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THE LINK BETWEEN CRYPTOCURRENCIES AND REGIONAL EQUITY INDEX: EVIDENCE FROM TVP- SV-VAR ANALYSIS

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ABSTRACT

This paper analyses the relationship between major cryptocurrencies (Bitcoin, Ethereum, and Tether) and selected regional equity markets of America, Asia, and Europe, while controlling for global financial factors including crude oil prices and the EUR/USD exchange rate. The primary objective is to identify and quantify the time-varying spillover effects and assess whether regional stock markets significantly influence cryptocurrency price dynamics during the period 2018–2023. For this purpose, the study utilises the Time-Varying Parameter Vector Auto-Regression model with stochastic volatility (TVP-SV-VAR) introduced by Primiceri (2005) and extended by Nakajima (2011), which allows us to observe possible changes in the economic structure. The study finds that spillover effects are strongest in the short term and decline over longer horizons. Among regional markets, MSCI Asia exerts the strongest influence on Bitcoin and Tether, whereas MSCI Americas has the largest impact on Ethereum. Notably, in the three key observation time points of this study, the market reaction intensity of Bitcoin and Ethereum has always been consistent, with a more prominent response during the COVID-19 outbreak. Tether's impulse response impact coefficients were generally lower, and its peak response occurred during COVID-19 vaccine distribution. The results also show that oil price shocks and exchange-rate movements contribute to cryptocurrency volatility, but with diminishing effects over time. Overall, the findings suggest that regional equity conditions are relevant but not sufficient for portfolio decision-making because cryptocurrency prices are also driven by macroeconomic, monetary, and behavioural factors not fully captured in the model. This derives valuable conclusions for portfolio managers, investors, and even government regulators.

Keywords: cryptocurrencies, regional equity markets, time-varying spillovers, TVP-SV-VAR, stochastic volatility, exchange rate dynamics, oil price shocks, portfolio risk management

JEL Classification: G100, G11, G15, G17, G18

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INTRODUCTION

Cryptocurrencies gained widespread attention and have emerged as a revolutionary force in the global financial space. Their creation was triggered by the emergence of Bitcoin; Nakamoto (2008) invented it, and from then on, Ethereum, Tether, and more emerged, making cryptocurrencies an asset class traded all over the world, attracting investors, economists, regulators, and the public. However, cryptocurrencies differ from conventional assets by their unique features: decentralisation, high volatility, and lack of centralised control. Their use has spread beyond speculation: Baur et al. (2018) establish that now they are media of exchange, means of payment, and risk hedgers. Kliber et al. (2019) also highlight context utility, emphasizing how Bitcoin is utilised as a diversifier in China/Japan, whereas it is utilised as a safe haven in corrupt economies such as Venezuela.

Despite the rapid expansion of cryptocurrency markets, there is no consensus regarding which economic and financial factors systematically drive cryptocurrency price movements. As these digital assets continue to develop, more and more people are focusing on the factors affecting cryptocurrency fluctuations. One such factor has been the traditional stock market. Regional stock indices are important indicators that measure the health and performance of regional economies. With this, attention has gradually been drawn to how the cryptocurrency market is influenced by different regions' stock markets. These indices can indicate the whole performance of the stock market in a given area and serve as critical references for learning about the financial conditions in the area.

Knowledge on whether regional equity markets pass the shocks to cryptocurrencies is relevant in cross-market risk management, portfolio diversification, and financial stability monitoring. The existing literature tends to examine traditional financial markets or selected macro-financial variables at once (Selmi et al. 2018; Kliber et al. 2019; Charfeddine et al. 2019). There is little evidence on the combined effect of financial markets and macroeconomic variables and their time-dependent interactions with cryptocurrencies, especially during crisis times like the COVID-19 pandemic.

LITERATURE REVIEW

The interaction of cryptocurrencies with extant traditional financial markets has become increasingly appealing to scholars, investors, and policy-makers in recent years (Baur et al. 2018; Corbet et al. 2018). The emergence of Bitcoin, Ethereum, and Tether has, over time, helped cryptocurrencies emerge into a new class of assets that reshape the old financial system. Cryptocurrencies have been characterised as digital money independent of any government control or interference (Xie 2019). A cardinal characteristic of cryptocurrencies is that they do not get issued by some sort of central authority, and this, in theory, protects them from government interference or tampering (Alqudah et al. 2023). They also come with considerable advantages: their settlements do not pass-through central banks and other financial institutions, thus bypassing a lot of redundant processes (Lipton & Treccani 2021; Bunjaku et al. 2017). Development of cryptography, popularly known as blockchain technology, has further accelerated the development of cryptocurrencies, guaranteeing stability and security to such a degree that their transactions are nearly non-fungible and non-interchangeable (Khan et al. 2019). Furthermore, Bunjaku et al. (2017) argued that the development of cryptocurrencies would probably replace the conventional means of payment. For cryptocurrencies to lead in the global payment system, they first must deal with core challenges, especially the fact that they are not fully regulated. Moreover, they too have their own shortcomings; for instance, their high volatility makes investment in them very risky (Bunjaku et al. 2017).

With decentralisation, scarcity, and volatility, such digital money has attracted significant interest within different stakeholder groups. Existing work has been concerned with the way that cryptocurrencies affect conventional finance markets, habitually analysing their function as either speculative or hedging assets (Selmi et al. 2018; Kliber et al. 2019). Cryptocurrency's potential for risk-hedging and diversification has also been investigated. Kliber et al. (2019) studied whether Bitcoin can serve as a haven asset depending on the nations' economic conditions, finding that Bitcoin acts as a safe haven asset in the case of Venezuela. However, Charfeddine et al. (2019) reported a weak link between crypto and standard asset classes, yet their portfolio tests indicate that cryptocurrencies are, in most situations, poor hedging instruments. Dyhrberg (2016) applied a GARCH model and concluded that Bitcoin lies between gold and the dollar as an asset: it plays a store-of-value role like gold and a means-of-payment role like the dollar. Another study concluded that there is a quite small probability that official currencies will be replaced by cryptocurrencies (Claeys et al. 2018).

Some scholars researched cryptocurrencies based on geographical regions. For example, Sami and Abdallah (2020) studied the cryptocurrency market and how it influences stock market performance in some specific regions of the world, namely the Middle East and North Africa (MENA) region. Dahir et al. (2019) examined the relationship between Bitcoin and stock markets in the BRICS countries. Findings revealed that the contribution of Bitcoin returns to equity market volatility is relatively limited. Kliber et al. (2019) studied how Bitcoin could be used in the stock markets of five countries and found that only in Venezuela does Bitcoin act as a safe haven asset. Klein et al. (2018), however, found that Bitcoin does not perform as a hedge or a safe haven in the case of stock markets in advanced economies. Bouri et al. (2019) examined the relationship between Asia-Pacific stock markets and cryptocurrencies, such as Japan's, and proposed ways investors could diversify. Hanif et al. (2022) provided a more extensive analysis by examining eight cryptocurrencies and four regional equity indices using the CoVaR framework to capture bidirectional spillover effects. However, our study differs in several important respects. First, we employ a TVP-SV-VAR model, which allows for time-varying dynamics and places primary emphasis on impulse response analysis rather than tail-risk spillovers. Second, we use weekly data, explicitly incorporating the COVID-19 period, whereas Hanif et al. (2022) rely on daily data and focus predominantly on the pre-pandemic cryptocurrency market.

The theoretical views of cryptocurrency price formation are also essential. Applying the quantity theory of money suggests that the balance of supply and demand of transactional media can influence prices. Ciaian et al. (2021) find that Bitcoin prices are significantly influenced by its transaction as well as speculative demand, confirming that supply, circulation, and transaction demand are key determinants of cryptocurrency prices. Thus, scarcity mechanisms that are inherent in cryptocurrencies can change the price. Furthermore, Keynesian speculative demand theory postulates that investors will change their investments between currencies and financial instruments to avoid losing capital. In other words, any fluctuation in interest rates can influence the demand for cryptocurrency because of the reallocation of portfolios. The literature on behavioural finance also suggests that investor sentiment, herding, and the effects of attention are some crucial forces that drive cryptocurrency volatility. Sovbetov (2018) finds that macro-financial variables such as interest rates and financial market conditions, along with trade volume, perceived attractiveness, and legalization, are some external drivers of cryptocurrency prices, providing empirical evidence that cryptocurrency valuation is affected not only by financial market variables but also by other broader indicators. These perspectives, thus, justify the need to include financial market variables, and at the same time consider the fact that other variables, such as macroeconomic and behavioural variables, also influence the dynamics of the prices. Some scholars analysed the other factors affecting cryptocurrency prices and returns. Oil prices and exchange rates are two prominent factors that have been considered in research in this field.

As a crucial global commodity, oil's price has the potential to influence cryptocurrencies (Okorie & Lin, 2020). According to Yin et al. (2021), specifically, the oil market shocks matter for crypto: supply shocks and oil price returns raise volatility, but demand-driven oil shocks tend to lower it. Jareño et al. (2021) studied links between the oil market and cryptocurrencies and found that oil demand shocks are strongly and positively correlated with every cryptocurrency in the sample except Tether. On the other hand, exchange rates can mirror the influence of currency fluctuations on asset prices and can serve as a confounding factor for cryptocurrencies (Corelli 2018). Bogdan Andrei Dumitrescu et al. (2023) studied the relationship between changes in the price of bitcoin and exchange rates in Europe. The study concluded that price variations in Bitcoin are significantly influenced by nominal changes in exchange rates during normal market periods. Other variables also exert an effect on the volatility of the price of cryptocurrencies. Nesrine Dardouri et al. (2023) looked at the effect of COVID-19 on Bitcoin, Ethereum, and Dogecoin prices, while Salisu & Ogbonna (2021) examined the effect of COVID-19 news on the return volatility in the digital currency market. Similarly, Lahmiri and Bekiros (2021) analysed self-similarity in cryptocurrency markets, and their findings indicated that COVID-19 significantly influenced the cryptocurrency's return and volatility. Other studies have focused on the forces internally affecting the crypto market; amongst such studies, it is reported that crypto beta and trading volume increase the prices of the cryptocurrencies, whereas the volatility of crypto negatively influences them significantly (Sovbetov 2018).

