurrency market. Using the daily data over the period 2020 M01 to 2022 M1, this study applied the Markov-Regime-switching and MGARCH-DCC approaches for eight cryptocurrencies. Overall, Markov-Regime-switching models reveal that there is an adverse effect of government interventions on cryptocurrencies. However, MGARCH-DCC models suggest that the best possible diversification opportunity exists between Dogecoin and Oil. For robustness, this study applies the MF-DFA and found a consistent result. The findings of this study would help investors and policymakers to formulate optimal investment decision-making.

1. Introduction

On March 11, 2020, the World Health Organization (WHO) declared COVID-19 a pandemic, triggering an unprecedented economic shock to world economy. Based on the latest worldwide figures as of November 07, 2022, there have been 637,695,929 identified cases, with 6,605,464 deaths (CSSE, 2022). In addition to medical measures such as treatment and vaccine development, governments have implemented non-medical policies to curb the pandemic, such as travel bans, lockdowns, school and industrial unit closures, and so on (Hale et al., 2021). Although these policies helped to slow the spread, they unintentionally harmed global economic activity, and many researchers are linking COVID-19 with the 2008 financial crisis (Batten et al., 2022a; Yarovaya et al., 2021). Moreover, the COVID-19 pandemic at the same time, adversely affected the global financial markets noticeably (Khan et al., 2020). In the case of the cryptocurrency market, due to a massive sale of cryptocurrencies, the market collapsed on March 8, 2020 and resulted in a loss of \$21 billion in a single day (Umar et al., 2021b). Unlike earlier studies, which focus on the influence of COVID-19 uncertainty and government interventions on stock markets (e.g., Abdullah et al., 2022; Aharon & Siev, 2021; Chowdhury et al., 2021; Jiang et al., 2022; Kheni and Kumar, 2021), this study focuses on the unexplored effect of government interventions on the cryptocurrency market.

The distinctions and connections between cryptocurrency and the traditional financial market can be explained in various forms. Firstly, cryptocurrencies are distinct in nature compared to fiat currencies as their supply is inelastic, their value is not backed by any

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asset, and there is no centralized organization to enforce rules and regulations. However, there is a long-term economic equilibrium between Bitcoin and the Swiss franc (Janson & Karoubi, 2021); Secondly, among cryptocurrencies, Bitcoin became a part of the traditional financial market when the Chicago Board Options Exchange began trading Bitcoin futures on December 10, 2017 and one week later the Chicago Mercantile Market also began trading Bitcoin futures (Shrestha, 2021); Thirdly, several recent studies already revealed the connectedness, risk spillover, and correlation between the cryptocurrency market and traditional financial markets such as stock market, commodity market, bond market, and currency exchange market (e.g., Cao & Xie, 2021; Elsayed et al., 2022; Wang et al., 2022); and Finally, the association between cryptocurrencies and traditional financial markets becomes more strong when investors add cryptocurrencies to the traditional financial assets in their portfolio and mean of daily transactions.

While cryptocurrencies are virtual assets, considering the linkage with traditional financial markets, one may ask how government interventions are associated with the cryptocurrency market? COVID-19 government interventions, i.e., workplace closure, stay-at-home regulations, quarantine, and school closure, interrupts the business cycle and retain employees at home, which decreases commercial transactions, household cash flows, and overall economic activity. Theoretically, policy uncertainty may affect the cryptocurrency market through different channels, i.e., i) systemic risk (Bouri et al., 2017; Demir et al., 2018; Jabotinsky & Sarel, 2020), ii) herding behavior (Evrin Mandaci and Cagli, 2022; Jabotinsky and Sarel, 2020), and iii) “money-under-the-mattress” approach (Jabotinsky & Sarel, 2020). Demir et al. (2018) and Yen and Cheng (2021) argued that the increased economic policy uncertainty frequently constrains investment flow owing to a fear factor that prevails in investors for investment loss, commonly referred to as risk-aversion behavior. For example, investors may move their money away from the cryptocurrency market into other financial markets or use it for household consumption. This cash outflow would reduce the liquidity of the cryptocurrency market and increase the volatility of the cryptocurrency in the future. Indeed, increased policy uncertainty can have a negative impact on investment by discouraging corporations from embarking on new investment ventures and forcing consumers to be more frugal in their spending habits (Mokni et al., 2022). In contrast, Cheng and Yen (2020) argued that effective policy responses could increase investors’ trust and confidence, which leads to a positive impact on the cryptocurrency market. Likewise, COVID-19 government interventions can influence (positively or negatively) investors in the cryptocurrency market. However, the effect of COVID-19 government interventions on the cryptocurrency market and portfolio diversification remains inconclusive.

From the portfolio diversifications perspective, a number of studies found cryptocurrency as a safe haven during the COVID-19 (e.g., Corbet et al., 2020; Mariana et al., 2021; Rubbiani et al., 2021) because they believe that during the early stage of COVID-19, the trading volume and returns increased significantly, which increased the cryptocurrency’s safe haven property. In contrast, a few studies found cryptocurrencies do not act as a safe haven during the pandemic and financial stress periods (e.g., Conlon et al., 2020; Ji et al., 2020). They suggest during COVID-19, cryptocurrencies behave like traditional assets, and cryptocurrencies cannot minimize the risk exposures. Since, both theoretically and empirically, how COVID-19 government interventions impact the cryptocurrency market and how the portfolio can be diversified are still remain unresolved, we make a humble attempt to address the issues. Therefore, this study aims to achieve the following objectives:

- i) To find out the impact of the COVID-19 government policy interventions on the cryptocurrency market.
- ii) To find a portfolio diversification benefit for cryptocurrencies during the COVID-19 pandemic.

For the analysis, this study has considered the major cryptocurrencies such as Bitcoin, Ripple, Dogecoin, Stellar, Ethereum, Bitcoin Cash, Cardano, and Tezos with worldwide COVID-19 new cases, new deaths, and stringency index¹ as the proxy of COVID-19 government interventions indicator. This study applied the Markov-Regime Switching model to examine the effect of government policy response on the cryptocurrency market. Moreover, this study used MGARCH-DCC to find out the optimum portfolio diversification strategy and MF-DFA to examine the robustness of the portfolio diversification strategy.

This paper aims to make several contributions to the literature. First, this paper is one of the first attempts to test the impact of COVID-19 government interventions on the digital currency market. Second, this paper considered the global data for testing the impact of government interventions on the cryptocurrency market. Third, this paper adds empirical evidence on cryptocurrency’s optimal portfolio diversification during the pandemic. Fourth, the findings of this paper will enable investors and hedgers to reduce risk through portfolio management and diversification and the development of appropriate hedging positions. Finally, the findings will assist policymakers in the formulation of regulatory policies by fine-tuning asset price volatility predictions for risk management.

The rest of the paper is organized as follows: Section 2 discusses the literature; section 3 elaborates on the methodology of this study; section 4 demonstrates the empirical evidence given by the data analysis results; in section 5, the discussions are added. Finally, section 6 deals with the conclusion and policy implications.

2. Brief literature review

Amid this pandemic, many researchers explored the impact of COVID-19 (new cases, new deaths, negative sentiments) on cryptocurrencies, and they examined the effect of COVID-19 on cryptocurrencies in terms of performance (e.g., Caferra & Vidal-Tomás, 2021; Corbet et al., 2021; Iqbal et al., 2021; Yousaf & Yarovaya, 2022), efficiency (e.g., Kakinaka & Umeno, 2022; Naeem et al., 2021), and safe haven property (e.g., Corbet et al., 2020; Ji et al., 2020; Kumar et al., 2022; Mariana et al., 2021).

¹ Stringency index is developed by Oxford University as the measurement of coronavirus government response tracker which is a combination of nine indicators and calculated through publicly available information of government responses regarding COVID-19.

2.1. Government interventions against COVID-19

Prior studies have explored how different policy uncertainty affects the cryptocurrency market, for example, economic or political policy uncertainty (e.g., [Colon et al., 2021](#); [Demir et al., 2018](#); [Mokni et al., 2022](#); [Umar et al., 2021a](#)), Chinese economic policy uncertainty (e.g., [Chen et al., 2021](#); [Yen & Cheng, 2021](#)), and Twitter-based economic policy uncertainty ([Wu et al., 2021](#)).

[Bouri et al. \(2017\)](#) were the first to use the implied volatility series for 14 equity markets to investigate the causal relationships between market shocks and Bitcoin returns. Their findings suggest that market shock affects Bitcoin return adversely. [Demir et al. \(2018\)](#) investigated the impact of the U.S. economic policy uncertainty on Bitcoin. The authors discovered that economic policy uncertainty negatively impacts Bitcoin returns using daily Bitcoin returns data. Using Generalized Quantile Regression and Ordinary Least Squares, [Chen et al. \(2021\)](#) found that Chinese economic policy uncertainty positively impacts bitcoin return at the upper quantile and found a negative impact at the lower quantile. Similarly, [Yen and Cheng \(2021\)](#) observed that Chinese economic policy uncertainty negatively impact on Bitcoin and Litecoin. [Jiang et al. \(2021\)](#) investigated the interconnections between economic policy uncertainty and found a negative spillover of economic policy uncertainty and COVID-19 on cryptocurrencies. Recently, [Mokni et al. \(2022\)](#) investigated the effect of economic policy uncertainty on five cryptocurrencies before and during COVID-19 and suggested Gold and cryptocurrencies cannot act as a strong hedge against economic policy uncertainty before and during the COVID-19 pandemic. Several other studies also found cryptocurrency market actively reacts to different policy uncertainty ([Colon et al., 2021](#); [Umar et al., 2021a](#); [Wu et al., 2021](#)).

