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Currency or commodity competition? Bitcoin price trends in the post-pandemic era

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Abstract

In the post-pandemic era, two issues including the currency competition between BTC and the US dollar and the competition between the commodity and monetary medium functions of BTC are critical. By applying the Markov switching model, the cyclical nature of the numbers of additional confirmed COVID-19 cases and deaths are verified on daily basis. So, these two factors are assumed to follow the Ornstein–Uhlenbeck process. Then, we estimate parameters to establish the structural characteristics of post-pandemic era and the start of post-pandemic era. In order to clarify these two issues, we use vector autoregression for testing the related macrocosmic and financial variables and BTC. Systematic evidences are provided regarding the relationships among BTC, related macrocosmic, related financial variables, related COVID-19 variables. Our findings provide a useful insight into currency competition and commodity competition on the basis of the impulse response of BTC to US dollar fluctuation and the impulse response of BTC to expected inflation and volatility in the post-pandemic era. These findings indicate increased currency competition between Bitcoin and the US dollar in the post-pandemic era. Therefore, currency competition should be more valued than Commodity Competition in the post-pandemic era. This provides a useful guideline for Bitcoin's management.

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1. Introduction

Despite the dissemination of COVID-19 vaccines and the disease gradually being considered less severe, the effects of COVID-19 on global financial markets remain same because the global supply chain remains constrained, and the supply and demand of commodities are out of balance. In addition, consumption patterns have changed, and some industries have been forced into industrial upgrading and reform. Thus, COVID-19 continues to affect the global economy. In particular, price volatility, including that of Bitcoin, is likely to remain high as long as COVID-19 is present.

Cryptocurrencies such as Bitcoin have emerged as a novel investment target. Several countries have moved toward legalizing cryptocurrency as a medium of exchange. The applications and development of blockchain have accelerated, driving appreciation of cryptocurrencies; specifically, the price of Bitcoin increased by 444% from 2020 to 2021.

The initial spread of COVID-19 caused bear markets for stocks, commodities, and even the US dollar in 2019–2020. The COVID-19 pandemic, fluctuations of the US dollar, and inflation have also affected the price of Bitcoin. The US government provided an economic relief package to individuals who lost their jobs due to the pandemic in 2020–2021, resulting in a decline in the US dollar. Bitcoin has tended to grow opposite of the US dollar because of the decentralized nature of cryptocurrencies; they are not affected by the easy money policies of any one government. Instead, the devaluation of traditional currencies encourage investment in cryptocurrencies.

In addition, easy money policy has increased inflation, and fund managers have been adding to their gold positions. Bitcoin is similar to gold in terms of scarcity and its use in transactions. Das, Le Roux, Jana, and Dutta (2020) compare the hedging performance of Bitcoin with that of gold, commodities, and the US dollar. The limited supply and monetization of Bitcoin makes it an affordable element which protects against rising prices. Therefore, numerous fund managers have added to their Bitcoin positions to hedge against inflation. However, Smith (2016) argues that Bitcoin is a digital gold because it has a direct exchange rate which the real gold does not have. Moreover, Bitcoin's daily price exhibits virtually zero correlation with gold, making Bitcoin difficult for its owners to hedge in (Yermack, 2015).

Bitcoin functions not only as a hedge but also as a speculative commodity (Šurda, 2014) or an asset. Glaser, Zimmermann, Haferkorn, Weber, and Siering (2014) reveals that Bitcoin is generally regarded as a speculative commodity and rarely used as a currency for payment. Understanding how to forecast Bitcoin price (BTC) can aid in portfolio investment and hedging and is thus crucial for financial institutions (Bouri, Gupta, Tiwari, & Roubaud, 2017a; Bouri, Molnar, Azzi, Roubaud, & Hagfors, 2017b; Dyhrberg, 2016; Eisl, Gasser, & Weinmayer, 2015). Bitcoin, similar to other risky financial assets, is characterized by leptokurtosis, heteroscedasticity, and long memory (Chan, Chu, Nadarajah, & Osterrieder, 2017; Phillip, Chan, & Peiris, 2019).

Numerous studies use time series analysis in research what factors affect the price of cryptocurrencies such as Bitcoin by the COVID-19 pandemic. Choi and Shin (2022) provide systematic evidence demonstrating the relationship among BTC, inflation, VIX, and gold prices and Blau, Griffith, and Whitby (2021) examine the time series relationship between BTC and forward inflation expectation rates under a vector autoregressive (VAR) model. Zhu, Dickinson, and Li (2017) employ a vector error correction (VEC) model to analyse the economic impact of BTC on economic variables such as the Consumer Price Index, US Dollar Index, and Dow Jones Industrial Average. However, the aforementioned studies focus on the role of Bitcoin before or during the COVID-19 pandemic, with none of them focusing on the post-pandemic era.