Taken together, existing studies have examined the relationship between cryptocurrencies and regional equity markets. These studies also analyse the impact of oil prices, exchange rates, and COVID-19-related uncertainty. For instance, Zeng et al. (2023) examine the interdependence of the Bitcoin market with the stock markets of China, India, and Pakistan. Dahir et al. (2019) investigate the relationship between Bitcoin and stocks for BRICS countries. In the MENA region, Sami and Abdallah (2020) examined the relationship between stock market performance and the cryptocurrency market. Various studies focused on how other variables relate to cryptocurrencies. For example, Yin et al. (2021) studied the effect of oil market shocks on the volatile nature of cryptocurrencies. Mohd. Heikal et al. (2022) examined the effect of the oil price on cryptocurrency returns, and Bogdan Andrei Dumitrescu et al. (2023) investigated the connection between exchange rate markets and bitcoin. Some scholars have also studied the effect of COVID-19 uncertainty on the digital currency market (Ftiti et al. 2021; Umar & Gubareva 2020). Existing empirical studies do not agree on what drives cryptocurrency returns. The studies largely evolve in isolation, by using a limited set of variables, employing static or partially time-varying frameworks, or excluding structurally disruptive events like the pandemic period. Consequently, limited evidence exists on how regional equity markets, oil prices, exchange rates, and COVID-19 shocks jointly and dynamically interact with cryptocurrency markets. This study addresses this gap by modelling these factors simultaneously within a unified time-varying framework.

Based on the findings of the literature review, this study uses regional equity indices as they capture broad regional financial conditions along with macro-financial environment, such as risk appetite, capital flow, and portfolio migration across geographically differentiated markets. Regional benchmarks, in contrast to single-country ones, enable identification of homogeneous spillovers across large economic blocs and give a more holistic proxy of investment sentiment in the region. MSCI regional indices are well-established, highly diversified, and commonly used in the empirical research of international asset-pricing and spillovers, which improves the comparability and external validity of the findings.

Furthermore, the WTI Crude Oil Futures Contract price is used as a proxy of the condition in the global commodity markets because it is highly liquid, has a deep derivatives market, and is dominant in financialised commodity markets. It is widely applied in the macro-financial spillover and connectedness studies due to its reflection of short-term market expectations and investors' positioning. Although Brent crude is also of relevance as a global benchmark, WTI futures were used in this study due to their enhanced availability of high-frequency financial data, greater integration with the U.S. financial markets, and frequent application in empirical literature on cross-asset transmission mechanisms.

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In spite of the three regional equity indices that had been introduced to reflect the geographically differentiated financial conditions, there was a single exchange-rate variable used to maintain model parsimony and stability of estimation. Time-varying parameter models are dimensionality sensitive. Having multiple currency pairs may result in redundancy as the major exchange rates are highly correlated. With one dominant exchange rate, multicollinearity and over-parameterisation in the TVP-SV-VAR are minimised, while still capturing the route by which the world currency flows influence the crypto-currency markets. So, the EUR/USD exchange rate was chosen since it is the most traded currency pair in the world, comprising most of the foreign-exchange turnover. So, it can be considered a marker index of currency market activity in the world, the level of liquidity in the international market, and the change in the sentiment towards risk.

The macroeconomic variables (policy interest rates, inflation expectations, monetary liquidity measures, etc.) were not considered since the study pays specific attention to the financial market transmission channels. Including macroeconomic variables can create mixed-frequency estimation problems. Investor sentiment and media attention were also not directly included in the models because they were difficult to measure (because they are behavioural factors). They are not consistent with high-frequency global proxies, and they might be subject to construct sentiment indices. To account for such indicators, the alternative modelling framework and data sources would have to be involved, which is not within the parameters of the current study. In addition, the effects of interest rates and investor sentiments can also be said to be indirectly shown via the equity markets, exchange rate, and commodity markets, which already represent market expectations.

AIMS AND OBJECTIVES

The paper aims to analyse the effect of regional equity indices on the cryptocurrency prices over time and assess the strength of such effects and their persistence using a TVP-SV-VAR model. The analysis has relied on the weekly observations of crypto closing prices, regional stock indices, WTI crude oil futures prices, and exchange rates. These indices are representative and can reflect the comprehensive performance observed in the stock market in the specific region, providing important references for understanding the financial situation in that region. Research tasks involve:

- estimating time-varying spillovers;
- comparing regional market effects;
- determining the impact of global control variables, i.e., oil prices and exchange rates.

METHODS

To investigate the dynamic relationships between the cryptocurrency market and external economic factors, this research utilized a Time-Varying Parameter Vector Autoregressive (TVP-SV-VAR) model, which accounts for stochastic volatility. This approach was enhanced by the integration of the Markov Chain Monte Carlo (MCMC) simulation method to explore how regional equity markets, oil prices, and exchange rate fluctuations influence the cryptocurrency market. To ensure the statistical validity of our time-series data, we first administered the Augmented Dickey-Fuller (ADF) test to confirm the stationarity of the datasets. Following this, a Vector Autoregressive (VAR) model was applied to ascertain the most appropriate lag order for the analysis. Finally, a comprehensive analysis was performed based on the generated impulse responses to understand the shock effects between the variables.

Modelling

VAR Model

Sims (1980) developed the Vector Autoregression (VAR) model, a non-structural econometric model built on the Autoregressive (AR) model. It is mainly employed for the analysis of dynamic relations among various economic variables and has nowadays become standard when dealing with a large number of macroeconomic research questions.

The basic mathematical expression of the VAR model is as follows:

$$Ay_t = F_1 y_{t-1} + F_2 y_{t-2} + \cdots + F_s y_{t-s} + \mu_t, t = s + 1 + \cdots n \tag{1}$$

In this context, y_t represents a *K*1* dimensional column vector comprising both explanatory and response variables at time t; *A* is a *K*K* dimensional coefficient matrix, incorporating lag components, indicating the linear relationship of the variables at the current time t with their past values; $F_1 \cdots F_S$ signify *K*K* dimensional coefficient matrices, representing the impacts of lags from 1-period to s-period, they capture the dynamic relationships of the variables at different lag orders; μ_t denotes a *K*1* dimensional vector of random disturbances. In this study, there are six variables used in each model, so K = 6.

According to Sims (1980) and Primiceri (2005), we can set matrices *A* to be 6*6 matrices with a main diagonal consisting of ones, and matrix *A* is invertible. The specific form is as follows:

$$A = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ a_{21} & 1 & 0 & 0 & 0 & 0 \\ a_{31} & a_{32} & 1 & 0 & 0 & 0 \\ a_{41} & a_{42} & a_{43} & 1 & 0 & 0 \\ a_{51} & a_{52} & a_{53} & a_{54} & 1 & 0 \\ a_{61} & a_{62} & a_{63} & a_{64} & a_{65} & 1 \end{bmatrix} \tag{2}$$

Therefore, multiplying both sides of equation (1) by A^{-1} yields:

$$y_t = B_1 y_{t-1} + B_2 y_{t-2} + \cdots + B_s y_{t-s} + A^{-1} \sum \varepsilon_t \,, \varepsilon_t \sim N(0, I_6) \tag{3}$$

$$\Sigma = \begin{bmatrix} \sigma_1 & 0 & 0 & 0 & 0 & 0 \\ 0 & \sigma_2 & 0 & 0 & 0 & 0 \\ 0 & 0 & \sigma_3 & 0 & 0 & 0 \\ 0 & 0 & 0 & \sigma_4 & 0 & 0 \\ 0 & 0 & 0 & 0 & \sigma_5 & 0 \\ 0 & 0 & 0 & 0 & 0 & \sigma_6 \end{bmatrix}$$

σ_i *represents the standard deviation of structural shocks,* ε_t *is the residual term,* I_6 *is the identity matrix,* $B_i = A^{-1} F_i, i = 1,2 \ldots s$*. Let's stack the row elements of* B_i *as a column vector* β *of dimensions* $6^2 s*1$*. Define* $X_t = I_6 \otimes (y'_{t-1}, \cdots, y'_{t-s})$, $\otimes$ denotes the Kronecker product. Equation (3) can be expressed as:

$$y_t = X_t \beta + A^{-1} \sum \varepsilon_t \tag{4}$$

TVP-SV-VAR Model

Although VAR models excel at predicting and estimating dynamic relationships among economic variables, they have certain limitations. This is because in VAR models, coefficients and disturbance term variances remain constant throughout the entire modelling process. To overcome this limitation, Primiceri (2005) proposed the TVP-SV-VAR model, later extended by Nakajima (2011), a refinement that effectively addresses the drawbacks of the standard VAR model. What sets this model apart is its assumption that all parameters follow a random walk process, endowing it with considerable flexibility when identifying potential time-varying traits in economic systems.