However, previous studies on cryptocurrency literature do not uncover the impact of COVID-19 government interventions on the cryptocurrency market. There are several studies conducted to examine the effect of COVID-19 government interventions on other financial markets. Studies related to the stock market and COVID-19 government interventions reveal mixed arguments; many studies found adverse effects (e.g., [Aharon & Siev, 2021](#); [Jiang et al., 2022](#); [Kheni and Kumar, 2021](#)); few studies found a positive effect ([Bouri et al., 2022](#); [Wang et al., 2021](#)); and others found mixed results based on countries' development levels (e.g., [Bakry et al., 2022](#); [Zaremba et al., 2021](#)). Besides, previous studies argued that the cryptocurrency market and stock market react similarly to uncertainty and correlate among them. [Wang et al. \(2022\)](#) examined the asymmetric contagion effects between stock and cryptocurrency markets, and the results show a dynamic correlation between stock and cryptocurrency markets. Moreover, they added that the volatility of cryptocurrency could predict the volatility of the stock market; as stock market investors begin to include cryptocurrencies in their investment portfolios, capital continues to flow into the cryptocurrency market, not only increasing its size but also strengthening the link between the two markets. [Cao and Xie \(2021\)](#) observed the risk transmission of cryptocurrencies and the Chinese financial market using MF-ADCCA and found a cross-correlation, long memory, and asymmetric multifractal characteristics between and stock and cryptocurrency market. [Elsayed et al. \(2022\)](#) investigated the volatility and return connections between traditional financial assets, global uncertainty measures, and Bitcoin. The authors found high volatility and return spillover across conventional financial assets, global uncertainty measures, and Bitcoin.

Based on the above discussion, there is a connection between government interventions and the financial market. However, it is unclear how COVID-19 government interventions affect the cryptocurrency market since empirical investigations are negligible. So, the hypothesis of our study is:

H_01 : There is no impact of COVID-19 government interventions on the cryptocurrency price.

2.2. Cryptocurrency portfolio diversification

Literature on diversification strategy primarily focuses on whether cryptocurrencies are diversifiers, safe haven assets, or hedges in comparison with the traditional (e.g., [Aloui et al., 2022](#); [Corbet et al., 2020](#); [Ji et al., 2020](#); [Kumar et al., 2022](#); [Mariana et al., 2021](#)) and they do not reveal how cryptocurrency portfolios react to the COVID-19 government interventions. According to [Baur and Lucey \(2010\)](#), a hedge is defined as an asset that is, on average negatively correlated with another asset or portfolio, and a diversifier is an asset that is positively (but not perfectly) correlated with another asset or portfolio. However, unlike a hedge or a diversifier, a safe haven asset has the unique property of having a negative correlation with a portfolio during extreme market conditions such as financial crisis; it compensates the investor for losses because the price of the safe haven asset increases when the price of the other asset or portfolio decreases.

Studies related to cryptocurrency diversification during COVID-19 are focused on the cryptocurrency market efficiency (e.g., [Kakinaka & Umeno, 2022](#); [Naeem et al., 2021](#)) and safe haven property ([Corbet et al., 2020](#); [Ji et al., 2020](#); [Kumar et al., 2022](#); [Mariana et al., 2021](#)). Studies before COVID-19 show that Bitcoin has the potential to be an excellent diversifier for specific currencies, stocks, and commodities ([Urquhart & Zhang, 2019](#)). However, recent studies based on the COVID-19 period found mixed findings. [Colon et al. \(2021\)](#) examined the safe haven property of Tether, Ethereum, and Bitcoin against the international equity index and found cryptocurrencies cannot be considered as a safe haven during COVID-19. Other studies on the initial stage of COVID-19 by [Ji et al. \(2020\)](#) and [Corbet et al. \(2020\)](#) also found that cryptocurrencies cannot be considered as a safe haven during COVID-19. Conversely, [Mariana et al. \(2021\)](#) found Ethereum could be viewed as a safe haven rather than Bitcoin.

Another stream of studies examined the cryptocurrencies' efficiency and multifractality, which attempt to reveal the diversification possibility. [Kakinaka and Umeno \(2022\)](#) applied MF-DFA to explore the major cryptocurrencies' multifractality and market efficiency during COVID-19. They observed different levels of time-varying multifractality, which shows outbreak has significantly altered the degree of asymmetry in cryptocurrency markets. Other studies also found different levels of time-varying multifractality and efficiency of cryptocurrencies during COVID-19 ([Naeem et al., 2021](#)). Overall, the above discussion reveals the different levels of cryptocurrency market efficiency and safe haven property. However, cryptocurrency portfolio construction and diversification strategy under COVID-

Table 1
Variable specifications.

Variable	Description	Data Source
BTC	Daily USD Closing Price of Bitcoin	Coindesk database
XRP	Daily USD Closing Price of Ripple	Coindesk database
DOGE	Daily USD Closing Price of Dogecoin	Coindesk database
XLM	Daily USD Closing Price of Stellar	Coindesk database
ETH	Daily USD Closing Price of Ethereum	Coindesk database
BCH	Daily USD Closing Price of Bitcoin Cash	Coindesk database
ADA	Daily USD Closing Price of Cardano	Coindesk database
XTZ	Daily USD Closing Price of Tezos	Coindesk database
GOLD	Daily USD Closing Price of Gold	DataStream
OIL	Daily USD Closing Price of Oil	DataStream
NC	Daily worldwide COVID-19 new cases	Our World in Data
ND	Daily worldwide new deaths from COVID-19	Our World in Data
COVID	PCA of NC and ND	Author's Calculation
SI	Daily average Stringency index	OxCGRT
OGRI	Daily average overall government policy response index	OxCGRT

Note: Coindesk database = <https://www.coindesk.com/>, Our World in Data = <https://ourworldindata.org/>, OxCGRT = Oxford Covid-19 Government Response Tracker (<https://github.com/OxCGRT/covid-policy-tracker/>).

19 government interventions are yet to be revealed.

H₀2: There is no portfolio diversification benefit of cryptocurrency during the COVID-19 pandemic.

3. Data and Methodologies

3.1. Data

Table 1 shows the variable specification, the daily price of eight cryptocurrencies, and Gold and Oil are taken as the safe haven asset for portfolio diversification. Data from January 24, 2020, to January 25, 2022, is taken as the sample period for this study to consider the initial and the peak stage of COVID-19. After matching with the COVID-19 and cryptocurrencies and commodities data, there are 524 daily observations available for all variables.

We use the Oxford COVID-19 Government Response Tracker (OxCGRT) data to consider different COVID-19 government interventions (Hale et al., 2021). Several previous studies of other financial markets used the Stringency index to measure COVID-19 government interventions (e.g., Abdullah et al., 2022; Bakry et al., 2022; Zaremba et al., 2021). In this study, for measuring the COVID-19 government response, the daily worldwide (225 countries) average value of the stringency index is taken as the primary independent variable. The sample country list is presented in the [supplementary material](#) (Table S.4). Moreover, the overall government policy response index (OGRI) is taken for the robustness test.

Furthermore, daily worldwide COVID-19 new cases (NC) and new deaths from COVID-19 (ND) are also considered to check their effects. However, there is a high correlation between NC and ND (Table 2). Consequently, the principal component analysis of NC and ND is taken as a COVID variable to avoid multicollinearity issues (Wold et al., 1987). The historical price of selected cryptocurrencies is presented in Fig. 1.

3.2. Estimators

This study aims to examine the impact of COVID-19 government interventions on the cryptocurrency price and the portfolio diversification benefit of cryptocurrency during the COVID-19 pandemic. We have used different models to address the above two different objectives of our study. First, we have applied the Markov Regime Switching model to examine the impact of the COVID-19 government policy response on cryptocurrency prices at different financial market regimes, such as bull and bearish markets, using the stringency index as the proxy of COVID-19 government policy response, and robustness is examined using the overall government policy response index. Where a bull market represents the favorable, and a bear market represents an unfavorable market condition, a bull phase is commonly linked with higher prices. In contrast, a bear phase is associated with a period of declining prices or stalling (Caferra & Vidal-Tomás, 2021). Second, the Multivariate Generalized Autoregressive Conditional Heteroscedastic Dynamic Conditional Correlation (MGARCH-DCC) model is applied to examine the portfolio diversification of cryptocurrency during the COVID-19 pandemic. The MGARCH-DCC allows us to examine the extent of volatility and correlations between cryptocurrency return and commodity return over time and their movement, positive or negative. We chose this methodology because MGARCH-DCC allows us to use both mean and variance to evaluate time variation and determine how asset correlations change over time (Batten et al., 2022b). The MGARCH-DCC technique is highly adaptable in terms of modeling individual volatility and is used to diversify portfolios with a wide range of assets. Additionally, we have employed Multivariate Markov Switching GARCH-DCC (MMS GARCH-DCC) (Haas & Liu, 2018) to examine the time-varying volatility and correlations over different regimes (see details in the [supplementary file](#)). Furthermore, to check the robustness of the proposed portfolio, we have applied Multifractal-Detrended Fluctuation Analysis (MF-DFA). DCC-MGARCH can provide information about conditional volatility and correlation among asset classes, which finally helps us

Table 2

Descriptive statistics, unit root tests & correlation analysis.