With the propagation of vaccination, the number of COVID-19 deaths have decreased despite the increasing rate of confirmed COVID-19 cases as the casual virus mutates. Considering COVID-19 to be less severe, numerous countries have cancelled their lockdown policies and instead sought to coexist with the disease and allow supply chains to recover. In the United States, the current inflation rate has exceeded the level considered acceptable by the government. The Federal Reserve has tightened its monetary policy and increased interest rates in an attempt to reduce inflation. This strategy could change the anticipated model of the relationship among inflation, the US dollar, and BTC in the post-pandemic era. By holding cryptocurrency, one cannot obtain interest income; therefore, Bitcoin is a less enticing investment option under the current monetary policy. Bitcoin is also a monetary medium. Bitcoin is a peer-to-peer electronic currency mainly used as an alternative to traditional currency. Jia (2013) analyses whether Bitcoin can provide a major function as a currency. Baur, Hong, and Lee (2018) explores whether Bitcoin is a monetary or investment medium. Because the considerable increase in the price of Bitcoin, the majority of investors consider it impractical as a currency for payment and have mostly ignored this function. Bitcoin's shortcomings as a payment medium are likely to emerge in the post-pandemic era because reducing inflation is a primary policy goal, and it is likely indicating an increase in interest rates.

The present study employs a Markov switching (MS) model to establish the structure of the post-pandemic era. After tracking the numbers of additional confirmed COVID-19 cases (NAC) and number of additional deaths (NAD) on daily basis, we discover that NAC and NAD have regime-switching (cyclical) behaviours, and the parameters of these regimes can be verified using the MS model. Furthermore, we assume that NAC and NAD would follow an Ornstein–Uhlenbeck (OU) mean reversion process, wherein the structural characteristics including the mean reversion speed, mean reversion level, and volatility of NAC and NAD could be obtained by calibrating the MS model. The mean reversion speed of NAC and NAD reflects the rate of increase and decrease in COVID-19 cases. The mean reversion level of NAC and NAD reflects the magnitude of the impact of each new mutant strain. The volatility of NAC and NAD captures the severity of each new mutant strain. We use these three characteristics to construct the parameters of the post-pandemic era and ascertain a potential start date.

In theory, the start of the post-pandemic era should trigger dramatic changes in monetary policy; this is because avoiding the consequences of the pandemic will no longer be the government's top priority. The behaviours of Bitcoin in terms of currency competition and commodity competition are increasingly giving indication of the post-pandemic era. Nevertheless, Bitcoin's opposing functions as a currency and a commodity may cause substantial price volatility in the post-pandemic era.

The relevant literature does not clearly define Bitcoin as a currency or commodity. Regardless of it that, Bitcoin is a payment medium or investment asset and COVID-19-related factors have influenced its price. Bitcoin's price trends may change in the post-pandemic era because the US Federal Reserve System changes its monetary policy or the uncertainty caused by the pandemic declines. In periods of high or expected inflation, demand for immediate payment increases, especially that for necessities. In such a situation, consumers are likely to prefer currency to cryptocurrency and it is strengthening the US dollar. Therefore, the shortcomings of Bitcoin as a payment medium are highlighted by the current inflationary environment. In addition, high inflation is likely to force the US Federal Reserve to raise interest rates, which will lead to US dollar appreciation. In the real world, saving money generates interest income, and interest rate changes can affect currency values;

however, a disadvantage of virtual currency is that it does not generate interest. Therefore, how currency competition between Bitcoin and the US dollar affects BTC in the post-pandemic era should be investigated.

We focus on the competition between cryptocurrency (i.e., Bitcoin) and traditional currency (i.e., the US dollar) and that between the commodity and monetary medium functions of Bitcoin in the post-pandemic era. In addition, we examine Bitcoin's price trends and the relationships among various macroeconomic factors, COVID-19-related factors, and BTC in the post-pandemic era.

Second, we adopt a VAR model to analyse the relationships between BTC and other variables. After a cointegration test, we derived a vector error correction (VEC) model from the VAR model. Brueckner and Vespignani (2021) investigate the dynamic relationship between COVID-19 infections in Australia and the performance of the Australian stock market. Milani (2021) use a global VAR model to study social responses and economic effects. We determine that BTC impulsively responds to fluctuations in the US dollar and to expected inflation and market volatility (represented by the Chicago Board Options Exchange's Volatility Index). Accordingly, it provides currency competition and commodity competition in the post-pandemic era.

The reminder of this paper is organized as follows. Section 2 presents the establishment of the post-pandemic era structure using the MS model. Not only the data and methodology are introduced but also the empirical findings are discussed in Section 3. The results and contributions of this paper are placed in the conclusion.

2. The Structure of the Post-pandemic Era

2.1. Analysis of NAC and NAD under the MS Model

First, we verify that NAC and NAD have regime-switching behaviours. Subsequently, we calibrate the MS model to estimate three characteristics, namely, mean reversion speed, mean reversion level, and volatility, which are used to establish the structural conditions of the post-pandemic era. These structural conditions are used to ascertain the starting point of the post-pandemic era.

2.2. Descriptive Statistics of NAC and NAD

We examine daily COVID-19 NAC and NAD data. The sample spans January 21, 2020, to January 21, 2022, for a total of 510 observations.

The volatility, skewness, and kurtosis of NAC are greater than those of NAD. However, the average growth rates of confirmed cases and deaths are 3.58% and 3.57%, respectively, suggesting a negligible difference. Further information cannot be obtained from the descriptive statistics. Instead, we approach the collected information from another perspective. As illustrated in Figure 1, NAC and NAD exhibit regime-switching behaviours. Thus, obtaining the parameters of the post-pandemic era structure by using an MS model and assuming that NAC and NAD follow an Ornstein–Uhlenbeck (OU) process is reasonable.

2.3. Cyclical Features of Confirmed COVID-19 Cases and Deaths

Data released by the World Health Organization (WHO) indicates that NAC and NAD exhibit cyclical trends, as illustrated in Figure 1 and Figure 2.