The TVP-SV-VAR model can be written in the following form:

$$y_t = X_t \beta_t + A_t^{-1} \Sigma_t \varepsilon_t, \; t = s+1, \ldots, n \tag{5}$$

According to Nakajima (2011), $\beta_t, \; A_t, and \; \Sigma_t$ are time-varying, and assuming that $\alpha_t = (\alpha_{2,1}, \alpha_{3,1}, \alpha_{3,2}, \alpha_{4,1}, \ldots, \alpha_{k,k-1})'$ is a stacked vector comprising lower-triangular elements in A_t and the stochastic fluctuation term matrix is $h_t = (h_{1,t}, h_{2,t}, \ldots h_{k,t})'$, where $h_{jt} = \log \sigma^2_{jt}$, $j = 1,\ldots,6$, $t = s + 1 \ldots n$. In addition, assume that the specific parameters in equation (5) all follow a random walk process, $\beta_{t+1} = \beta_t + \mu_{\beta t}$, $\alpha_{t+1} = \alpha_t + \mu_{\alpha t}$, and $h_{t+1} = h_t + \mu_{ht}$.

$$\begin{bmatrix} \varepsilon_t \\ \mu_{\beta t} \\ \mu_{\alpha t} \\ \mu_{ht} \end{bmatrix} \sim N \left[0, \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & \Sigma_\beta & 0 & 0 \\ 0 & 0 & \Sigma_\alpha & 0 \\ 0 & 0 & 0 & \Sigma_h \end{bmatrix} \right], \tag{6}$$

where $\beta_{t+1} \sim N(\mu_{\beta 0}, \Sigma_{\beta 0}), \alpha_{t+1} \sim N(\mu_{\alpha 0}, \Sigma_{\alpha 0}), h_{t+1} \sim N(\mu_{h0}, \Sigma_{h0})$.

Model Setting

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We construct three models for Bitcoin, Ethereum, and Tether. The general formula for establishing the TVP-SV-VAR model is as follows:

$$y_t = X_t\beta_t + A_t^{-1}\sum\nolimits_t \varepsilon_t$$

Model 1: TVP-SV-VAR (Bitcoin)

$$y_t = (MSCI\ Ame_t, MSCI\ Eur_t, MSCI\ Asia_t, WTI_t, Exchange_t, bit_t)'$$

Model 2: TVP-SV-VAR (Ethereum)

$$y_t = (MSCI\ Ame_t, MSCI\ Eur_t, MSCI\ Asia_t, WTI_t, Exchange_t, eth_t)'$$

Model 3: TVP-SV-VAR (Tether)

$$y_t = (MSCI\ Ame_t, MSCI\ Eur_t,\ MSCI\ Asia_t,\ WTI_t,\ Exchange_t, tet_t)'$$

With the TVP-SV-VAR model set within a nonlinear framework, the highest likelihood estimation involves significant computational demands (Nakajima 2011; Yang et al. 2022). Every different combination of parameters necessitates heavy calculation in the evaluation of the likelihood function and repetition of filtering until the maximum value is found. We therefore follow Nakajima's approach to using the MCMC method in our empirical work. With the TVP-SV-VAR model set within a nonlinear framework, the highest likelihood estimation involves significant computational demands (Nakajima 2011; Yang et al. 2022). Every different combination of parameters necessitates heavy calculation in the evaluation of the likelihood function and repetition of filtering until the maximum value is found. We therefore follow Nakajima's approach to using the MCMC method in our empirical work.

Data Collection

In this article, we utilize the closing price of Bitcoin, Ethereum, and Tether (selected based on market capitalization), and choose the WTI Crude Oil Futures Contract Price as the benchmark crude oil price, and the exchange rates between the most frequently used currencies (EUR/USD), and the three regional equity indices for America, Europe, and Asia are respectively represented by MSCI AC Americas, MSCI AC Europe, and MSCI AC Asia Pacific. In a bid to ensure data sufficiency and the reliability of the empirical results, we chose weekly data for all eight variables, starting from 1st January, 2018, and ending on 1st January, 2023. All series are from Investing.com.

Table 1. Variables.

Variables	Descriptions	Sources
BIT	Bitcoin price	Investing.com.
ETH	Ethereum price	Investing.com.
TET	Tether price	Investing.com.
MSCIAMR	The MSCI AC Americas Index (MIAM00000PUS): Comprising 802 constituents, including a mix of large and mid-cap stocks from two Developed Markets (DM) and five Emerging Markets (EM) countries. (MSCI AC Americas Index, 2008). Developed Markets countries in the Americas index include: Canada and the US. Emerging Markets countries include: Brazil, Chile, Colombia, Mexico, and Peru.	Investing.com.
MSCASIA	The MSCI AC Asia Pacific Index (MIAP00000PUS): Comprising 1,545 constituents, including a mix of large and mid-cap stocks from 5 Developed Markets countries (DM) and 8 Emerging Markets (EM) countries. (MSCI AC Asia Pacific Index, 2008). Developed Markets countries in the Asia Pacific index include: Australia, Hong Kong, Japan, New Zealand, and Singapore. Emerging Markets countries include: China, India, Indonesia, Korea, Malaysia, the Philippines, Taiwan, and Thailand.	Investing.com.
MSCIEUR	The MSCI AC Europe Index (MIER00000PUS): Comprising 477 constituents, including a mix of large and mid-cap stocks from 15 Developed Markets countries and 5 Emerging Markets countries (MSCI AC Europe Index, 2008). Developed Markets countries in the Europe index include: Austria, Belgium, Denmark, Finland, France, Germany, Ireland, Italy, the Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, and the UK. Emerging Markets countries include: the Czech Republic, Greece, Hungary, Poland, and Turkey.	Investing.com.
WTI	Crude Oil Futures Contract Price as the benchmark crude oil price	Investing.com.
Exchange	the exchange rates between the most frequently used currencies (EUR/USD)	Investing.com.

Empirical Analyses

ADF Test

The TVP-SV-VAR model is an extension of the VAR model, which imposes certain requirements on the stationarity of variables. In this study, the Augmented Dickey-Fuller (ADF) test is selected to examine the stationarity of variables. Those results are presented in Table 2.

Table 2. ADF test result. Note: *** and ** indicate significance at the 1% and 5% levels, respectively. *(Source: calculated by EViews 12 software)*

Variables	ADF statistics	Critical value (1%)	Critical value (5%)	Critical value (10%)	P-value	Stationarity
MSCI AMR	-1.2839	-3.4554	-2.8725	-2.5727	0.6376	NO
dln(Msci AMR)	-17.150	-3.4555	-2.8725	-2.5727	0.0000***	YES
MSCI EUR	-2.1734	-3.4554	-2.8725	-2.5727	0.2167	NO
dln(Msci EUR)	-15.988	-3.4555	-2.8725	-2.5727	0.0000***	YES
Msci ASIA	-1.6001	-3.4554	-2.8725	-2.5727	0.4811	NO
dln (Msci ASIA)	-15.912	-3.4555	-2.8725	-2.5727	0.0000***	YES
BIT	-1.2942	-3.4554	-2.8725	-2.5727	0.6329	NO
dln(BIT)	-16.041	-3.4555	-2.8725	-2.5727	0.0000***	YES
ETH	-1.4118	-3.4554	-2.8725	-2.5727	0.5764	NO
dln(ETH)	-15.361	-3.4555	-2.8725	-2.5727	0.0000***	YES
TET	-6.7978	-3.4554	-2.8725	-2.5727	0.0000***	YES
dln(TET)	-11.646	-3.4555	-2.8726	-2.5728	0.0000***	YES
WTI	-1.5142	-3.4554	-2.8725	-2.5727	0.5250	NO
dln(WTI)	-13.448	-3.4555	-2.8725	-2.5727	0.0000***	YES
Exchange	-1.4314	-3.4555	-2.8725	-2.5727	0.5667	NO
dln(Exchange)	-19.240	-3.4555	-2.8725	-2.5727	0.0000***	YES

According to Table 2, it can be observed that the original series only exhibits stationarity for the variable TET at a 1% significance level, while the remaining variables are non-stationary sequences. After applying logarithmic form and first-order differencing, all variable sequences become stationary and are significant at a 1% significance level. Therefore, in this study, the TVP-SV-VAR model was created using the logarithmic form and first-order differenced series (Zhang 2020; Wang 2020).

Determination of the Optimal Lag Order

First, we need to establish a VAR model for the six variables in the three models to choose the optimal lag order. Tables 3, 4, and 5 make it clear that two lags are the ideal number for the Bitcoin and Ethereum models, and three lags are the ideal number for the Tether model, based on the AIC criteria (Akaike 1974).

Table 3. VAR lag order selection criteria (Bitcoin). *(Source: calculated by EViews 12 software)*

Lag	LogL	LR	FPE	AIC	SC	HQ
0	3349.656	NA	1.64e-19	-26.2248	-26.1414*	-26.1912*
1	3408.419	114.3001	1.38e-19	-26.4033	-25.8200	-26.1687
2	3445.031	69.4908	1.37e-19*	-26.4081*	-25.3249	-25.9724
3	3481.003	66.5836	1.37e-19	-26.4079	-24.8247	-25.7711
4	3510.734	53.6318	1.44e-19	-26.3587	-24.2756	-25.5208
5	3541.701	54.4041*	1.51e-19	-26.3192	-23.7362	-25.2802

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Table 4. VAR lag order selection criteria (Ethereum). *(Source: calculated by EViews 12 software)*

Lag	LogL	LR	FPE	AIC	SC	HQ
0	3280.730	NA	2.82e-19	-25.68416	-25.60083*	-25.65064*
1	3339.360	114.0407	2.36e-19	-25.86165	-25.27838	-25.62703
2	3375.721	69.01502	2.36e-19*	-25.8645*	-24.78127	-25.42877
3	3409.067	61.72279	2.41e-19	-25.84366	-24.26051	-25.20685
4	3440.415	56.54891*	2.51e-19	-25.80717	-23.72408	-24.96927
5	3469.283	50.71763	2.66e-19	-25.75124	-23.16820	-24.71223

Table 5. VAR lag order selection criteria (Tether). *(Source: calculated by EViews 12 software)*

Lag	LogL	LR	FPE	AIC	SC	HQ
0	4207.460	NA	1.97e-22	-32.95263	-32.86931*	-32.91911*
1	4262.989	108.0090	1.69e-22	-33.10580	-32.52253	-32.87118
2	4305.994	81.62581	1.60e-22	-33.16074	-32.07753	-32.72503
3	4342.925	68.35732	1.59e-22*	-33.1680*	-31.58488	-32.53123
4	4377.073	61.60033	1.62e-22	-33.15351	-31.07042	-32.31560
5	4411.569	60.60547*	1.64e-22	-33.14172	-30.55868	-32.10271

Markov Chain Monte Carlo (MCMC) Simulation Results

The three models' parameter estimation results are displayed in Tables 6, 7, and 8. The sample size of the MCMC algorithm is set at 10000. Consequently, the first 1000 samples are not considered. We mainly observe the last two columns, as the validity of the model parameter estimation result mainly depends on sampling convergence and the inefficiency factor. The CD statistic (Geweke 1991) gauges the convergence of the Markov chain, with the null hypothesis that the estimated parameters of the model exhibit convergence to that of the posterior distribution at the significance level of 5%. The inefficiency factor reflects the validity of the estimation result. It can be seen from Tables 6, 7 and 8 that the 95% credible intervals encompass all the estimated posterior means, and the standard deviations are small; at the 5% significance level, all CD statistics are below the critical value of 1.96, signifying that the models do not exhibit refusal to converge towards the posterior distribution; the inefficiency factors are small values, and all values are less than 100. Therefore, we can obtain effective parameter results by using the MCMC algorithm for three models.