	BTC	XRP	DOGE	XLM	ETH	BCH	ADA	XTZ	OGRI	SI	NC	ND	GOLD	OIL	COVID
N	524	524	524	524	524	524	524	524	524	524	524	524	524	524	524
Mean	10.05	-0.79	-3.8	-1.76	6.83	5.98	-1.04	1.19	3.85	3.92	13.96	10.09	7.49	3.93	0
Median	10.4	-0.77	-4.62	-1.43	7.19	6.04	-1.06	1.11	3.99	4	14.47	10.43	7.49	3.98	0.32
Standard deviation	0.78	0.7	2.13	0.8	1.18	0.45	1.5	0.4	0.54	0.35	1.63	1.37	0.06	0.42	1
Minimum	8.51	-1.97	-6.48	-3.4	4.71	5.03	-3.73	0.27	0.66	2.38	5.97	1.39	7.3	0	-5.76
Maximum	11.12	0.61	-0.38	-0.31	8.48	7.34	1.09	2.12	4.15	4.39	16.72	11.25	7.63	4.47	1.09
Skewness	-0.23	0.15	0.11	-0.19	-0.15	0.31	-0.14	0.27	-3.69	-2.56	-2.22	-3.36	-0.66	-2.36	-2.9
Kurtosis	-1.59	-1.46	-1.82	-1.42	-1.57	-0.65	-1.61	-0.72	12.98	7.1	5.55	12.19	0.79	14.46	8.84
ZA	-3.91***	-4.66***	-5.23***	-4.69***	-3.81***	-3.52***	-3.96***	-3.27***	-14.69***	-11.47***	-9.4	-8.97	-4.06***	-7.76	-11.23***
Δ ZA	-12.97***	-13.94***	-14.08***	-13.23***	-13.7***	-13.27***	-13.53***	-14.35***	-12.85***	-11.21***	-20.76***	-18.99***	-13.69***	-14.74***	-18.99***
BTC	1														
XRP	0.89***	1													
DOGE	0.91***	0.93***	1												
XLM	0.97***	0.89***	0.90***	1											
ETH	0.97***	0.93***	0.96***	0.94***	1										
BCH	0.86***	0.88***	0.88***	0.90***	0.85***	1									
ADA	0.96***	0.92***	0.97***	0.94***	0.98***	0.86***	1								
XTZ	0.76***	0.80***	0.76***	0.77***	0.78***	0.77***	0.79***	1							
OGRI	0.30***	0.21***	0.26***	0.32***	0.31***	0.05	0.32***	0.22***	1						
SI	0.030	-0.06	0.000	0.08*	0.02	-0.15***	0.040	0.000	0.94***	1					
NC	0.64***	0.53***	0.54***	0.62***	0.65***	0.33***	0.63***	0.40***	0.82***	0.62***	1				
ND	0.49***	0.37***	0.39***	0.51***	0.48***	0.23***	0.47***	0.30***	0.94***	0.83***	0.91***	1			
GOLD	0.22***	0.17***	0.13***	0.25***	0.27***	0.04	0.24***	0.12***	0.54***	0.40***	0.64***	0.58***	1		
OIL	0.80***	0.76***	0.78***	0.77***	0.82***	0.71***	0.82***	0.63***	-0.02	-0.30***	0.40***	0.16***	0.21***	1	
COVID	0.57***	0.46***	0.48***	0.57***	0.58***	0.29***	0.56***	0.36***	0.90***	0.74***	0.98***	0.98***	0.63***	0.29***	1

Note: ZA = Unit Root Test of Log Transformed Variable, Δ ZA = Unit Root Test of first difference, *** Coefficients are significant at the 1 % level, ** are significant at the 5 % level, and * are significant at the 10 % level. Source: Authors' own estimation.

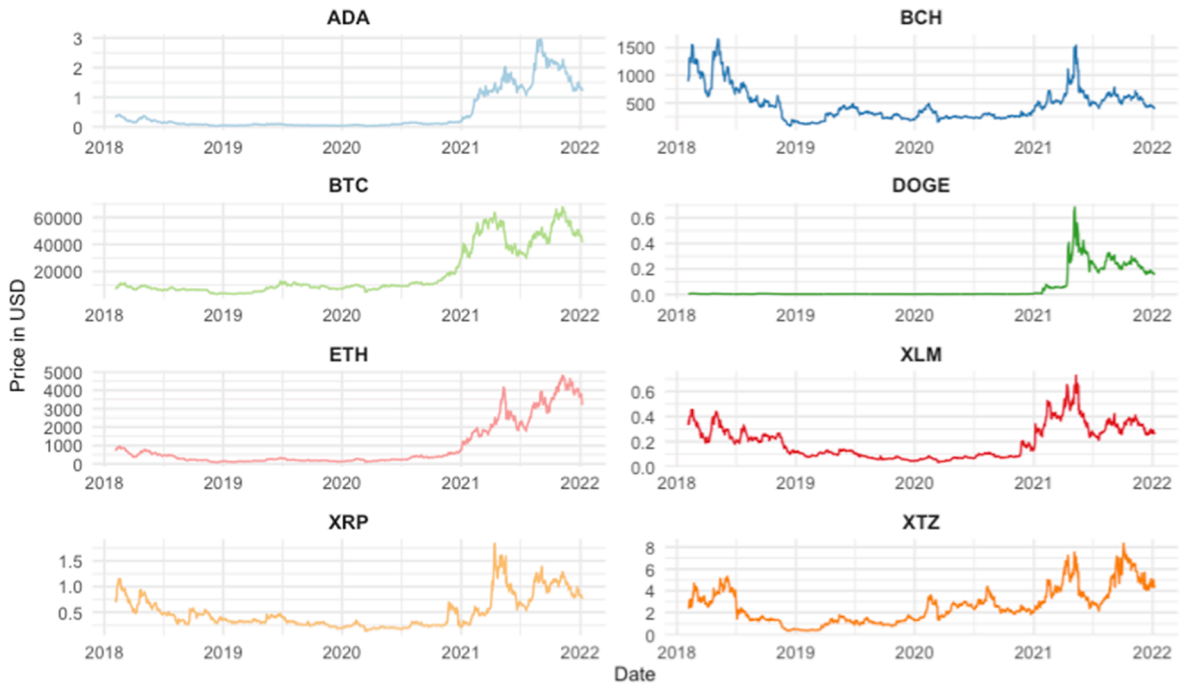


Fig. 1. Historical price of selected cryptocurrencies before and during COVID-19. Source: Authors' own illustration using daily closing price data.

rank the asset correlation. However, MF-DFA is applied for evaluating and ranking the cryptocurrency portfolio as an additional tool in our study. The MF-DFA method aids in assessing efficiency and determines the degree of cryptocurrency portfolio efficiency (Kakinaka & Umeno, 2022; Naeem et al., 2021).

3.3. Markov regime switching model

The Markov-regime switching model proposed by Hamilton (1990, 2010) assumes that time series generates the Y_t as an autoregressive with the order of regime-switching variance. The two-state Markov regime-switching model is specified in equation 1. Here $\Phi(Lag)$ is used as the lag operator, σ is the standard deviation derived from the regime at time t and index by $S_t = 1, \dots, k$, which is a distinct unobservable predictor.

$$\phi(Lag)Y_{it} = \alpha + \mu(S_{it})\epsilon_{it}, \epsilon_t \left(0, \sigma_{S_t}^2 \right) \tag{1}$$

The time series is divided into two regimes that distinguish multiple hidden patterns in the Markov regime-switching model, and a specific prediction model can be designed for each regime. Where regime 1 (bull market) is determined by the high mean and low variance (where $\mu_1 > \mu_2$ and $\sigma_1 < \sigma_2$). In contrast, regime 2 (bear market) is determined by low mean and high variance (where $\mu_2 < \mu_1$ and $\sigma_2 > \sigma_1$) (Maheu & McCurdy, 2000). Moreover, the transition of states in a Markov regime-switching model is stochastic. The switching process' dynamics are known and controlled via a transition matrix. This study applied the two-state Markov regime-switching model based on the Akaike information criterion, which illustrates the transition probability matrix in Equation 2. The calculated transition probabilities are used to calculate the estimated duration of each regime as per Equation 3. Where $k =$ state number 1 or 2.

$$P = \begin{bmatrix} P_{11} & \dots & P_{1k} \\ \vdots & \ddots & \vdots \\ P_{k1} & \dots & P_{kk} \end{bmatrix} \tag{2}$$

$$d_k = \frac{1}{1 - p_{11}} = \frac{1}{P_{1k}} \tag{3}$$

3.4. Dynamic Conditional correlation (DCC) MGARCH model

The Multivariate Generalized Autoregressive Conditional Heteroscedastic Dynamic Conditional Correlation (MGARCH-DCC) model proposed by Engle (2002) and Pesaran and Pesaran (2010) are applied in this study and computed cross-asset conditional volatility and correlation to find out the optimum portfolio diversification strategy using the following equations (4 and 5):

$$\tilde{\rho}_{ij,t-1}(\lambda) = \frac{q_{ij,t-1}}{\sqrt{q_{ii,t-1}q_{jj,t-1}}} \tag{4}$$

$$q_{ij,t-1} = \bar{\rho}_{ij}(1 - \lambda_1 - \lambda_2) + \lambda_1 q_{ij,t-2} + \lambda_1 \tilde{r}_{i,t-1} \lambda_2 \tilde{r}_{j,t-1} \tag{5}$$

Where r_{ij} is the (i, j) th unconditional correlation and $\tilde{r}_{j,t-1}$ are the standardized asset returns. Moreover, parameters λ_1 and λ_2 represent that $\lambda_1 + \lambda_2 < 1$ and $1 - \lambda_1 + \lambda_2$ shows the parameters if the volatility is mean-reverting. If the $1 - \lambda_1 + \lambda_2$ parameter is equal to zero, that shows the integrated GARCH (IGARCH) process.

3.5. Multifractal-Detrended fluctuation analysis

For the robustness test, this study applied Multifractal-Detrended Fluctuation Analysis (MF-DFA) suggested by [Kantelhardt et al. \(2002\)](#). MF-DFA provides a spectrum of generalized Hurst exponents to examine a time series stationarity or random walk behavior. Based on their relative efficiency, the cryptocurrency portfolios are ranked using these Hurst exponents of q th order. [Kantelhardt et al. \(2002\)](#) define the methodology as the follows:

First, the relevant profile of a correlated time series, $i= 1, \dots, N$, is determined via integration:

$$X(i) = \sum_{k=1}^i [x_k - (x)], i = 1, \dots, N \tag{6}$$

Where (x) denotes the mean and N denotes the length of the series. Following the determination of the matching profile, $X(i)$ is further subdivided into $Nsint(N/s)$, which are the non-overlapping windows of equal length 's'. Because the length N of the series may not be an integer manifold of the window size s , and because the technique may neglect a brief section of the profile $Y(i)$ at the end, the sub-division is conducted starting from the opposite end, yielding a total of $2Ns$ segments. In each of the $2Ns$ windows, a polynomial of degree m fits the profile, and the variance is computed using the following formula:

$$F^2(s, \nu) = \frac{1}{s} \sum_{i=1}^s Y[(\nu - 1)s + i] - y_\nu(i)^2 \tag{7}$$

For each window $\nu, \nu = 1, \dots, N_s$ and

$$F^2(s, \nu) = \frac{1}{s} \sum_{i=1}^s Y[N - (\nu - N_s)s + i] - y_\nu(i)^2 \tag{8}$$

where $\nu = N_{(s+1)}, \dots, 2Ns$. $y_\nu(i)$ is the fitting polynomial in window ν . The q th order fluctuation function is then computed by averaging over all windows.

$$F_q(s) = \left\{ \frac{1}{2Ns} \sum_{\nu=1}^{2N_s} [F^2(s, \nu)]^{\frac{q}{2}} \right\}^{1/q} \tag{9}$$

In general, the index variable q can have any actual value other than zero. If q is negative, it amplifies tiny variations; otherwise, it amplifies large fluctuations.