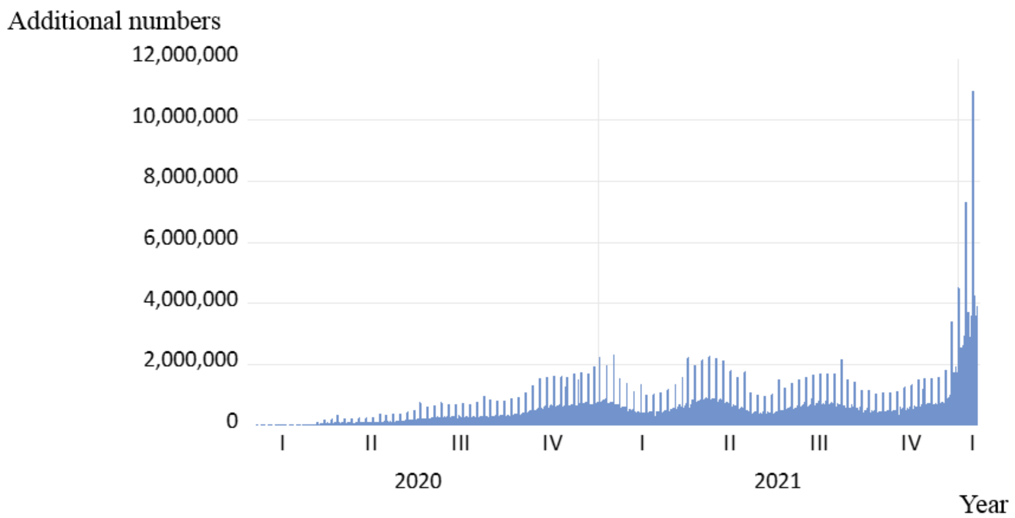

Figure 1. Number of additional confirmed COVID-19 cases (NAC).

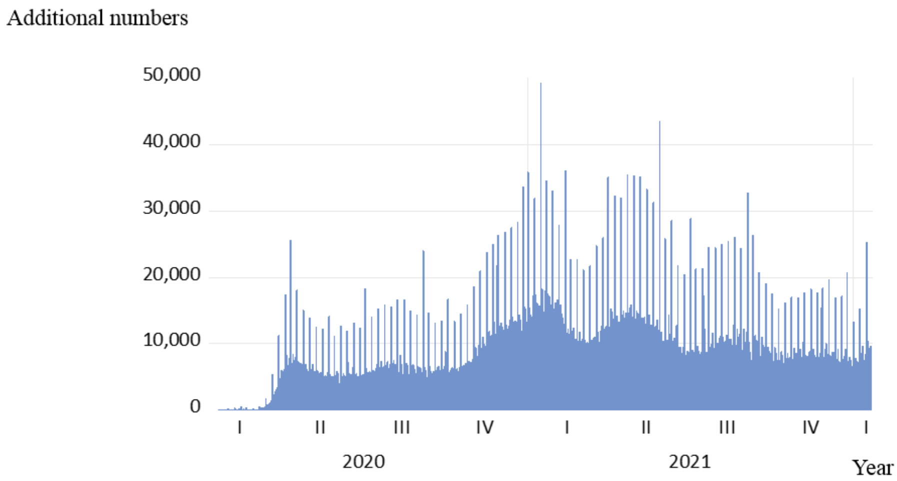

Figure 2. Number of additional confirmed COVID-19 deaths (NAD).

The trends of NAC and NAD are negatively correlated. In addition, the cyclical peaks of NAD gradually decline. The cyclical patterns of NAC and NAD are considered to influence BTC in the post-pandemic era. So, we apply the MS model which is fit for the processes of available variables and estimate parameters for probability transformation, as illustrated in Table 1.

Table 1 reveals that the durations of NAD and NAC are 10.238 and 10.706, respectively, in the high regime and 3.279 and 3.124, respectively, in the low regime. In addition, NAC remains in the high regime longer than NAD does. These findings indicate that NAC and NAD, similar to the business cycle, both follow OU processes.

Table 1. Probability transformation and duration of confirmed cases and deaths.

Confirmed cases			
Transform probability		**Duration**	
0.907	0.320	10.706	1.471
0.093	0.680	1.103	3.124
Deaths			
Transform probability		Duration	
0.902	0.305	10.238	1.439
0.098	0.695	1.108	3.279

Note: Two regimes are assumed in the MS model: A high regime and a low regime.

2.4. Estimated Parameters of NAC and NAD Based on OU Processes

Consider a variable $x(t)$ to follow an OU process of the form

$$dx(t) = \kappa\left[\theta - x(t)\right]dt + \sigma dW(t),$$

Where θ represents the mean-reversion level of $x(t)$, κ represents the speed of mean reversion, σ denotes the volatility of $x(t)$, and $W(t)$ is standard Brownian motion.

NAC and NAD are assumed to follow an OU process, including its mean-reversion speed, mean-reversion level, and volatility. Using these three parameters, we construct the stochastic processes of NAC and NAD in the post pandemic era.

Table 2. Estimated NAC and NAD parameters based on OU processes.

Parameters	**NAC**	**NAD**
κ	0.883	0.593
θ	0.188	0.053
σ	0.436	0.688
SSE	484.761	487.660

Note: SSE represents the sum of squares error.