Table 6. Parameter's estimation result (Bitcoin). Note: $y_t = X_t\beta_t + A_t^{-1}\sum_t \varepsilon_t$,the lower-triangular elements in A_t can be converted and expressed as $\alpha_t = (\alpha_{2,1}, \alpha_{3,1}, \alpha_{3,2}, \alpha_{4,1}, \dots, \alpha_{k,k-1})'$ and stochastic fluctuation term matrix is $h_t = (h_{1,t}, h_{2,t}, \dots h_{k,t})'$.*(Source: calculated by OX Metrics 6.0 software)*

Parameter	Mean	Stdev	95%L	95%U	Geweke	Inef.
(Σβ)1	0.0226	0.0025	0.0184	0.0281	0.803	12.53
(Σβ)2	0.0226	0.0026	0.0182	0.0285	0.422	19.63
(Σa)1	0.0718	0.0235	0.0406	0.1282	0.386	95.52
(Σa)2	0.0636	0.0188	0.0374	0.1138	0.875	58.41
(Σh)1	0.3810	0.0436	0.3038	0.4730	0.155	52.39
(Σh)2	0.3864	0.0589	0.2827	0.5137	0.004	63.40

Table 7. Parameter's estimation result (Ethereum). Note: same as Table 6. *(Source: calculated by OX Metrics 6.0 software)*

Parameter	Mean	Stdev	95%L	95%U	Geweke	Inef.
(Σβ)1	0.0225	0.0026	0.0181	0.0283	0.829	13.49
(Σβ)2	0.0224	0.0025	0.0183	0.0281	0.170	11.06
(Σa)1	0.0678	0.0203	0.0389	0.1186	0.021	78.21
(Σa)2	0.0637	0.0181	0.0376	0.1035	0.802	68.41
(Σh)1	0.3892	0.0437	0.3113	0.4820	0.082	47.61
(Σh)2	0.4146	0.0585	0.3110	0.5418	0.003	78.57

Table 8. Parameters estimation result (Tether). Note: same as Table 6. *(Source: calculated by OX Metrics 6.0 software)*

Parameter	Mean	Stdev	95%L	95%U	Geweke	Inef.
(Σβ)1	0.0223	0.0024	0.0182	0.0276	0.008	10.85
(Σβ)2	0.0227	0.0026	0.0183	0.0283	0.397	7.91
(Σa)1	0.0667	0.0205	0.0381	0.1187	0.018	81.81
(Σa)2	0.0630	0.0172	0.0382	0.1038	0.963	57.61
(Σh)1	0.4401	0.0758	0.3021	0.6026	0.034	36.56
(Σh)2	0.4143	0.0495	0.3268	0.5234	0.000	36.35

Figures 1, 2, and 3 show the autocorrelation coefficient diagram (first row), sample trend path diagram (second row), and posterior density distribution graph (third row). It can be clearly seen from Figures 1, 2, and 3 that the sample autocorrelation function decays rapidly from a high level; the sample path also tends to converge and presents a stable state; the posterior distribution density function presents a normal distribution.

Therefore, according to Figures 1, 2, 3, and Tables 6, 7, 8, it can be known that the sample data in the three models obtained through MCMC sampling is effective, there is no autocorrelation, and the model's fitting degree is high.

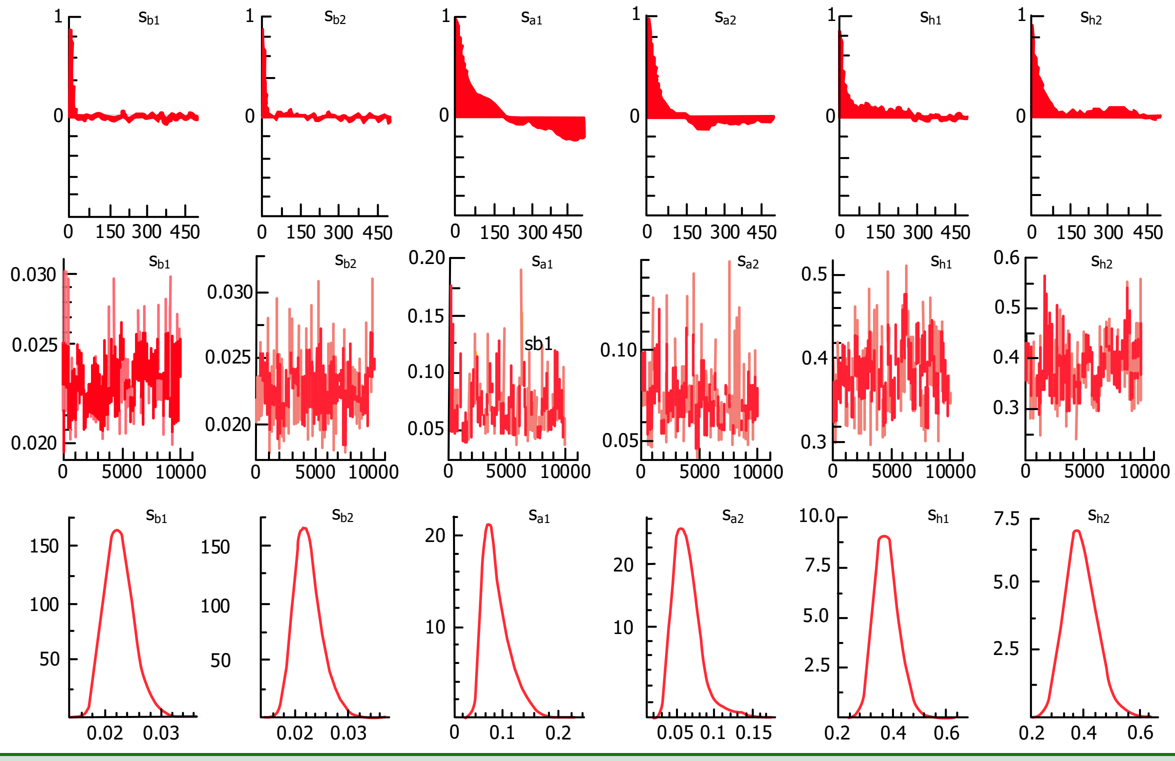

Figure 1. MCMC parameter simulation path distribution (Bitcoin). Note: Sample autocorrelation (first row), sample path (second row), and posterior density (third row).

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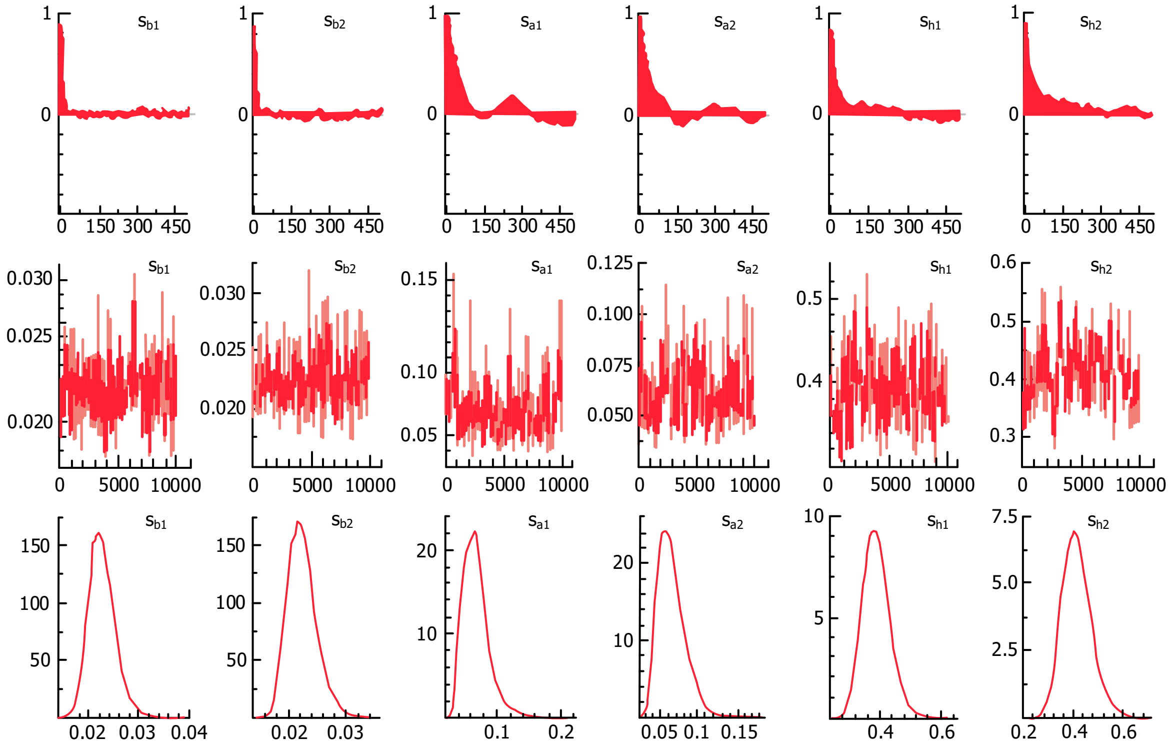

Figure 2. MCMC parameter simulation path diagram (Ethereum). Note: Sample autocorrelation (first row), sample path (second row), and posterior density (third row).