$F_q(s)$ will increase as s increases, and if $F_q(s)$ behaves like a power-law of s , the series is scaling for that particular q . In this instance,

$$F_q(s) \propto s^{h_q} \tag{10}$$

By comparing the slopes of $F_q(s)$ log–log plots versus s , the scaling exponents h_q can be calculated. This technique yields a set of computed scaling exponents, effectively the generalized Hurst exponents $H = (h_2)$. The Hurst exponent value can be used to determine the behavior of a time series over time as well as the extent of market efficiency. If the Hurst exponent is in the $0.5 < H < 1$ range, the time series has a positive/persistent correlation. To put it another way, it has long-term memory. In contrast, if the Hurst exponent is in the range $0 < H < 0.5$, negative/anti-persistence correlation (mean-reverting process) is prominent in the time series. In contrast, an uncorrelated Brownian process (i.e., a pure random walk process) is characteristic of the time series if the Hurst exponent exceeds 0.5, indicating that the market is efficient.

Using the range of h_q acquired from the $F_q(s)$ log–log plots, the multifractal scaling exponent $\tau(q)$ may be calculated:

$$\tau(q) = qh(q) - 1 \tag{11}$$

The spectrum of generalized Hurst exponents $h(q)$ can be used to determine the singularity strength and spectrum indicated by and $f(x)$, respectively

$$\alpha = h(q) + qh'(q) \text{ and } f(x) = q[\alpha - h(q)] + 1 \tag{12}$$

Table 3
Markov Regime Switching model results.

	BTC	XRP	DOGE	XLM	ETH	BCH	ADA	XTZ
<i>Regime 1</i>								
Intercept	12.475*** (0.533)	4.115*** (0.360)	7.936*** (1.605)	1.041*** (0.313)	23.145*** (0.441)	4.832*** (0.689)	4.064*** (0.364)	4.217*** (0.221)
COVID	-0.071 (0.068)	0.541*** (0.031)	-0.148 (0.209)	0.506*** (0.029)	1.170*** (0.067)	0.469*** (0.055)	0.804*** (0.035)	0.474*** (0.021)
SI	-0.436*** (0.136)	-1.332*** (0.091)	-2.443*** (0.407)	-0.855*** (0.076)	-3.997*** (0.111)	0.337* (0.177)	-1.56*** (0.089)	-0.72*** (0.056)
RSE	0.215	0.299	0.629	0.241	0.202	0.248	0.365	0.21
R-squared	0.420	0.563	0.123	0.613	0.95	0.335	0.678	0.702
TP1	0.996	0.998	0.996	0.995	0.993	0.993	0.993	0.983
TP2	0.004	0.002	0.004	0.005	0.007	0.007	0.007	0.017
<i>Regime 2</i>								
Intercept	12.859*** (0.187)	3.9*** (0.441)	-2.735*** (0.285)	-6.45*** (0.39)	14.292*** (0.502)	7.397*** (0.113)	5.02*** (0.712)	3.495*** (0.277)
COVID	0.407*** (0.018)	1.408*** (0.065)	0.363*** (0.027)	-0.033 (0.034)	0.963*** (0.044)	0.077*** (0.011)	-0.329*** (0.091)	0.162*** (0.026)
SI	-0.865*** (0.045)	-1.146*** (0.107)	-0.748*** (0.07)	1.374*** (0.103)	-2.063*** (0.127)	-0.450*** (0.028)	-1.134*** (0.18)	-0.658*** (0.071)
RSE	0.171	0.21	0.285	0.215	0.375	0.119	0.27	0.16
R-squared	0.688	0.901	0.407	0.825	0.764	0.62	0.168	0.457
TP1	0.002	0.014	0.007	0.003	0.008	0.008	0.004	0.026
TP2	0.998	0.986	0.993	0.997	0.992	0.992	0.996	0.974

Note: TP= Transition probability, RSE = Residual standard error, Standard Errors are in parentheses, *** Coefficients are significant at the 1 % level, ** are significant at the 5 % level, and * are significant at the 10 % level, Source: Authors' own estimation.

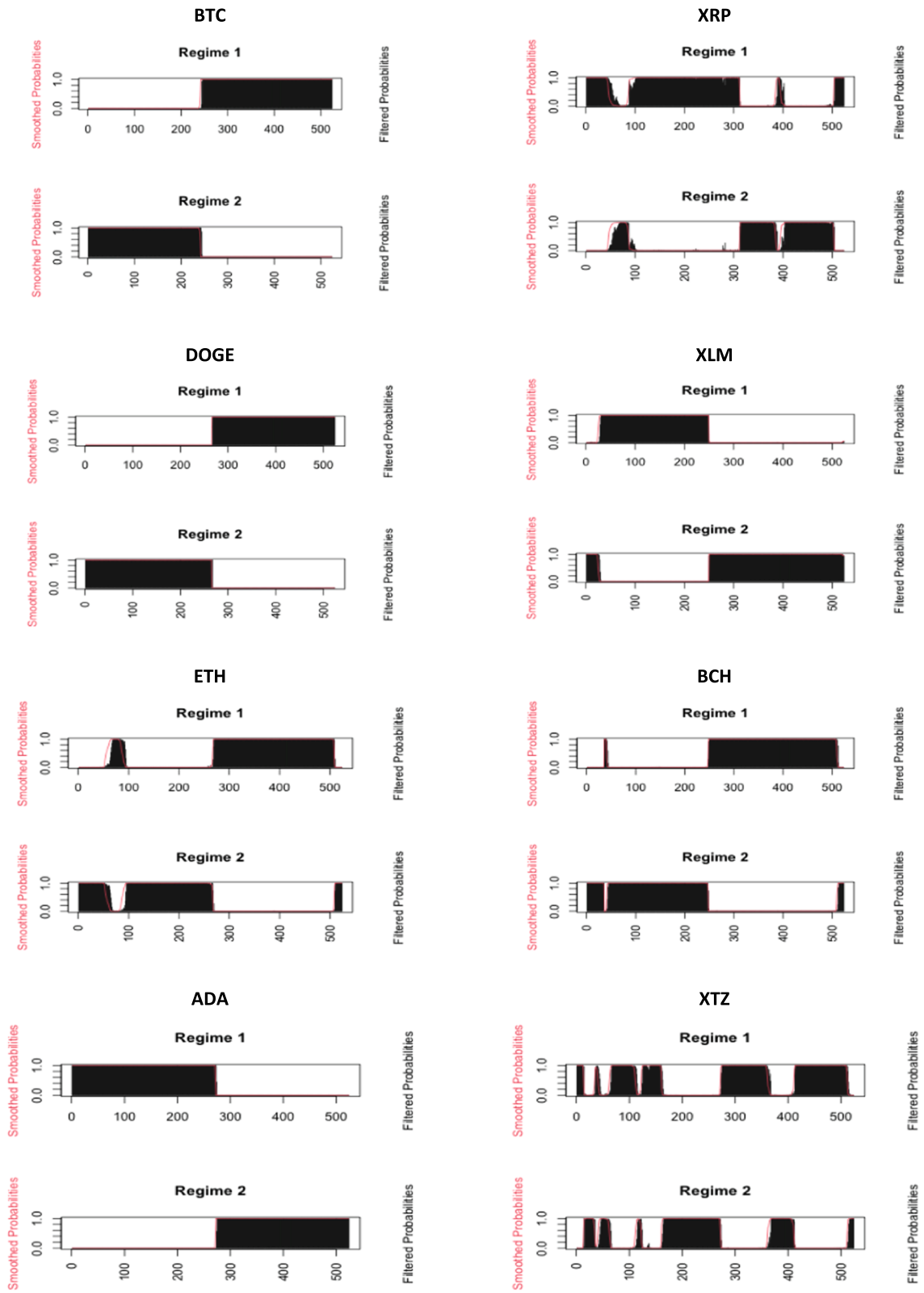


Fig. 2. Smooth Probabilities vs Filtered Probabilities. Source: Authors' own estimation.

Finally, we examine the efficiency of the cryptocurrency portfolio using the Δh (Wang et al., 2009), which is designated as:

$$\Delta h = \frac{1}{2} (|h(-5) - 0.5| + |h(5) - 0.5|) \quad (13)$$

According to Equation 13, small fluctuations ($q = -5$) and large fluctuations ($q = +5$) follow a random walk process (Kristjanpoller et al., 2020), and so an Δh value close to 0 translates into a high degree of efficiency. This suggests that a portfolio is efficient if the Δh value is near zero, whereas a portfolio with a high Δh value is inefficient.

Additionally, similar to Čuljak et al. (2022), our study also estimated a number of portfolio performance metrics, i.e., Sharpe ratio (Sharpe, 1963), MSquared (Modigliani & Modigliani, 1997), Jensen's alpha (Jensen, 1968), and Information ratio (Bacon, 2021). The risk-free rate is proxied by Treasury Yields, and the benchmark asset is proxied by Standard and Poor's 500.

4. Empirical findings

4.1. Descriptive statistics & correlation analysis

Descriptive statistics and correlation analyses are conducted on the log-transformed data to obtain summarized information. Descriptive statistics and correlation analysis outcomes are demonstrated in Table 2. The mean of the new case is very high; it demonstrates that on an ordinary daily, 13.96 people are affected by COVID-19, and 10.09 people are dying worldwide. The average logged price of Bitcoin is USD 10.05, but XRP, DOGE, XLM, ADA, and XTZ average price is meager compared to BTC, ETH, and BCH. All cryptocurrencies are highly volatile except XRP, XLM, and XTZ, as their standard deviations are very high. Skewness shows that all variables are negatively skewed, except the XRP, DOGE, BCH, and XTZ, which are positively skewed.