In Table 2, the mean reversion speed of NAC is 0.883, which is considerably higher than that of NAD (0.593). This finding indicates that the number of infections changes as the virus mutates, and the mean reversion speed of NAC is rapid because infections cannot be controlled. However, deaths can be controlled through precautionary measures; thus, the mean-reversion speed of NAD gradually declines over the study period. In addition, the mean-reversion level of NAC is 0.188, and the mean-reversion level of NAD is 0.053. With further dissemination of vaccines, the long-term mean-reversion level of NAD may decrease. NAD is more volatile than NAC because the NAD base is lower than the NAC base. This also reflects that death, rather than infection and it is more likely to cause panic.

In summary, the estimated parameters of NAC and NAD are very different. On the basis of these differences, we can describe and construct the structure of the post pandemic era. The structure of the post pandemic era is defined as follows:

Restriction 1: NAD mean reversion level of <0.053.

Restriction 2: NAC mean reversion level of <0.188.

This definition holds true even if the time when both Restriction 1 and Restriction 2 are met is dynamic. On the basis of these findings, we determine that the post pandemic era began on April 16, 2020. Our empirical analysis of BTC trends in the post pandemic era uses this date as the start of the era.

Because the long-term mean-revision level of NAD is lower than the of NAC and the NAD and NAC trends are negatively related, the effects of these two variables on BTC may differ. We therefore construct several VAR models. Mode-I is a VAR model without the COVID-19 factors, Model-II is a VAR model with NAC, and Model-III is a VAR model with NAD.

3. Empirical Analysis of Three VAR Models

We use two dimensions, commodity functional and currency functional, to select variables and analyse currency competition and commodity competition. The analysis of macroeconomic factors influencing BTC and those interacting with COVID-19 are included in these models.

We investigate the following variables: the Chicago Board Options Exchange's Volatility Index (VIX), the Commodity Research Bureau Futures Index (CRB), expected inflation (EPI) as determined from the difference between the nominal and inflation-protected 5-year treasury security yields, the US dollar index (USD), the number of confirmed additional cases of COVID-19 (NAC), and the number of additional deaths from COVID-19 (NAD). The COVID-19 data is obtained from the WHO and Bloomberg. The daily time series data are from January 21, 2020, to January 21, 2022. We include EPI and CRB in the models to investigate the monetary medium function of Bitcoin and VIX to analyse its commodity function. In addition, we include USD to analyse its competition with Bitcoin.

The baseline model, Model-I, comprises five variables, whereas Model-II and Model-III both consider six variables. To avoid spurious regression, we first perform the Augmented Dickey–Fuller unit root test on the original data to test the stationarity. Bitcoin, USD, CRB, and VIX are all nonstationary and NAC and NAD are stationary. USD, CRB, and VIX are all stationary after the first difference. Because all variables are integrated, we must test their cointegration using an appropriate VAR model. We construct three VAR models (i.e., Model-I, Model-II, and Model-III) and examine the cointegration of the variables using the Johansen cointegration test. After the cointegration test, we construct VEC models based on the VAR models with cointegration constraints.

3.1. Analysis of BTC in Three VAR Models

The largest value of log likelihood is Model-II, the second is Model-III and the smallest value of that is Model-I. Therefore, the least informative model is Model-I, and Model-III is slightly more informative than Model-II. The R^2 values for Model-II and Model-III are approximately the same. According to the lowest Bayesian information criterion (BIC), the appropriate lags in Model-II and Model-III are 5 days and 1 day, respectively." [1]

Model-III has the highest number of significant VEC coefficients indicating that it provides the most reasonable explanation of the variable relationships. We discover that NAC increases impulse response fluctuation and extends the duration of shock. This finding is consistent with the long high regimes of NAC and NAD described in Section 2, and this factor cannot be ignored in any analysis of the impulse response of BTC to other factors.

A comparison of the impulse response functions and variance decomposition for Model-II and Model-III reveals how other factors related to BTC affect the structure of the post pandemic era.

3.2. Impulse Response Function in Model-II and Model-III

In Model-III, the impulse response of BTC to USD is positive in the short term, as illustrated in Figure 3. However, in Model-II, the impulse response of BTC to USD is initially positive, becoming negative on day 3 and then becoming positive again from day 5 until shock convergence. Thus, Model-II indicates that currency competition between Bitcoin and the US dollar occurs in the short term.

[1] The lowest BIC of Model-II is −25.12567, and the lowest BIC of Model-III is −25.64552.

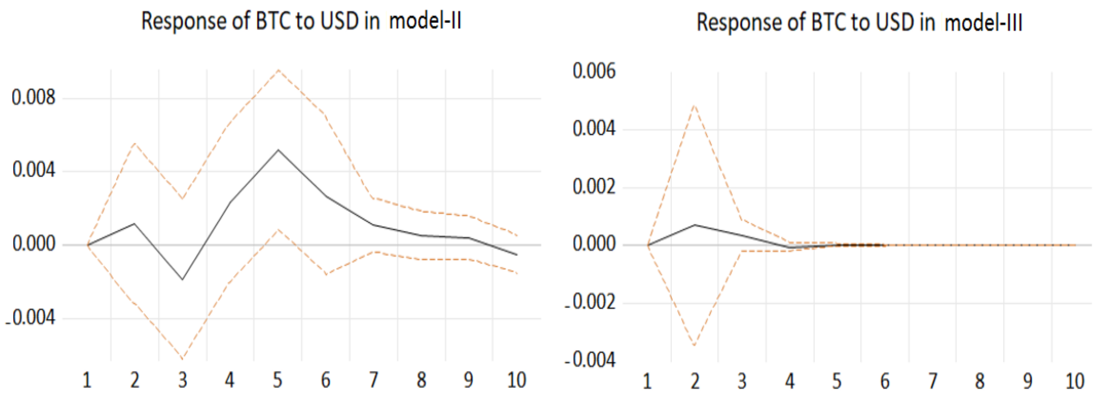

Figure 3. Response of Bitcoin price to US dollar fluctuation in model-II and model-III.