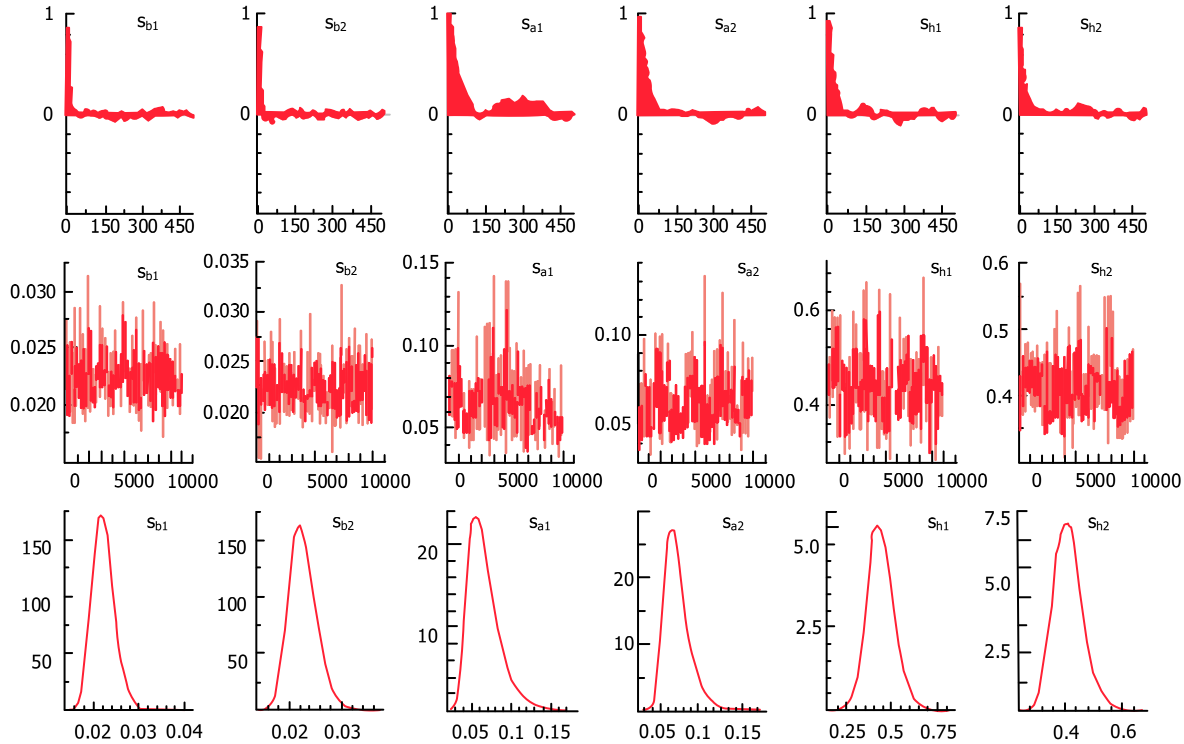

Figure 3. MCMC parameter simulation path diagram (Tether). Note: Sample autocorrelation (first row), sample path (second row), and posterior density (third row)

RESULTS

Impulse Response Analysis

The different lag periods' impulse response function reflects the dynamic effect of the shock on the explanatory variable on the response variable at different lag periods. Figures 4, 5, and 6 represent the impulse responses of Bitcoin, Ethereum, and Tether, where a positive standard deviation shock is applied to MSCI AC Americas, MSCI AC Europe, MSCI AC Asia Pacific, crude oil price, and exchange rates. The impulse response results with lags of 4 periods (one month), 8 periods (two months), and 12 periods (three months), are represented by red, purple, and blue lines, respectively. The horizontal axis indicates the time, while the vertical axis indicates the percentage deviation of the response variable from its original value after explanatory variables are subjected to a shock.

Impulse Response Results at Different Lags Periods (Bitcoin)

Figure 4. Impulse response results at different lag periods (Bitcoin).

Looking at Figure 4, over the four periods, MSCI Asia had the most pronounced effect on Bitcoin. When a positive shock is imposed on the MSCI Asia, Bitcoin exhibits a negative impulse response firstly, while shifted to positive in mid-2020, then flipped back to negative in 2022, with the impulse response coefficient ranging between -0.004 and 0.002. MSCI America came next, with a coefficient range of -0.003 to 0.002, and interestingly, its trend ran counter to that of MSCI Asia, firstly with a positive response, then a shift to a negative response, and exhibited a trend of converging to the zero axis. Bitcoin's impulse response to MSCI Europe was negative at first, turned positive in early 2020, and gradually exhibited a trend of converging around 0.003. In addition, Bitcoin reacted positively to WTI crude and exchange rates at first; the effect of the exchange rate turned negative early in 2020 and stayed negative up to 2023, whereas WTI had an overall negative effect on Bitcoin up to 2021, and a short-lived positive was seen in 2022, before it returned to negative levels in

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2023. The influence of Bitcoin on itself was overall positive over the time frame, except for short spells of negativity in late 2020 and mid-2021.

In the 8-periods, Bitcoin's impulsive responses to various variables indicate unmistakable weakening, largely fluctuating around the 0-axis. After 2021, the influences of MSCI Europe, MSCI Asia, WTI, and Bitcoin itself on Bitcoin are predominantly positive, albeit with small coefficients. While Bitcoin generates negative impulse responses to MSCI America and exchange rates. The change in 12 periods is unnoticeable, and the impulse response curve almost coincides with the 0-axis.

In summary, Bitcoin's impulse response graphs exhibit obvious time-varying characteristics, more pronounced with smaller lag periods. And MSCI Asia has the largest effect, followed by MSCI America. The effect of oil prices and exchange rate on Bitcoin has undergone positive-negative transitions; they initially exerted a positive effect and shifted to a negative one in the subsequent long term.

Impulse Response Results at Different Lags Periods (Ethereum)

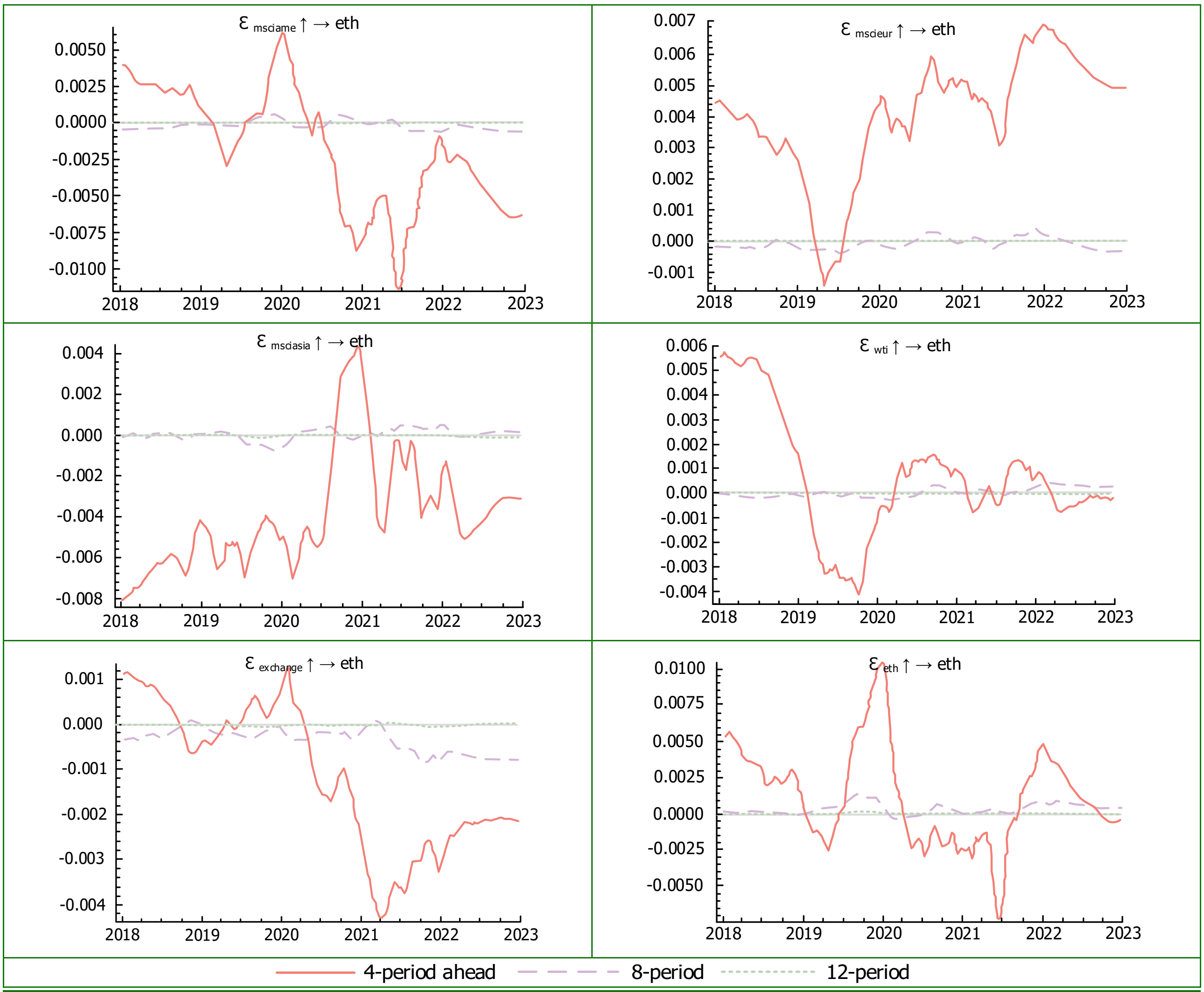

Figure 5. Impulse response results at different lag periods (Ethereum).