Furthermore, to check the stationarity of the variables, Zivot and Andrews (1992) unit root test is applied to log closing price (ZA) and return of cryptocurrency (ΔZA). Unit root test results tend to indicate that all variables used for Markov regime-switching model (ZA) and all variables (ΔZA) used for MGARCH-DCC are stationary.

Pearson correlation analysis is applied to check the correlations between all variables, and the results are presented in Table 2. Results demonstrate that all daily new cases and new worldwide deaths are positively correlated with all cryptocurrencies and commodities. There is a negative correlation between the stringency index and BCH. Moreover, there is a significant positive correlation between the overall government response index (OGRI), cryptocurrencies, and Gold expect Oil.

4.2. COVID-19 government interventions and cryptocurrency market results

4.2.1. Markov-Regime switching model results

This study developed eight Markov-Regime Switching models by considering each cryptocurrency's price as the dependent variable, stringency index (SI) taken as the primary independent variable (as the proxy of government interventions for COVID-19), and COVID (PCA of NC and ND) as COVID-19 control variables. All variables are transformed using the natural logarithm. The results of the Markov-Regime Switching Model are exhibited in Table 3. Two regimes are selected using the Akaike information criterion, representing the cryptocurrency market's bull and bear market conditions, where regime 1 denotes the bull market, and regime 2 denotes the bear market condition (Caferra & Vidal-Tomás, 2021). A bull phase is commonly linked with higher prices, and a bear phase is associated with a period of declining prices or stalling.

According to the result of the Bitcoin model, transition probabilities matrix values indicate distinct regimes' persistence in the cryptocurrency market. The probability of staying in the same regime is higher for Bitcoin than switching to another regime. BTC model indicates a 99.60 % probability of staying in regime 1 and 0.40 % probability of switching into regime 2. Moreover, for regime 2, a 99.80 % probability of remaining in regime 2 and only a 0.20 % probability of switching to regime 1. Fig. 2 illustrates the smooth probabilities and filtered probabilities plots.

Furthermore, the stringency index has a significant negative impact on both regimes as the p-values of coefficients are within the significance level. The coefficients of regime 1 and regime 2 of the stringency index are -0.436 and -0.865 , respectively. Thus, it indicates significant negative effects of government interventions in both regimes, and the coefficient of SI in regime 2 is higher than in regime 1. The r-squared values of regimes 1 and 2 indicate BTC model can explain the regimes by 42.00 % and 68.80 %, respectively.

XRP, DOGE, ETH, ADA, and XTZ models also show similar results to Markov Switching models of BTC. However, SI significantly negatively impacts DOGE and BCH only in regimes 1 and 2, respectively. The smooth probabilities and filtered probabilities plots of all models are presented in Fig. 2. Moreover, all cryptocurrency models have similar transition probability results, and a previous study on the COVID-19 period also found comparable transition probabilities (Caferra & Vidal-Tomás, 2021). Also, the coefficient of SI indicates a statistically significant negative impact of government policy interventions on the cryptocurrency market. Previous studies with other financial markets also found similar results (e.g., Aharon & Siev, 2021; Jiang et al., 2022; Kheni and Kumar, 2021). Overall, the result of the Markov-regime switching model supports the hypothesis of this study.

Table 4
Markov Regime Switching model robustness test results.

Details	BTC	XRP	DOGE	XLM	ETH	BCH	ADA	XTZ
<i>Regime 1</i>								
Intercept	8.391*** (0.312)	-7.653*** (1.458)	6.158 (4.018)	-16.284*** (1.231)	4.858*** (0.563)	6.89*** (0.116)	2.687*** (0.348)	0.679*** (0.157)
COVID	0.051 (0.049)	0.161 (0.099)	-0.098*** (0.098)	0.001 (0.009)	0.174** (0.087)	0.102*** (0.018)	0.968*** (0.051)	-0.09*** (0.02)
OGRI	0.580*** (0.084)	1.896*** (0.367)	-1.981* (1.008)	3.82*** (0.309)	0.735*** (0.151)	-0.339*** (0.029)	-1.256*** (0.088)	0.063 (0.04)
RSE	0.219	0.249	0.666	0.212	0.395	0.108	0.405	0.128
R-squared	0.765	0.109	0.015	0.342	0.728	0.643	0.608	0.21
TP1	0.993	0.995	0.996	0.996	0.997	0.992	0.996	0.979
TP2	0.007	0.005	0.004	0.004	0.003	0.008	0.004	0.021
<i>Regime 2</i>								
Intercept	13.547*** (0.205)	1.822*** (0.244)	-3.197*** (0.25)	0.363 (0.244)	11.867*** (0.267)	-2.081** (0.831)	6.507*** (1.719)	4.051*** (0.302)
COVID	0.669*** (0.025)	0.515*** (0.036)	0.469*** (0.037)	0.531*** (0.037)	0.953*** (0.032)	0.102*** (0.018)	-0.29*** (0.095)	0.661*** (0.046)
OGRI	-1.057*** (0.051)	-0.787*** (0.062)	-0.652*** (0.063)	-0.71*** (0.061)	-1.528*** (0.067)	2.128*** (0.215)	-1.494*** (0.431)	-0.707*** (0.079)
RSE	0.154	0.286	0.288	0.266	0.198	0.245	0.281	0.277
R-squared	0.77	0.417	0.395	0.488	0.808	0.374	0.078	0.563
TP1	0.005	0.001	0.025	0.005	0.004	0.007	0.004	0.014
TP2	0.995	0.999	0.975	0.995	0.996	0.993	0.996	0.986

Note: TP= Transition probability, RSE = Residual standard error, Standard Errors are in parentheses, *** Coefficients are significant at the 1 % level, ** are significant at the 5 % level, and * are significant at the 10 % level, Source: Authors' own estimation.

Table 5
MGARCH-DCC model results.

	Multivariate Normal Distribution			Multivariate t Distribution		
	λ_1	λ_2	$1 - (\lambda_1 + \lambda_2)$	λ_1	λ_2	$1 - (\lambda_1 + \lambda_2)$
BTC	0.084 (0.073)	0.825*** (0.089)	0.091	0.084 (0.073)	0.089*** (9.217)	0.827
XRP	0.705** (0.355)	0.294 (0.199)	0.001	0.705** (0.356)	0.198 (1.486)	0.097
DOGE	0.578*** (0.195)	0.356*** (0.137)	0.066	0.578*** (0.190)	0.135*** (2.629)	0.287
XLM	0.454 (0.348)	0.102 (0.262)	0.444	0.454 (0.348)	0.270 (0.378)	0.276
ETH	0.076 (0.053)	0.859*** (0.058)	0.065	0.076 (0.053)	0.058*** (14.875)	0.866
BCH	0.138** (0.066)	0.834*** (0.064)	0.028	0.138** (0.066)	0.063*** (13.145)	0.799
ADA	0.165*** (0.063)	0.719*** (0.070)	0.116	0.165*** (0.062)	0.070*** (10.297)	0.765
XTZ	0.180** (0.086)	0.569*** (0.151)	0.251	0.180** (0.086)	0.151*** (3.771)	0.669
SI	0.204*** (0.055)	0.764*** (0.055)	0.032	0.204*** (0.055)	0.055*** (13.960)	0.741
GOLD	0.007*** (0.001)	0.991*** (0.001)	0.002	0.007*** (0.001)	0.001*** (1533.838)	0.992
OIL	0.280*** (0.077)	0.601*** (0.058)	0.119	0.280*** (0.078)	0.058*** (10.351)	0.662
δ_1	0.923			0.017		
δ_2	0.007			0.936		
$\delta_1 + \delta_2$	0.930			0.953		
MLL	9298.393			12251.360		
df	–			4.001		

Note: λ_1 = decay factors for variance and λ_2 = decay factors for covariance. MLL = Maximized Log-Likelihood, df = Degrees of Freedom. Source: Authors' own estimation.

Table 6
Unconditional Volatilities' Rank.

Rank	Variables	Description	Unconditional Volatility
1	DOGE	Dogecoin	0.192
2	OIL	Oil	0.155
3	XRP	Ripple	0.086
4	XTZ	Tezos	0.082
5	XLM	Stellar	0.081
6	ADA	Cardano	0.077
7	BCH	Bitcoin Cash	0.068
8	ETH	Ethereum	0.065
9	BTC	Bitcoin	0.048
10	SI	Stringency index	0.023
11	GOLD	Gold	0.011

Source: Authors' own estimation.

4.2.2. Markov-regime switching model robustness test using overall government response index

Another eight models are developed to check the robustness of the Markov-switching model results by regressing the cryptocurrency log-transformed price with COVID-19 control variables and overall government response index (OGRI) as the independent variable. Where OGRI used as the proxy of government interventions for COVID-19. The robustness models' results are presented in Table 4, which revealed similar results to the SI results (Table 3). Moreover, robustness models' smooth and filtered probabilities are plotted in Fig. A.1 (Appendix A). Previous models' results (Stringency Index) show a high likelihood of staying in the same regime. Likewise, robustness models also show similar results. A previous study of cryptocurrency during COVID-19 also found similar transition probabilities (e.g., Caferra & Vidal-Tomás, 2021). Moreover, all coefficients of OGRI are statistically significant except on regime 1 of XTZ. Furthermore, r-squared values are very similar to previous results. Overall, results indicate that results are robust. Therefore, results denote that there is a significant negative impact of government interventions on the cryptocurrency market, which is similar to the previous studies on other financial markets (e.g., Aharon & Siev, 2021; Jiang et al., 2022; Kheni and Kumar, 2021).