An increase in BTC in response to the shock of inflation implies that the importance of commodity competition is becoming more and more apparent; a decrease in BTC in response to the shock of inflation implies that the importance of currency competition is becoming more and more apparent. In Model-II and Model-III, BTC decreases after a negative EPI shock in the short term and increases after a positive EPI shock in the long term. As displayed in Figure 4, the shock volatility (either EPI shock or CRB shock volatility) predicted by Model-II is greater than that predicted by Model-III, and the effects of both EPI and CRB shocks in Model-II persist longer than those in Model-III. This indicates that the effects of currency competition last longer than those of commodity competition in the post pandemic era.

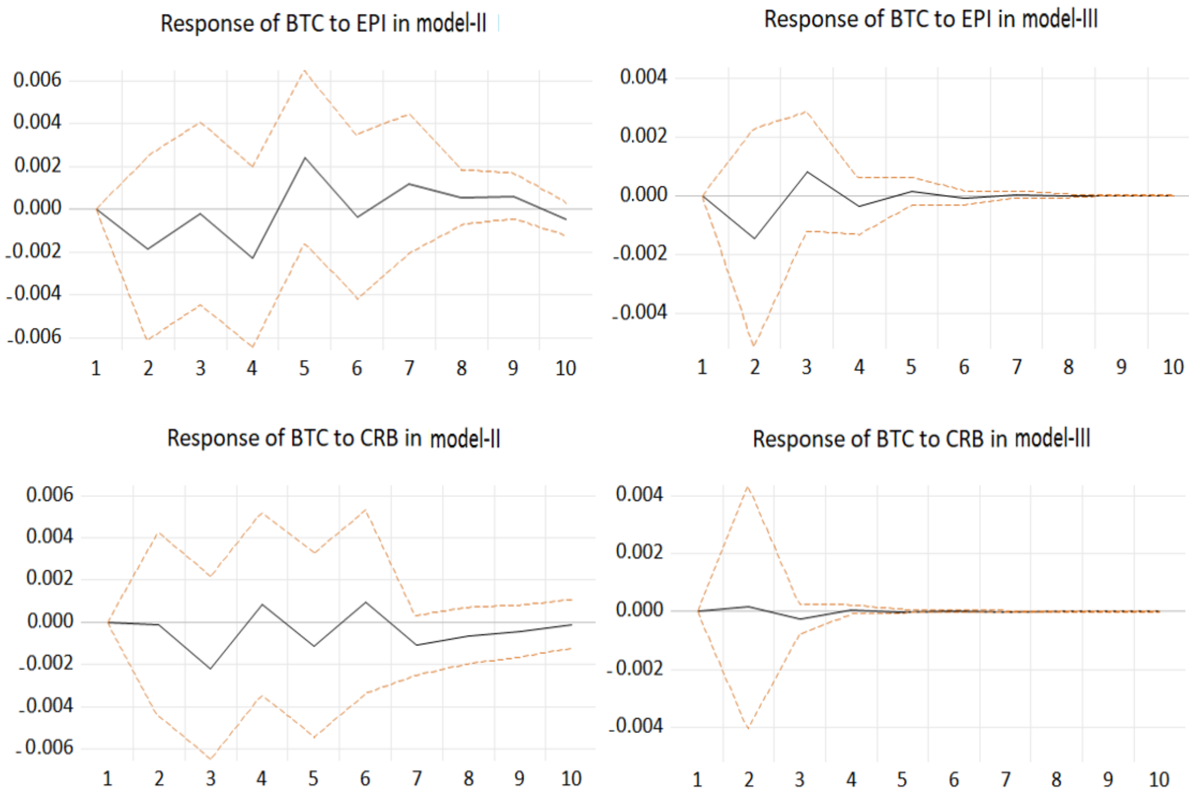

Figure 4. Response of Bitcoin price to inflation in model-II and model-III.

The impulse response of BTC to VIX is initially negative in both Model-II and Model-III in Figure 5, indicating that the negative COVID-19 shock to BTC persists. However, after period 7, the impulse response becomes positive in Model-II. This indicates that Bitcoin exhibits a commodity function, being used for hedging.