Analysing Figure 5, in the 4-periods, MSCI Americas has the most substantial effect on Ethereum among the three regional equity markets, with an impulse response coefficient ranging from -0.013 to 0.005. Ethereum's impulse response to MSCI America begins positively, experiences a slight negative reflection in mid-2019, turns positive again in early 2020, reaching a peak positive effect of 0.005, and then transitions to a negative effect, reaching a nadir below -0.010 and maintaining the negative influence until 2023. MSCI Asia's response to Ethereum is largely negative, except for a brief positive spike in late 2020. Conversely, Ethereum's response to MSCI Europe is largely positive, except for a brief negative dip in mid-2019. Ethereum's response to WTI is mixed, firstly with a positive response, and oscillates between positive and negative effects, finally exhibiting a trend of converging to the zero axis. With regard to the exchange rate, Ethereum reacted positively initially but then reverted to a negative reaction from mid-2020 to 2023. Ethereum's autonomous effect varies between positive and negative, with negative effects occurring in 2019, 2020, and 2021.

In the 8-periods, Ethereum's impulse responses to three regional equity markets exhibit noticeable attenuation, primarily fluctuating around the 0-axis. While Ethereum's impulse response to exchange rates is slightly more pronounced, it predominantly exhibits negative effects. And Ethereum itself mainly shows a positive effect, with a small effect coefficient. In addition, there is negligible alteration across 12 periods, and the impulse response curve closely aligns with the 0-axis.

In general, Ethereum impulse response graphs exhibit obvious time-varying characteristics, with patterns becoming more apparent as the lag periods decrease. MSCI Americas has the most significant effect on Ethereum among the three regional equity markets. In mid-2019, Ethereum showed varying degrees of negative impulse responses to different variables, possibly associated with adverse events in the decentralised financial platform and market fluctuations related to Ethereum's value and market capitalisation.

Impulse Response Analysis at Different Lags Periods (Tether)

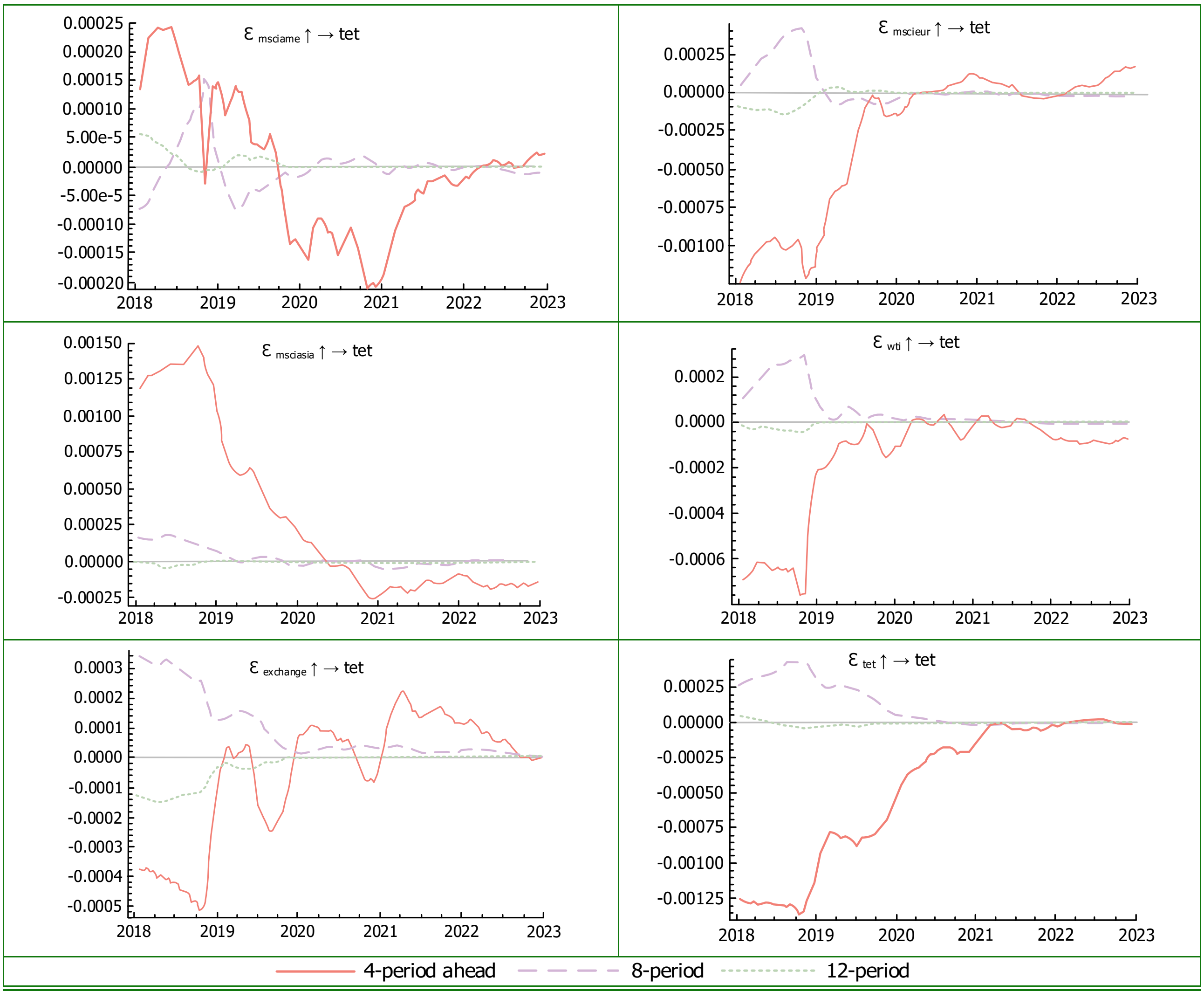

Figure 6. Impulse response analysis at different lag periods (Tether).

Analysing Figure 6, in the 4 periods, Tether exhibits a small impulse response coefficient for six variables, ranging from -0.001 to 0.0016. The effect of MSCI Asia on Tether is slightly more noticeable than other variables, remaining positive from the initial period to mid-2020 and transitioning to a negative influence with a converging trend towards the 0-axis. Similarly, the initial impulse response to MSCI Americas is also positive, but it shifts to a negative effect from 2020 to 2022, with a tendency to converge towards the 0-axis in 2023. Additionally, Tether's responses to MSCI Europe, WTI, and itself follow a similar trend, starting with an initial negative effect and gradually diminishing, ultimately converging towards the

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0-axis. Moreover, the initial impulse response to exchange rates is also negative, followed by a periodic transition with positive correlation and negative correlation, and finally, it also shows a convergence trend to the 0-axis.

In the 8-periods, although the impulse responses of Tether have diminished and converged towards the 0-axis, in the period 2018 - 2019, Tether exhibited different degrees of positive responses to other variables. However, in the 12-periods, apart from an initial positive reflection towards MSCI Americas and an initial negative reflection towards MSCI Europe and exchange rates, the impulse responses to other variables almost coincided with the 0-axis.

In general, Tether's response to MSCI Asia is a little more pronounced compared to the other variables, while the impulse response magnitude of Tether on other variables is relatively small, with coefficients fluctuating between -0.001 and 0.0016, which indicates that Tether maintains relative stability in the face of external shocks.

Impulse Response Analysis at Different Time Points

The time-point impulse response reflects the dynamic effect of the shock on the explanatory variable on the response variable at a specific point in time. We impose a positive standard deviation shock on the selected variables in the context of three specific time points. This study chooses three special time points regarding COVID-19 to study the effect of the epidemic on economic variables. March 2-8, 2020 (2020.10): WHO declared COVID-19 a global pandemic. December 7-13, 2020 (2020.50): Many countries began to roll out COVID-19 vaccines and conduct global vaccination efforts. August 23-29, 2021 (2021.34): Some countries began to relax epidemic controls. Issues 2020.10, 2020.50, and 2021.34 are represented by red lines, black lines, and purple lines, respectively. The horizontal axis indicated the lag periods, and the vertical axis indicated the percentage of the response variable that deviates from the original value after being impacted.