4.3. Cryptocurrency portfolio diversification during COVID-19

4.3.1. MGARCH-DCC model results

To determine the optimal portfolio for portfolio diversification benefits during a crisis period like the COVID-19 pandemic, the MGARCH-DCC model is applied, containing eight cryptocurrencies, two commodities, and the stringency index. All variables' daily return is taken for the MGARCH-DCC. Summary of λ_1 and λ_2 (Decay Parameters) of all variables, maximum likelihood estimates are

Table 7

Unconditional volatilities and correlation matrix.

	BTC	XRP	DOGE	XLM	ETH	BCH	ADA	XTZ	SI	GOLD	OIL
BTC	0.048 (9)										
XRP	0.489	0.086 (3)									
DOGE	0.324	0.218	0.192 (1)								
XLM	0.6	0.695	0.332	0.081 (5)							
ETH	0.782	0.533	0.294	0.631	0.065 (8)						
BCH	0.739	0.588	0.328	0.658	0.735	0.068 (7)					
ADA	0.655	0.566	0.287	0.701	0.691	0.645	0.077 (6)				
XTZ	0.599	0.538	0.249	0.612	0.67	0.662	0.625	0.082 (4)			
SI	-0.114	-0.07	-0.024	-0.079	-0.137	-0.048	-0.112	-0.115	0.023 (10)		
GOLD	0.16	0.037	0.07	0.032	0.154	0.098	0.104	0.059	-0.093	0.011 (11)	
OIL	0.069	0.036	0.007	0.019	0.031	0.067	0.043	0.029	-0.024	0.029	0.155 (2)

Note: Unconditional volatilities are presented along the diagonal elements of the matrix. Source: Authors' own estimation.

Table 8

Unconditional correlation rank (top five and last five combinations).

Rank	Combination	Description	Unconditional Correlation
11	DOGE.OIL	Dogecoin and Oil	0.007
12	XLM.OIL	Stellar and Oil	0.019
14	XTZ.OIL	Tezos and Oil	0.029
15	ETH.OIL	Ethereum and Oil	0.031
16	XLM.GOLD	Stellar and Gold	0.032
51	XRP.XLM	Ripple and Stellar	0.695
52	XLM.ADA	Stellar and Cardano	0.701
53	ETH.BCH	Ethereum and Bitcoin Cash	0.735
54	BTC.BCH	Bitcoin and Bitcoin Cash	0.739
55	BTC.ETH	Bitcoin and Ethereum	0.782

Source: Authors' own estimation.

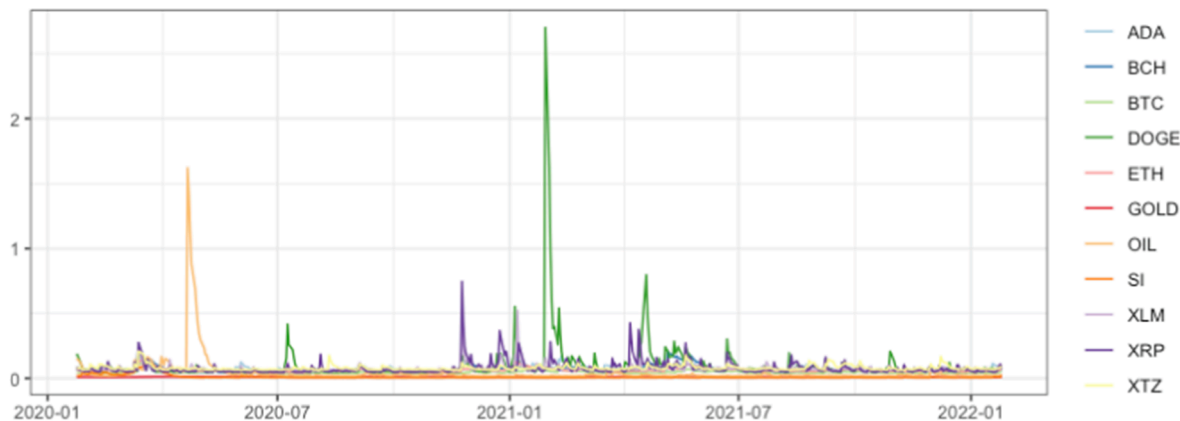


Fig. 3. Conditional volatility results. Source: Authors' own estimation.

presented in Table 5, with the comparison of multivariate normal distribution and t -distribution. Results of both models indicate that the Multivariate t -distribution model is more appropriate here as the Maximized Log-Likelihood value is higher (12251.360). Moreover, the degree of freedom (4.001) is lower than 30; thus, this study will consider the t -distribution results (Pesaran & Pesaran, 2010).

The results of t -distribution indicate that all assets decay parameters (λ_1 and λ_2) are highly significant. Moreover, $1 - (\lambda_1 + \lambda_2)$ values of all assets are less than one, indicating that all conditional volatilities are mean returning with a steady volatility decline. Therefore, no IGARCH process exists as the value of all assets $1 - (\lambda_1 + \lambda_2)$ is not equal to zero. Furthermore, the sum of correlation decay $\delta_1 + \delta_2$ is lower than 1. Thus, results indicate that conditional correlations also mean returning, which shows that cryptocurrency and commodity prices will slowly return to their normal position (Iqbal et al., 2021; Naeem et al., 2021).

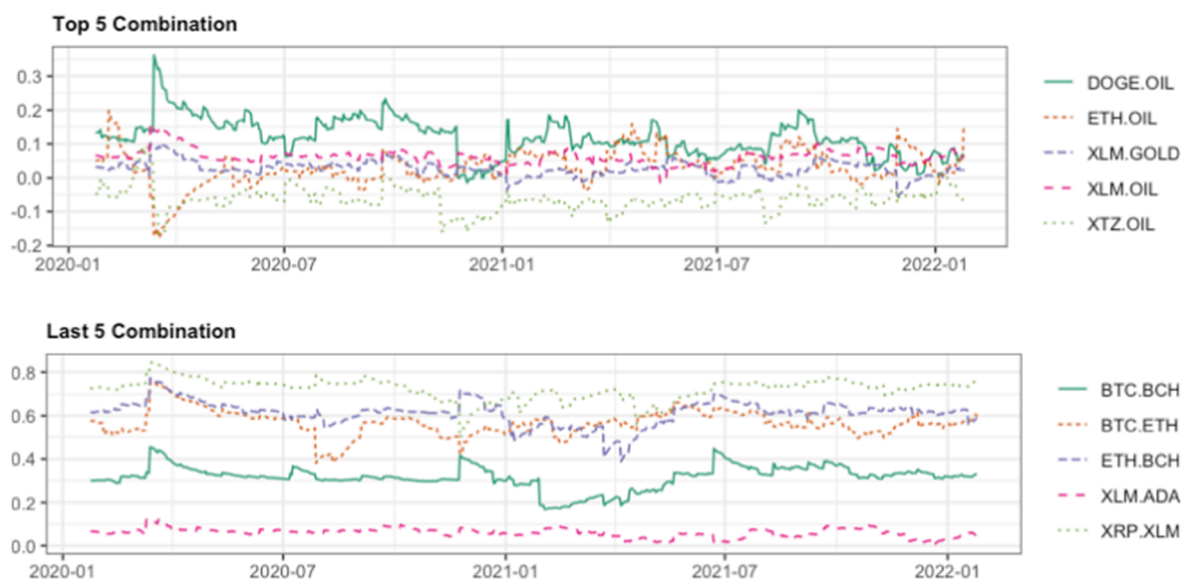


Fig. 4. Conditional correlation (Combination of cryptocurrencies and commodities). Source: Authors' own estimation.

The U-Hat test is applied to examine the Test of Serial Correlation of Residuals, and results are presented in Appendix B (Table B.1). The result of the U-Hat test is insignificant as the Lagrange Multiplier Statistic p-value (0.847) is insignificant, which indicates that there is no serial correlation (Pesaran & Pesaran, 2010). Therefore, this situation indicates a diversification opportunity in the cryptocurrency market during COVID-19.

Nevertheless, it is necessary to examine the correlation and volatilities of the assets for a diversification strategy. Thus, this study estimated unconditional volatilities and correlations using the t -distribution of the MGARCH-DCC model. Table 6 demonstrates the rank of Unconditional Volatilities, and Table 7 presents the unconditional volatilities and correlation matrix. Results show that Dogecoin has the highest unconditional volatility, and Gold has the lowest unconditional volatility. Moreover, Bitcoin, Ethereum, and Bitcoin Cash show moderate volatility compared to other cryptocurrencies. The results of the unconditional correlation matrix in Table 7 demonstrate the pairwise co-movement between cryptocurrencies and Gold. Table S.3 (supplementary material) presents the results of the pairwise unconditional correlation according to their correlation values. The top five and last five pairs of cryptocurrency and commodities are listed in Table 8. The results show that Bitcoin and Ethereum (0.782) have the highest correlation. On the other hand, Dogecoin and Oil (0.007) have the lowest correlation and are ranked first, respectively. Low correlations among assets indicate possible portfolio diversification opportunities (Baur & Lucey, 2010).

Fig. 3 presents the values of Conditional volatilities of cryptocurrencies and commodities. The value of this plot indicates the time-varying nature of the volatilities of cryptocurrencies and commodities. The volatilities of DOGE indicate an upward trend at the beginning of July 2020 and reach the highest point in February 2021, indicating the third wave of COVID-19 (Yousaf & Ali, 2020). After June 2021, all cryptocurrency volatilities show a close moment among them. Thus, results show that there is a portfolio diversification possibility (e.g., Corbet et al., 2020; González et al., 2021; Ji et al., 2020; Mariana et al., 2021).

Conditional correlations of the top five and last five pairs of cryptocurrencies and commodities are plotted in Fig. 4, which shows similar results with conditional and unconditional correlation matrix results. The correlation between BTC and ETH always tends to be near 1, indicating no possible diversification benefit. However, the combination of Dogecoin and Oil, Stellar and Oil, Tezos and Oil, Ethereum and Oil, and Stellar and Gold tend to be good portfolio combinations as their correlations are low during the COVID-19 pandemic period (Baur & Lucey, 2010). Previous studies also found similar results during COVID-19 (e.g., Corbet et al., 2020; Ji et al., 2020; Melki & Nefzi, 2022). Additionally, we have analyzed the regime-specific volatility and correlation of the assets using MS MGARCH-DCC (Haas & Liu, 2018), and the results are presented in Table S.2, Figure S.1, and Figure S.2 (see details in the supplementary file). The results of MS MGARCH-DCC tend to indicate that the investors may explore regime-specific volatility and correlation for portfolio construction.