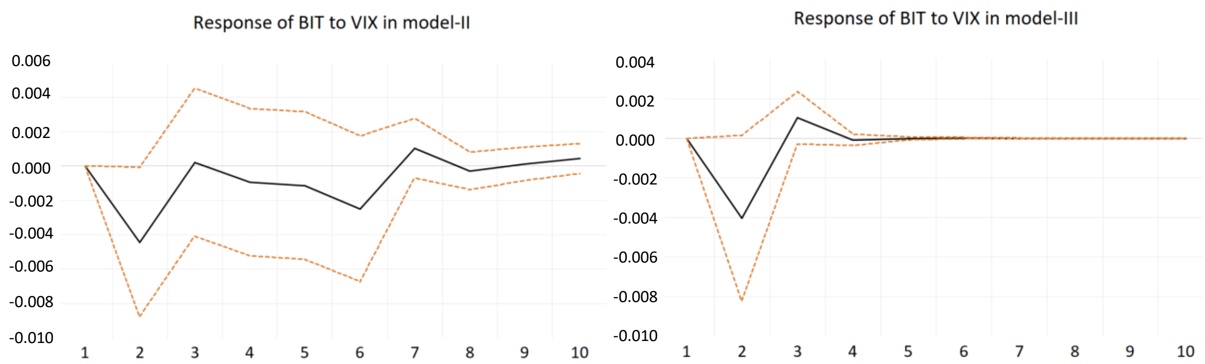

Figure 5. Response of Bitcoin price to VIX in model-II and model-III.

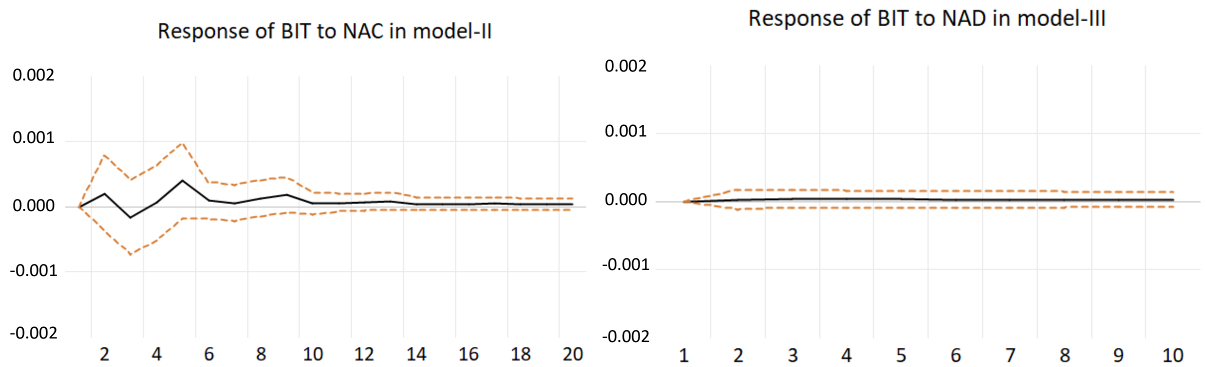

Figure 6. Response of Bitcoin price to NAC and NAD in model-II and model-III.

Figure 6 exhibits the impulse response of BTC to NAD and it is positive, especially in Model-III, because governments have tended to maintain policies of quantitative earning during COVID-19, thereby it is enhancing Bitcoin's hedging effect. However, the impulse response of BTC to NAC in the short term is negative in Model-II. This illustrates that Model-II more effectively reflects the currency competition between BTC and USD and thus the situation in the post-pandemic era.

3.3. Variance Decomposition in Model-II and Model-III

Variance decomposition indicates the amount of the relative importance of each variable contributes to the other variables in a VAR model. Variance decompositions of model-II and model-III are represented in Table 3 and 4.

Table 3. Variance decomposition of BTC in model-III.

Period	S.E.	BTC	USD	CRB	VIX	EPI	NAD
1	0.0473	100.000	0.000	0.000	0.000	0.000	0.000
2	0.0476	99.169	0.022	0.001	0.716	0.092	2.66E-05
3	0.0476	99.085	0.027	0.004	0.763	0.121	8.21E-05
4	0.0476	99.078	0.027	0.005	0.763	0.126	1.20E-04
5	0.0476	99.077	0.027	0.005	0.763	0.128	1.58E-04
6	0.0476	99.077	0.027	0.005	0.763	0.128	1.94E-04
7	0.0476	99.077	0.027	0.005	0.763	0.128	2.29E-04
8	0.0476	99.077	0.027	0.005	0.763	0.128	2.61E-04
9	0.0476	99.077	0.027	0.005	0.763	0.128	2.92E-04
10	0.0476	99.077	0.027	0.005	0.763	0.128	3.21E-04

Table 3 presents the variance decomposition of BTC, which reveals that a disturbance by itself results in almost no change, even as the lag increases. The proportions of the variance decomposition of BTC that could be explained by USD, VIX, and NAD exhibit minimal changes as the lag period increases, and the first three disturbances of CRB and EPI exhibited only minimal change.

Table 4 illustrates that an increase in BTC is predominantly explained by a shock to the price itself; whereas a decrease in BTC is explained well by other shocks, except at the beginning of the sample period. Model-II reveals several phenomena. The proportions of BTC variance decomposition that can be explained by USD fluctuation increase gradually, indicating that monetary policy is affected by NAC. In addition, consumption is influenced by NAC, and because human behaviour affects economic variables, the proportions of variance explained by CRB, VIX, and EPI also gradually increase. Finally, the proportions of BTC variance decomposition that can be explained by fluctuations in BTC decrease with the lag period.

Table 4. Variance decomposition of BTC in model-II.