Impulse Response Results at Different Time Points (Bitcoin)

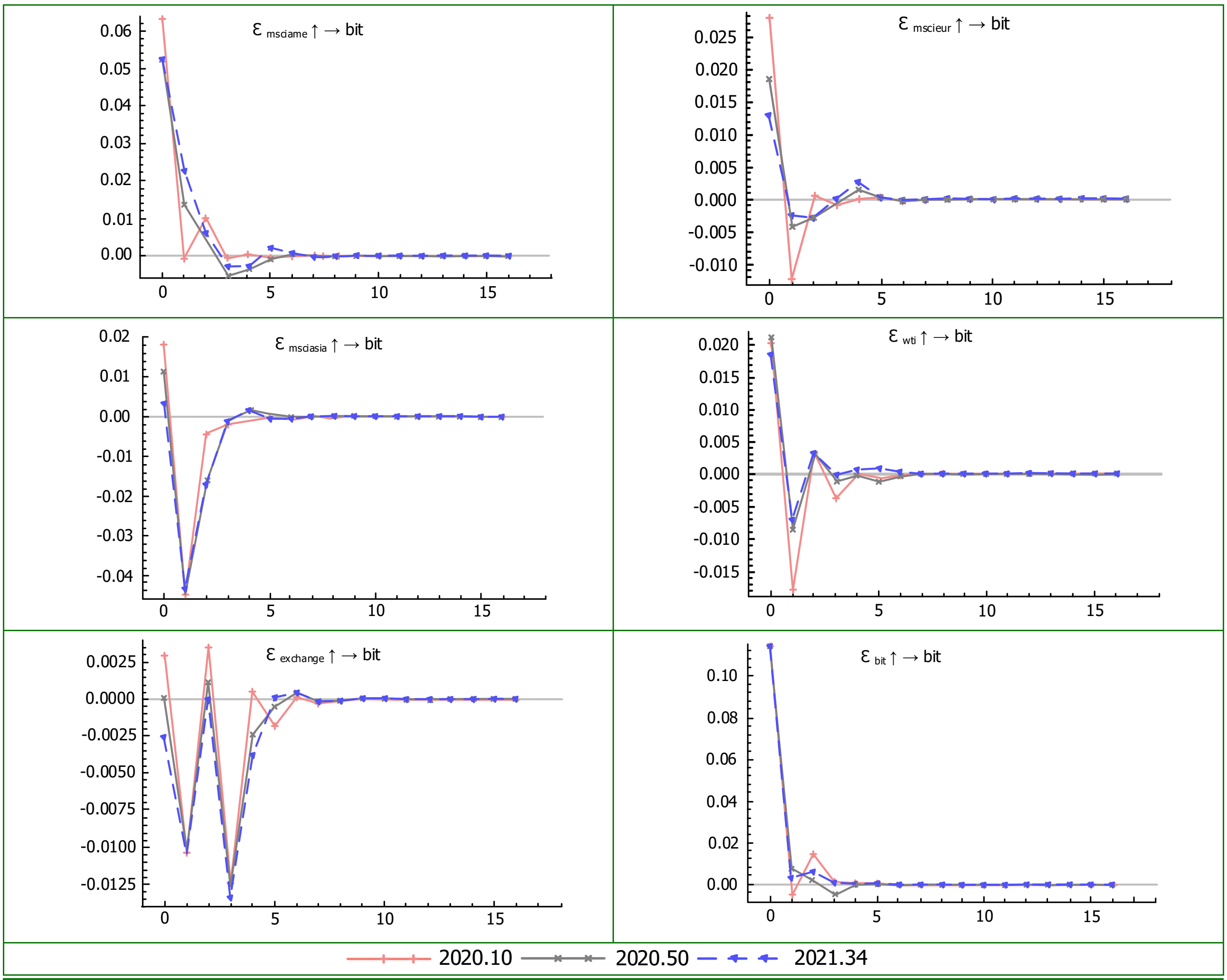

Figure 7. Impulse response results at different time points (Bitcoin).

Figure 7 shows the impulse responses of Bitcoin to each variable at three different time points. It is evident that the impulse response curves at the designated three time points almost overlap on the six graphs. The trends of Bitcoin's responses to three regional equity markets and WTI are analogous, like a shape 'V', with initial positive responses shifting to negative effects, diminishing, turning positive at a lag of 5 periods, and then converging to the 0-axis. This indicates that the effect of regional equity markets and WTI on Bitcoin is more pronounced if considered in the short term than in the long term for the three time points. Interestingly, Bitcoin's impulse responses to exchange rates differ; its shape is like 'W', with many alternations between positive and negative effects. While Bitcoin's self-response remains consistently positive, diminishing over time, and finally converging to zero effect. Moreover, the magnitude of their influence on Bitcoin varies, apart from the impact itself, MSCI America having the largest impact coefficient [-0.01, 0.06], followed by MSCI Asia [-0.04, 0.02]. Analysing from the time points perspective, at the time point 2020.10, Bitcoin's responses are slightly more pronounced than at the other two time points, indicating a greater effect of the COVID-19 outbreak event on Bitcoin prices.

In summary, Bitcoin's impulse response during the outbreak period (2020.10) is most pronounced. Among the three regional equity markets, MSCI Americas has an immense effect on Bitcoin in the context of COVID-19. Bitcoin's responses are concentrated in the short term, converging towards the 0-axis over longer durations.

Impulse Response Results at Different Time Points (Ethereum)

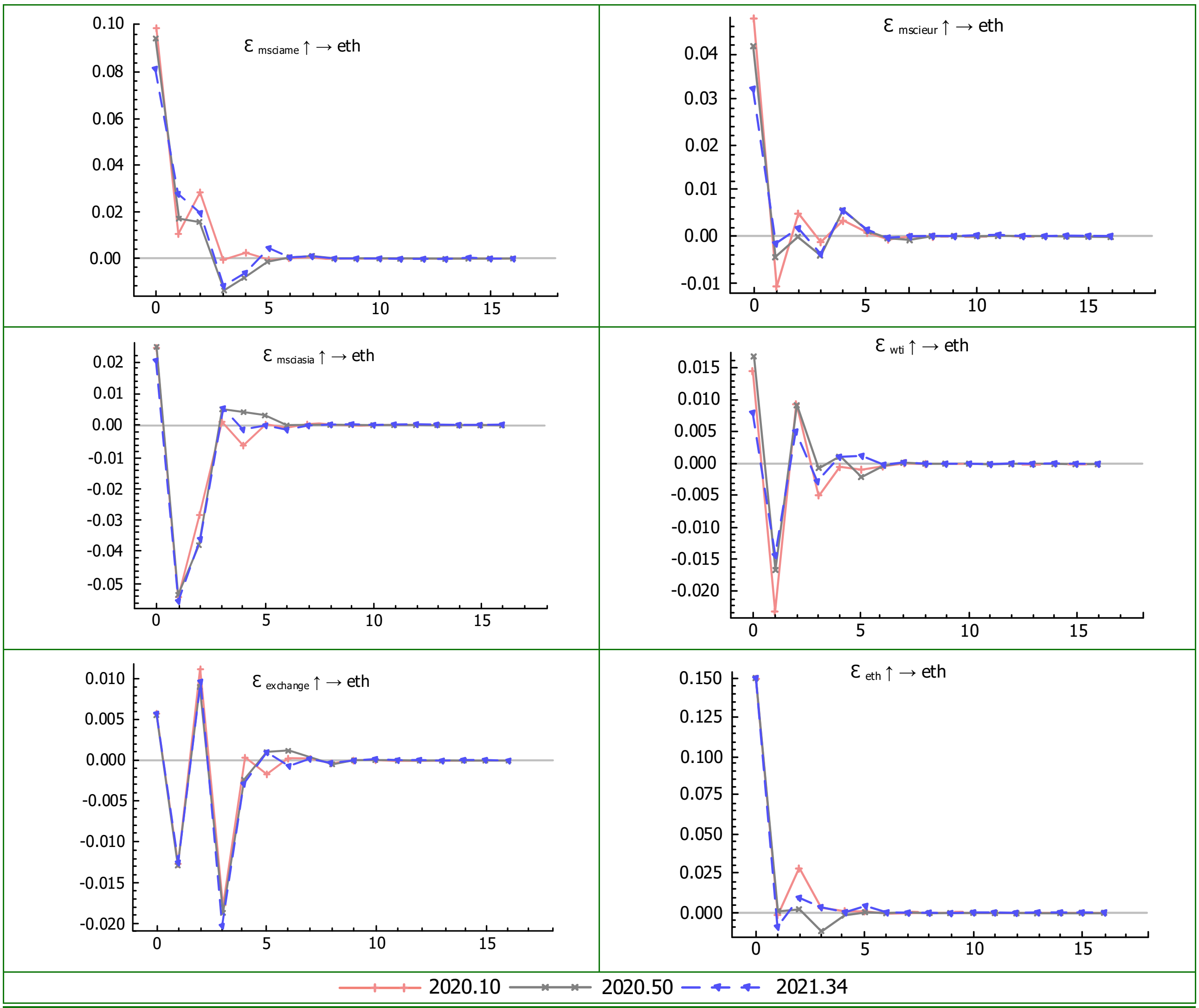

Figure 8. Impulse response results at different time points (Ethereum).

Figure 8 indicates that Ethereum's impulse responses to the six variables are on the same pattern across the three varying points in time, with only slight differences in the size of impact. The responses of Ethereum to regional equity markets and WTI crude oil follow a similar pattern: initially positive, turning negative in the 1-lag period (but MSCI Americas turns

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negative at 3-lags), then oscillating back to positive before finalizing in the direction of the zero axis. Its responses to exchange rates vary dynamically between positive and negative, showing high variability. As for self-impact, Ethereum mostly exerts a positive influence, with just a short-lived negative blip during the vaccine rollout phase. Analysing from the time-points perspective, Ethereum's responses are most pronounced at the outbreak period (2020.10) time point, with MSCI Americas having the largest impact coefficient [-0.02, 0.10], apart from its own impact.

In summary, the impact direction and trend of variables on Ethereum are generally in tune at the three time points, with the strongest response observed during the COVID-19 outbreak (2020.10). And apart from the effect itself, the impulse response to MSCI Americas is more pronounced.