4.3.2. Portfolio diversification robustness test using MF-DFA and portfolio performance

To check the robustness of MGARCH-DCC cryptocurrency portfolio combinations results, MF-DFA is applied on the top five cryptocurrency and commodity portfolios (DOGE.OIL, XLM.OIL, XTZ.OIL, ETH.OIL, and XLM.GOLD). For the analysis, equal weights are allocated among two asset portfolios (e.g., Kristjanpoller et al., 2020; Vidal-Tomás et al., 2019). Cryptocurrency and commodity

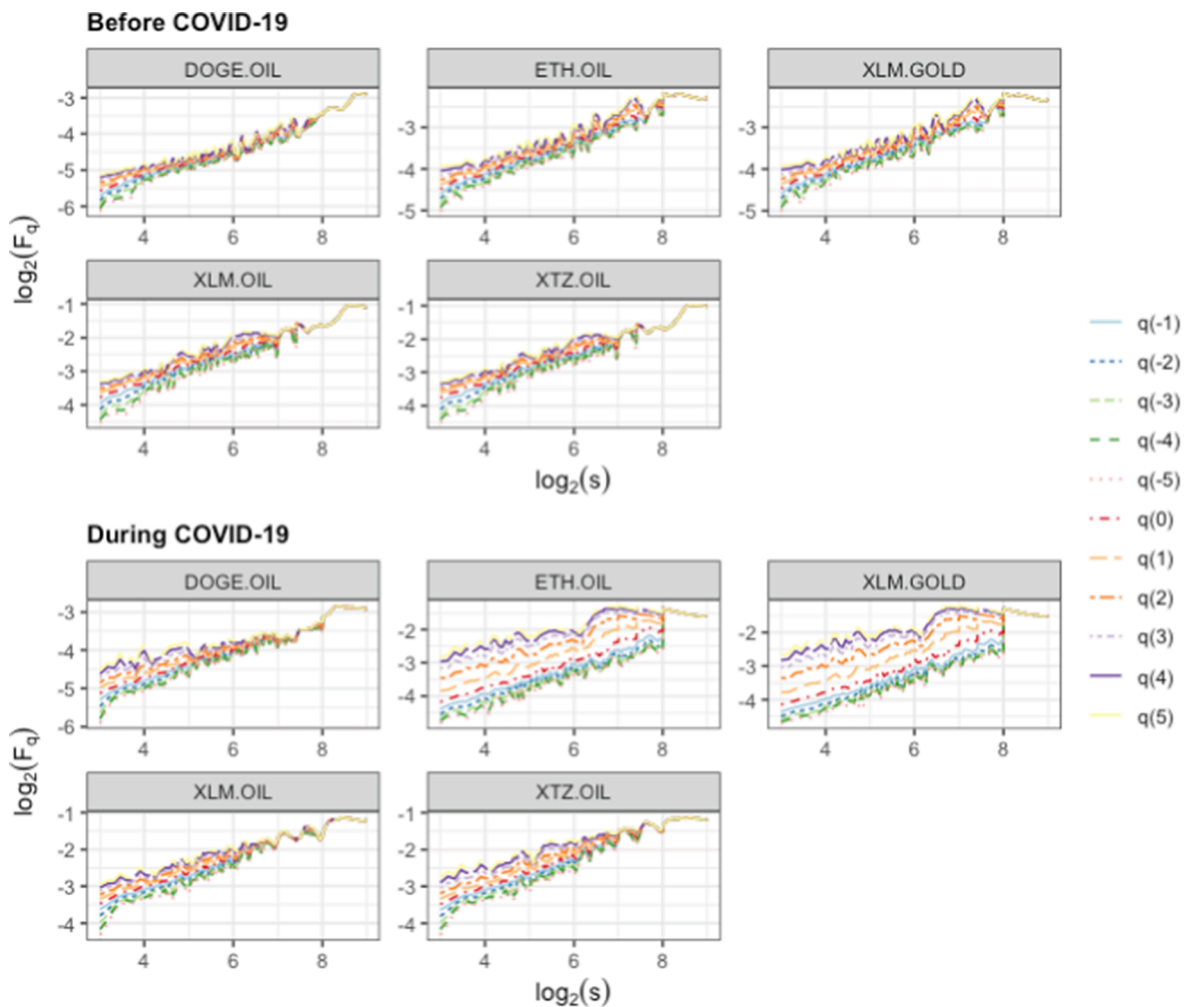


Fig. 5. Multifractal fluctuation function. Source: Authors' own estimation.

market prices react and change daily to new the occurrence of events or new information. As a result, it is critical to assess the speed and precision with which portfolio prices react to such events or information, which eventually demonstrates their efficiency. Furthermore, to avoid biases of results, this study divided the MF-DFA robustness test into two sub-periods, before COVID-19 and during COVID-19 (Kakinaka & Umeno, 2022). Thus, before COVID –19 (5 February 2018 to 23 January 2020: 512 days) and during COVID-19 (24 January 2020 to 7 January 2022: 512 days), the daily return of portfolios is taken for the analysis.

Following the relevant studies on the efficiency of cryptocurrency portfolios, this study begins by investigating the fractality of the cryptocurrency portfolio time series by charting the log–log plots of the q th order fluctuation function along the length scale (Naeem et al., 2021). Fig. 5 shows the graphs used to identify the crossover before and during COVID-19. These graphs, fluctuation function based on scale, indicate that the volatility of cryptocurrency portfolio returns grows with scale and that a long-term power-law multifractal correlation exists between daily cryptocurrency portfolio returns and scale.

After identifying the crossover, we compute the generalized Hurst exponent $h(q)$, and Table 9 summaries result for large and minor fluctuations. Following Kristjanpoller et al. (2020), the range of q is taken between (-5) to (+5) for the cryptocurrency portfolio. Portfolios show multifractality both before and during the COVID-19 periods, as the values of the generalized Hurst exponents fall as q increases. This change in $H(q)$ indicates that the Portfolios multifractality is weakening.

Portfolio efficiency is ranked using Equation 13, and Table 10 presents the results. A portfolio is efficient if the Δh value is close to zero; thus, a high Δh value suggests a less efficient portfolio. Results show that before COVID-19, Ethereum and Oil (ETH.OIL) was the most efficient combination among the portfolios. Moreover, during COVID-19, Dogecoin and Oil (DOGE.OIL) is the most efficient

Table 9
Generalized Hurst exponents.

q	DOGE.OIL	XLM.OIL	XTZ.OIL	ETH.OIL	XLM.GOLD
Before COVID-19					
-5	0.806	0.808	0.828	0.678	0.6684
-4	0.792	0.786	0.805	0.662	0.6511
-3	0.777	0.759	0.778	0.643	0.6309
-2	0.759	0.728	0.747	0.621	0.6074
-1	0.74	0.694	0.712	0.596	0.5807
0	0.72	0.658	0.676	0.568	0.5514
1	0.7	0.623	0.642	0.539	0.5209
2	0.68	0.591	0.61	0.51	0.4911
3	0.661	0.562	0.582	0.484	0.4639
4	0.644	0.538	0.559	0.46	0.4403
5	0.63	0.518	0.539	0.44	0.4203
During COVID-19					
-5	0.683	0.662	0.686	0.945	0.992
-4	0.668	0.643	0.666	0.924	0.973
-3	0.651	0.621	0.643	0.897	0.947
-2	0.632	0.597	0.615	0.862	0.912
-1	0.609	0.57	0.583	0.81	0.858
0	0.584	0.542	0.547	0.718	0.759
1	0.556	0.514	0.505	0.569	0.591
2	0.526	0.487	0.461	0.414	0.418
3	0.494	0.461	0.417	0.305	0.302
4	0.465	0.438	0.378	0.236	0.231
5	0.441	0.419	0.346	0.191	0.186

Source: Authors' own estimation.

Table 10
Portfolio efficiency ranking.

Before COVID-19			During COVID-19		
Rank	Portfolios	Δh	Rank	Portfolios	Δh
1	ETH.OIL	0.119	1	DOGE.OIL	0.121
2	XLM.GOLD	0.124	2	XLM.OIL	0.121
3	XLM.OIL	0.163	3	XTZ.OIL	0.170
4	XTZ.OIL	0.183	4	ETH.OIL	0.377
5	DOGE.OIL	0.218	5	XLM.GOLD	0.403

Source: Authors' own estimation.

Table 11
Portfolio Performance results.

Performance Metrics	DOGE.OIL	XLM.OIL	XTZ.OIL	ETH.OIL	XLM.GOLD
Sharpe	0.120	0.030	-0.057	0.034	0.034
Jensen's Alpha	2.865	0.082	-0.718	0.174	0.161
MSquared	0.797	0.129	-0.196	0.052	0.043
Information Ratio	3.049	0.725	-0.590	0.380	0.332

Source: Authors' own estimation.

portfolio combination (0.12). These results support the findings of MGARCH-DCC result (see Table 5). This confirms the robustness of the results; considering COVID-19 impacts and other factors, Dogecoin and Oil is the most efficient portfolio combination. Previous studies also found similar diversification properties of commodities with cryptocurrency (e.g., Corbet et al., 2020; Ji et al., 2020; Melki & Nefzi, 2022).