Period	S.E.	BTC	USD	CRB	VIX	EPI	NAC
1	0.047	100.000	0.000	0.000	0.000	0.000	0.000
2	0.048	98.921	0.063	0.000	0.868	0.146	0.002
3	0.048	98.560	0.216	0.210	0.865	0.147	0.003
4	0.048	98.037	0.450	0.240	0.896	0.374	0.003
5	0.048	96.535	1.612	0.288	0.938	0.619	0.010
6	0.049	95.945	1.905	0.326	1.195	0.619	0.010
7	0.049	95.743	1.952	0.377	1.238	0.679	0.010
8	0.049	95.699	1.964	0.395	1.241	0.691	0.011
9	0.049	95.670	1.970	0.402	1.240	0.706	0.012
10	0.049	95.643	1.979	0.402	1.248	0.715	0.012

3.4. Granger Causality Test

On the basis of our analysis of impulse response and variance decomposition, we anticipate that NAC will increase the probability of currency competition in the post-pandemic era, thus increasing the volatility of BTC. However, according to the VEC model of NAC and NAD, NAC may lack predictive power. Model-II and Model-III demonstrate the Granger causality between BTC and the other factors.

As presented in Table 5, USD is only a Granger causal factor for BTC fluctuation in Model-II. This is consistent with our previous finding that currency competition plays a major role in Model-II. In addition, VIX and EPI are Granger causal factors for USD, implying that monetary policy is highly correlated with USD. This leads to an unreasonable phenomenon in which BTC is a Granger causal factor for EPI and NAC in Model-II. However, commodity function plays a role in Model-III. As presented in Table 6, VIX and NAD are Granger causal factors affecting BTC. This indicates that BTC can be predicted on the basis of VIX and NAD. VIX is also a Granger causal factor affecting USD, possibly because such panic indicators affect monetary policy. In addition, VIX is a Granger causal factor for CRB, probably because raw material costs rise during periods of panic. NAD is also a Granger causal factor for VIX, possibly because an increase in NAD creates panic, thereby increasing VIX. All of these Granger causal relationships align with our expectations.

Table 5. Granger causality test of model-II.

Model-II							
	BTC				**USD**		
Excluded	**Chi-sq**	**Df**	**Prob.**	**Excluded**	**Chi-sq**	**Df**	**Prob.**
USD	9.367	5	0.095*	BTC	4.613	5	0.465
CRB	2.161	5	0.826	CRB	5.987	5	0.308
VIX	5.154	5	0.397	VIX	15.288	5	0.009*
EPI	2.159	5	0.827	EPI	13.035	5	0.023*
NAC	4.206	5	0.520	NAC	0.768	5	0.979
	CRB				VIX		
Excluded	Chi-sq	Df	Prob.	Excluded	Chi-sq	Df	Prob.
BTC	7.109	5	0.213	BTC	8.745	5	0.120
USD	10.917	5	0.053*	USD	11.194	5	0.048*
VIX	4.471	5	0.484	CRB	0.654	5	0.985
EPI	2.518	5	0.774	EPI	4.490	5	0.481
NAC	2.704	5	0.746	NAC	5.570	5	0.350
	EPI				NAC		
Excluded	Chi-sq	Df	Prob.	Excluded	Chi-sq	Df	Prob.
BTC	9.297	5	0.098*	BTC	12.142	5	0.033*
USD	6.148	5	0.292	USD	6.710	5	0.243
CRB	2.137	5	0.830	CRB	4.037	5	0.544
VIX	8.251	5	0.143	VIX	18.374	5	0.003*
NAC	0.637	5	0.986	EPI	2.262	5	0.812

Note: *Significant at the 10% level.

Table 6. Granger causality test of Model-III.

Model-III							
BTC				**USD**			
Excluded	**Chi-sq**	**df**	**Prob.**	**Excluded**	**Chi-sq**	**df**	**Prob.**
USD	0.190	1	0.663	BTC	2.21E-04	1	0.988
CRB	0.031	1	0.860	CRB	1.35E-04	1	0.991
VIX	3.327	1	0.068*	VIX	15.568	1	0.000*
EPI	0.457	1	0.499	EPI	2.385	1	0.123
NAD	3.076	1	0.080*	NAD	4.51E-06	1	0.998
CRB				VIX			
Excluded	Chi-sq	df	Prob.	Excluded	Chi-sq	df	Prob.
BTC	0.425	1	0.515	BTC	0.505	1	0.478
USD	0.037	1	0.848	USD	1.327	1	0.250
VIX	4.460	1	0.035*	CRB	0.036	1	0.850
EPI	0.445	1	0.505	EPI	0.026	1	0.872
NAD	1.112	1	0.292	NAD	4.332	1	0.037*
EPI				NAD			
Excluded	Chi-sq	df	Prob.	Excluded	Chi-sq	df	Prob.
BTC	0.318	1	0.573	BTC	0.117	1	0.733
USD	1.19E-05	1	0.997	USD	0.060	1	0.807
CRB	1.261	1	0.261	CRB	0.497	1	0.481
VIX	2.297	1	0.130	VIX	0.262	1	0.609
NAD	0.207	1	0.650	EPI	0.432	1	0.511

Note: *Significant at the 10% level.

4. Conclusion

We apply an MS model to verify that two COVID-19-related factors (NAC and NAD) are cyclical, based on the assumption that these factors follow an OU process. The estimated parameters are used to establish the structural characteristics and start date of the post pandemic era, confirming that the post pandemic era has begun.

We use VAR models to execute an analysis of the post pandemic era. Our findings reveal that the effect of currency competition will increase in the post pandemic era. We also apply VAR models to analyse how the factors, including COVID-19-related factors, influence BTC competition. We include the US dollar and expected inflation in the VAR models to examine currency competition. In addition, we include CRB and VIX in the VAR models to analyse Bitcoin's commodity and currency functions. Because the impact of COVID-19 continues into the post pandemic era, the first contribution of our model is that it provides a realistic analysis of BTC.

The Granger causality results reveal that VIX and NAD predict BTC. The impulse response functions and variance decomposition for Model-II and Model-III indicate the factors affecting BTC. The impulse response functions indicate that the shock volatility of NAC is greater than that of NAD. This finding indicates that, despite the decline in the COVID-19 fatality rate, the number of daily cases remains a key factor because it substantially affects monetary policy and consumption. This effect cannot be ignored. The USD and EPI impulse response analyses using Model-II indicate currency competition between Bitcoin and the US dollar in the short term.

According to the variance decomposition for Model-II, the variance explained by USD, EPI, CRB, and VIX gradually increase. These findings provide evidence supporting the existence of currency competition between Bitcoin and USD and competition between Bitcoin's commodity and currency functions. Our empirical study extends the body of research concerning impulse response functions, variance decomposition, and Granger causality tests for BTC in the post-pandemic era.

References

Baur, D. G., Hong, K., & Lee, A. D. (2018). Bitcoin: Medium of exchange or speculative assets? *Journal of International Financial Markets, Institutions and Money, 54*, 177-189. https://doi.org/10.1016/j.intfin.2017.12.004

Blau, B. M., Griffith, T. G., & Whitby, R. J. (2021). Inflation and bitcoin: A descriptive time-series analysis. *Economics Letters, 203*, 109848. https://doi.org/10.1016/j.econlet.2021.109848

Bouri, E., Gupta, R., Tiwari, A. K., & Roubaud, D. (2017a). Does bitcoin hedge global uncertainty? evidence from wavelet-based quantile-in-quantile regressions. *Finance Research Letters, 23*, 87-95. https://doi.org/10.1016/j.frl.2017.02.009

Bouri, E., Molnar, P., Azzi, G., Roubaud, D., & Hagfors, L. I. (2017b). On the hedge and safe haven properties of bitcoin: Is it really more than a diversifier? *Finance Research Letters, 20*, 192-198. https://doi.org/10.1016/j.frl.2016.09.025

Brueckner, M., & Vespignani, J. (2021). COVID-19 infections and the performance of the stock market: An empirical analysis for Australia. *Economic Papers: A Journal of Applied Economics and Policy, 40*(3), 173-193. https://doi.org/10.2139/ssrn.3624676

Chan, S., Chu, J., Nadarajah, S., & Osterrieder, J. (2017). A statistical analysis of cryptocurrencies. *Journal of Risk and Financial Management*, *10*(2), 1-23.

Choi, S., & Shin, J. (2022). Bitcoin: An inflation hedge but not a safe haven. *Finance Research Letters*, *46*, 102379. https://doi.org/10.1016/j.frl.2021.102379

Das, D., Le Roux, C. L., Jana, R. K., & Dutta, A. (2020). Does bitcoin hedge crude oil implied volatility and structural shocks? A comparison with gold, commodity and the US dollar. *Finance Research Letters*, *36*, 101335. https://doi.org/10.1016/j.frl.2019.101335

Dyhrberg, A. H. (2016). Bitcoin, gold and the dollar – a garch volatility analysis. *Finance Research Letters*, *16*, 85-92. https://doi.org/10.1016/j.frl.2015.10.008

Eisl, A., Gasser, S. M., & Weinmayer, K. (2015). Caveat emptor: Does bitcoin improve portfolio diversification? *Available at SSRN 2408997*. https://doi.org/10.2139/ssrn.2408997

Glaser, F., Zimmermann, K., Haferkorn, M., Weber, M. C., & Siering, M. (2014). *Bitcoin-asset or currency? revealing users' hidden intentions*. Retrieved from Revealing Users' Hidden Intentions (April 15, 2014). ECIS: https://ssrn.com/abstract=2425247

Jia, L. P. (2013). Theory practice and effect. *Studies of International Finance*, *12*, 14-25.

Milani, F. (2021). COVID-19 outbreak, social response, and early economic effects: A global VAR analysis of cross-country interdependencies. *Journal of Population Economics*, *34*(1), 223-252. https://doi.org/10.1007/s00148-020-00792-4

Phillip, A., Chan, J., & Peiris, S. (2019). On long memory effects in the volatility measure of cryptocurrencies. *Finance Research Letters*, *28*, 95-100. https://doi.org/10.1016/j.frl.2018.04.003

Smith, J. (2016). *An analysis of bitcoin exchange rates*. Retrieved from https://ssrn.com/abstract=2493797

Šurda, P. (2014). *The origin classification and utility of Bitcoin*. Retrieved from https://ssrn.com/abstract=2436823

Yermack, D. (2015). Is Bitcoin a real currency? An economic appraisal. In Handbook of Digital Currency. In (pp. 31-43): Academic Press.

Zhu, Y., Dickinson, D., & Li, J. (2017). Analysis on the influence factors of bitcoin's price based on vec model *Financial Innovation*, *3*(1), 1-13. https://doi.org/10.1186/s40854-017-0054-0