Finally, portfolio performance metrics are estimated and presented in Table 11. The Sharpe ratio is a measurement of an investment's return in relation to its risk. The Sharpe ratio is the excess return over the risk-free rate per unit of volatility or total risk (Sharpe, 1963). The MSquared is a more advanced and useful variant of the Sharpe ratio that calculates the portfolio's risk-adjusted return by multiplying the Sharpe ratio by the standard deviation of any benchmark market index and then adding risk-free return (Modigliani & Modigliani, 1997). Jensen's alpha is a risk-adjusted performance metric that indicates the average return on a portfolio or investment that is higher or lower than that anticipated by the capital asset pricing model (CAPM), given the overall portfolio or investment's beta and average market return (Jensen, 1968). The information ratio compares and quantifies the active return of a portfolio to a benchmark index in terms of portfolio return volatility. It is calculated by dividing the active return by the tracking error (Bacon, 2021). In all cases, the higher the value, the better the portfolio performance. Results tend to suggest that among all

performance metrics, DOGE.OIL outperforms other portfolios. These results are consistent with the outcome of MF-DFA and suggest that during COVID-19, Dogecoin and Oil (DOGE.OIL) is the most efficient portfolio combination.

5. Discussions

The Markov switching model results indicate that the COVID-19 government interventions negatively impacts the cryptocurrency market, which is robust and supports this study's hypothesis. Results suggest that travel bans, lockdowns, school and industrial unit closures, and other restrictive measures negatively impact the cryptocurrency market. Earlier studies on the conventional financial markets are also consistent with these findings (e.g., Aharon & Siev, 2021; Jiang et al., 2022; Kheni and Kumar, 2021). Closures, lockdowns or travel bans, and other restrictive measures are considered to be barriers to economic growth and increase uncertainty, raising investor herding and risk-aversion behavior. It is also worth noting that such interventions lead to food price hikes and enormous job loss, while adaptation to work-from-home and home quarantine policies are also costly, which may indicate disruptions in future household income, reducing the incentive to invest in the cryptocurrency market.

The results of MGARCH-DCC tend to indicate that there is a portfolio diversification possibility among cryptocurrency and commodities. There is a time-varying nature among the cryptocurrencies, and the volatility peaked in February 2021. However, volatility decreased after July 2021, indicating the market started to return to its efficient position after the peak time of COVID-19 (Iqbal et al., 2021; Naeem et al., 2021). Moreover, the best possible combination of the portfolio is Dogecoin and Oil, Stellar and Oil, Tezos and Oil, Ethereum and Oil, and Stellar and Gold, as their correlations are low during the COVID-19 pandemic period, while cryptocurrencies cannot be considered as safe haven assets during COVID-19 as their correlations are not highly negative (Baur & Lucey, 2010). Furthermore, the MF-DFA portfolio efficiency ranking supports the results of MGARCH-DCC, which indicates that the results are robust and diversification strategy would work significantly under COVID-19 government interventions. The rationality behind cryptocurrency volatility and diversification findings is linked to the nature of the current crisis once again. The pandemic crisis is primarily to blame for the financial turbulence. By implementing government interventions, both the industrial and consumer sectors are impacted, resulting in a reduction in returns, an increase in the cryptocurrency market's volatility, and the weakening of their safe haven property. The sharp drop in cryptocurrency prices during COVID-19 has prompted investors to move their money to more appealing assets like Gold or Oil.

6. Conclusion and policy implications

This study offers new empirical evidence on the impact of COVID-19 government interventions on the cryptocurrency market and suggests the optimum portfolio diversification strategy during the COVID-19 pandemic. We have used the Markov switching model to analyze the impact of COVID-19 government interventions on the cryptocurrencies' closing prices and found that there was a negative impact; an alternative measure of COVID-19 government interventions (OGRI) is also used to ensure the robustness of our results. This can be attributed to government interventions preparing investors around the globe to be habituated with the new normal, which helps the market return to its efficient position. Moreover, MGARCH-DCC results show some optimal portfolio diversification strategies during the pandemic and suggest investing in Dogecoin and Oil, Stellar and Oil, Tezos and Oil, Ethereum and Oil, and Stellar and Gold. The results are robust using alternative estimates of MF-DFA.

Along with our humble contribution to the growing body of the financial market and COVID-19 literature, this study also made some policy recommendations for investors, portfolio managers, and regulators. First, investors and portfolio managers should not consider Bitcoin and Ethereum as the optimal portfolio combination because their correlations are positive and very high. Second, investors and portfolio managers can choose the combination of Gold or Oil with other cryptocurrencies during the crisis period, as cryptocurrencies have a low correlation between Gold and Oil. Third, regulators should consider the negative impact of government action on pandemics and act in such a manner that would not impact the liquidity of the financial market. Fourth, governments should be aware of the adverse impact of COVID-19-related restrictions that have left a significant economic impact on the financial market's trading environment. Finally, the findings of this study should inspire governments and regulators to launch public awareness campaigns, which can lead to more trading activity that will reduce the volatility of cryptocurrency.

Finally, this study is limited to considering only eight cryptocurrencies and two commodities. Future studies can choose more assets to get more insight into government regulation and suggest more diversification strategies. Furthermore, future studies can consider high-frequency data to capture more insightful information using the expected shortfall framework or tail risk diversification. Moreover, future studies can also examine the impact of government action plans on treasury bonds or the commodity market.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Appendix A

(See Fig. A1).

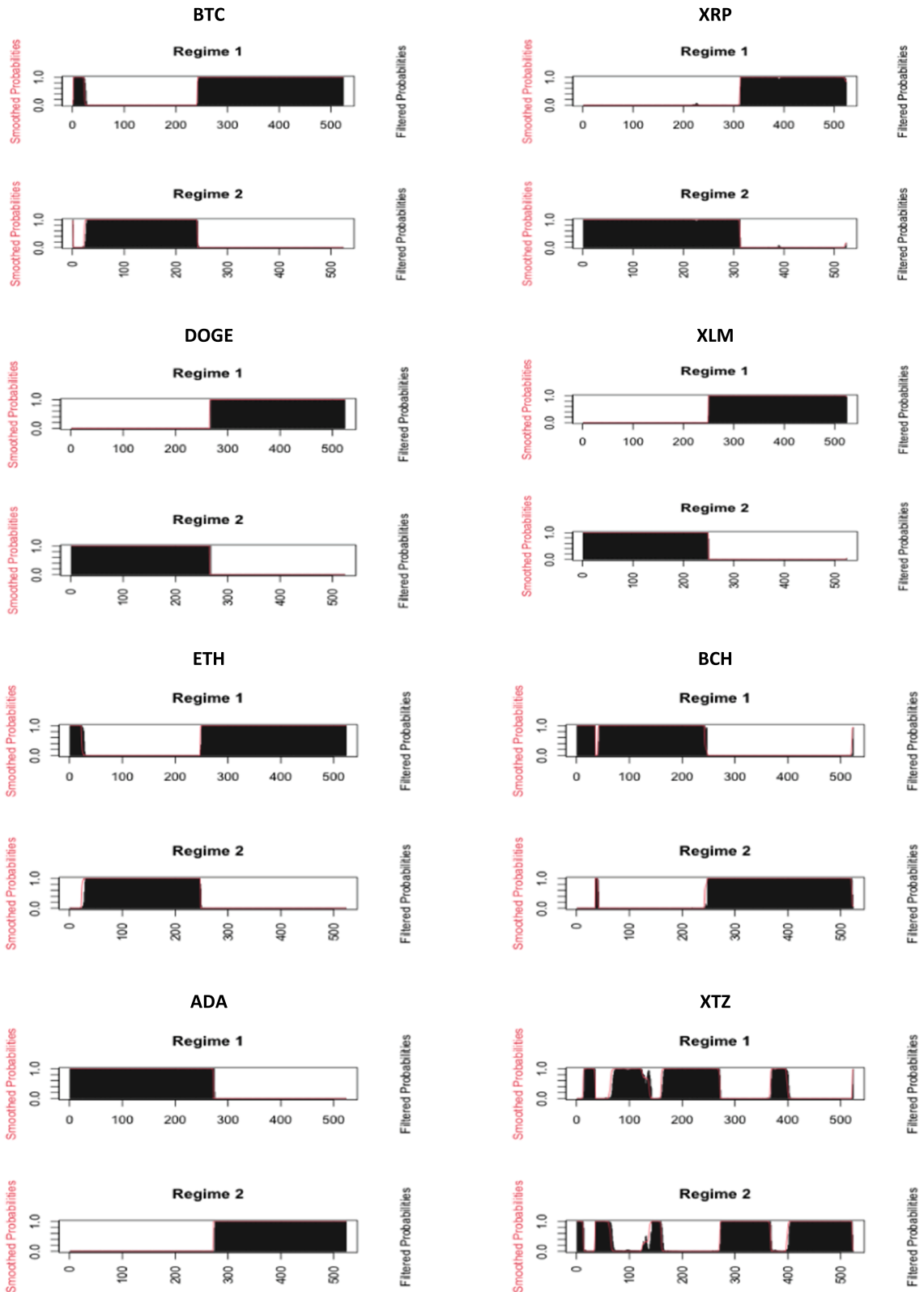


Fig. A1. Smooth Probabilities vs Filtered Probabilities of the Robustness Model. Source: Authors' own estimation.

Appendix B

(See Table B1).

Table B1

Test of Serial Correlation of Residuals.

Regressor	Coefficient	Standard Error	T-Ratio[Prob]
RES(-1)	-0.043545	0.04522	-0.96296[0.336]
RES(-2)	0.048615	0.04528	1.0736[0.284]
RES(-3)	0.0049651	0.045474	0.10919[0.913]
RES(-4)	-0.013802	0.045599	-0.30268[0.762]
RES(-5)	-0.062162	0.045658	-1.3615[0.174]
RES(-6)	0.01312	0.045738	0.28686[0.774]
RES(-7)	0.026005	0.045739	0.56856[0.570]
RES(-8)	-0.020141	0.045696	-0.44077[0.660]
RES(-9)	0.021233	0.045757	0.46404[0.643]
RES(-10)	0.034928	0.045864	0.76155[0.447]
RES(-11)	0.06112	0.045942	1.3304[0.184]
RES(-12)	0.0094302	0.046044	0.20481[0.838]
Lagrange Multiplier Statistic CHSQ(12) = 7.1640[0.847]F Statistic F(12,360) = 0.58996[0.851]			

Source: Authors' own estimation.

Appendix C. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.intfin.2022.101691>.

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