Impulse Response Results at Different Time Points (Tether)

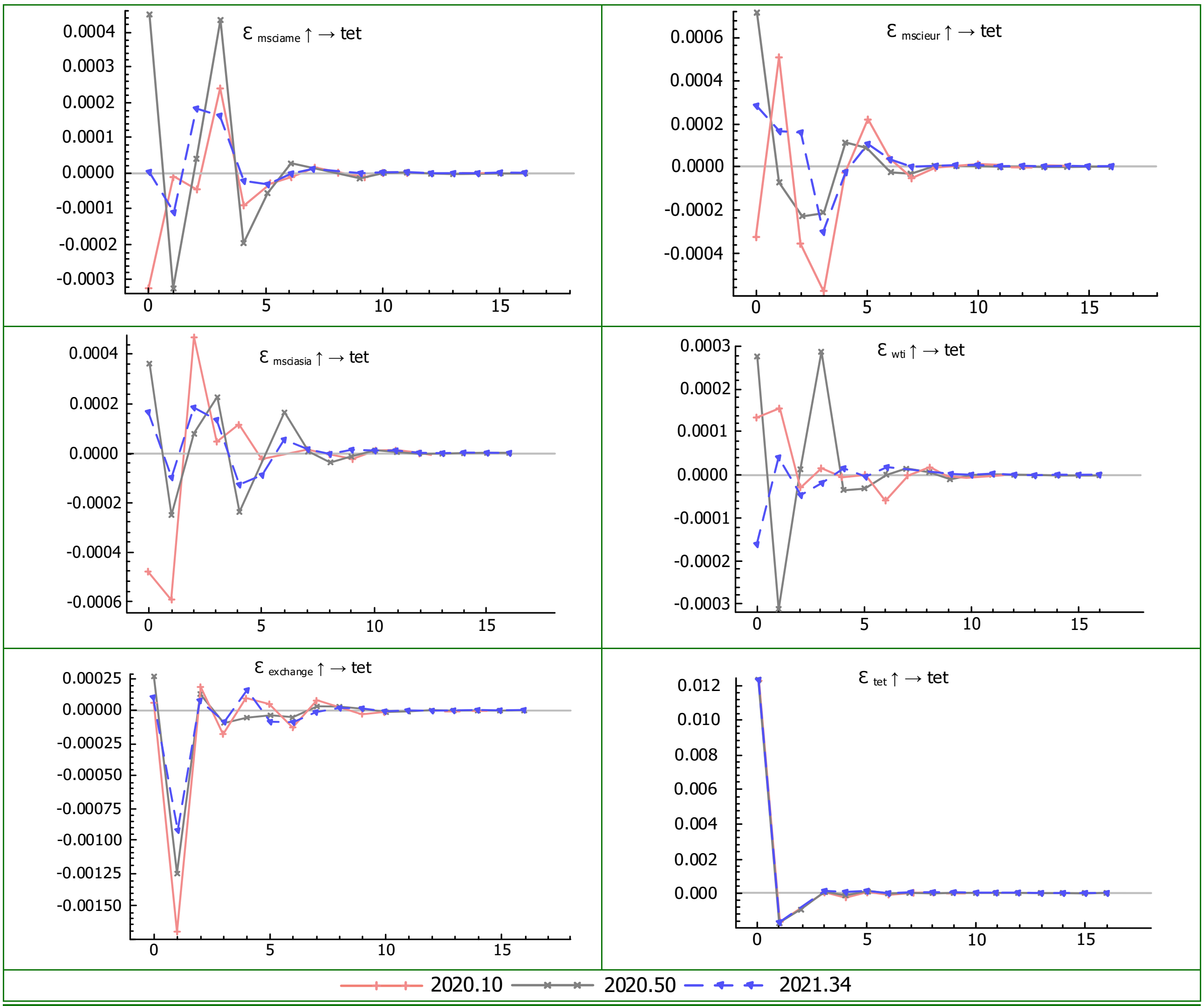

Figure 9. Impulse response results at different time points (Tether).

From Figure 9, the impulse response of Tether to the three regional equity markets and WTI are at three time points similar, showing apparent volatility in the first 5 periods and then converging back to the 0-axis before the 10-lag periods. The impulse response to MSCI Europe and MSCI Asia is more pronounced at the COVID-19 pandemic outbreak time points (2020.10), while it is more pronounced at vaccine distribution time points (2020.50) for MSCI Americas and WTI. In addition, the impulse response to the exchange rate and Tether itself is different from others. The impulse response curves to the exchange rate at three time points have the same trend, resembling the shape of a 'V' with the curve at the bottommost corresponding to the COVID-19 pandemic outbreak time points. Even though the response to Tether itself remains nearly unchanged at the three time points, it initially displays a positive effect, experiences brief negative effects over two periods, and then converges towards the 0-axis.

In summary, Tether exhibits different responses at the three time points, with noticeable variations in the early stages and a gradual convergence towards the 0-axis in later periods. Although the coefficients of the impulse responses are quite small, primarily ranging from -0.001 to 0.001, apart from its own effect, the most significant impact coefficient is observed on MSCI Europe, ranging from -0.0006 to 0.0007.

DISCUSSION

The paper follows Primiceri (2005) and Nakajima (2011) to employ the TVP-SV-VAR model using the Markov Chain Monte Carlo (MCMC) method. We selected this empirical method as it has some advantages. Specifically, the TVP-SV-VAR model integrates the characteristics of time-varying parameters, stochastic volatility, and multivariate vector autoregression, making it particularly well-suited for analysing temporal dynamics and volatility within financial markets.

From the different lag periods impulse response analysis, we can know: the impulse response graphs of Bitcoin, Ethereum, and Tether demonstrate obvious time-varying patterns. From the perspective of the intensity of the shocks, the effect of regional equity markets, WTI, and exchange rates on cryptocurrency prices tends to gradually diminish over time. The 4-period impulse response is the most pronounced, the effect diminishes notably in the 8-period, and the effect is nearly negligible in the 12-period. At the same time, cryptocurrencies mostly exhibit a positive response to themselves, and this influence is more notable in the short term, diminishing over time. Within the regional equity markets analysis, MSCI Asia emerges as the most influential market for both Bitcoin and Tether, while MSCI Americas has the most significant effect on Ethereum. These results align with the findings of Zeng et al. (2023), who pointed out that MSCI Americas exerts the most pronounced effect on Ethereum.

From the performed impulse response analysis for various points in time, it follows that the general pattern of reaction at the three chosen time points is typical for cryptocurrencies: a positive response at the beginning, a short-lived negative deviation, and gradual convergence to the zero axis. One can notice that Bitcoin and Ethereum are characterised by similar degrees of responsiveness for the three time points, with a slightly higher response at the time point of the COVID-19 outbreak, in October 2020. In contrast, Tether displays heightened sensitivity at the vaccine distribution time point (2020.50), and some of its initial response is negative, distinguishing it from Bitcoin and Ethereum. The time point impulse responses are pronounced in the first 5-lag periods and gradually converge to the 0-axis over time, indicating that the effect of uncertainties related to the pandemic of COVID-19 on cryptocurrencies is mainly short-term, diminishing, and disappearing over time. The finding is in line with Kim and Lee (2021), who mentioned that the complexity level of the cryptocurrency field was highest during the outbreak period of COVID-19. The finding is also consistent with Salisu & Ogbonna (2021), who observed that the effect of COVID-19 is greatly reduced entering the second wave.

Regarding the discussion of the situation in the cryptocurrency market. For Bitcoin, it is interesting that the time period from 2020 to 2021 may have been affected by the COVID-19 pandemic and therefore experienced varied variations. For Ethereum, impulse response graphs indicate large time-varying trends. Ethereum had various degrees of negative impulse responses to the other variables in mid-2019, perhaps due to its internal issues during the time, such as vulnerabilities and security weaknesses in decentralised finance (DeFi) systems or capital movement-driven market volatility. Similarly, the COVID-19 pandemic negatively affected Ethereum. For Tether, however, the coefficients of impact on other variables were relatively low, ranging from -0.001 to 0.0016. This would mean that the effect of these variables on Tether was minimal. This is highly likely because Tether (USDT) is a stablecoin whose price is pegged against the U.S. dollar, and because of this, it is quite stable in the crypto market. In general, Tether is more stable than Bitcoin and Ethereum. That said, investors need to be on their guard, paying close attention to market developments and the risks that come with stablecoins. Our results reinforce the words of Goodell and Goutte (2021), who noted that Tether is a safe-haven asset in times of negative market movements. Unlike the majority of cryptocurrencies, which do not demonstrate characteristics of a safe haven, Tether's unique behaviour is most probably credited to its stablecoin status.

CONCLUSIONS

The results of our work mirror the dynamic and intricate relationships between cryptocurrencies and financial factors and hold significant implications for research on time-varying effects for Bitcoin, Ethereum, and Tether. The study objectives were largely achieved: the TVP-SV-VAR framework successfully identified time-varying spillover effects between regional equity markets and cryptocurrencies and demonstrated that these effects are strongest in short horizons and decline over time. The analysis confirms heterogeneous regional influences, with Asia exerting stronger effects on Bitcoin and Tether and the Americas influencing Ethereum more significantly. The results also indicate that COVID-19 intensified short-term

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spillovers but did not produce persistent long-run transmission. This research, thus, deepens our knowledge of the relationships among cryptocurrencies and various economic variables, making it of great reference to policymakers and investors.

Recommendations for Policymakers

A critical mandate involves the rigorous exploration of deeper cross-variable relationships. This necessitates the commissioning of comprehensive empirical studies focused on the complex and often non-linear interdependent linkages between established macroeconomic indicators and the evolving cryptocurrency asset class. The attainment of a clear systemic comprehension of these relationships is fundamentally central to accurately forecasting the mechanics of market movements and discerning emergent trends. This analytical clarity, in turn, proves instrumental in the informed and effective formulation of tailored, adaptive regulatory frameworks designed for the nascent digital asset ecosystem.

The implementation of a structured, regular evaluation protocol for stablecoin market performance is strongly advised as a macro-prudential measure. This framework should mandate the continuous assessment of key stablecoin instruments, specifically those of significant market capitalisation such as Tether (USDT), in order to meticulously evaluate their systemic responsiveness and operational resilience when subjected to various exogenous shocks and heterogeneous external macroeconomic factors. Such diligent oversight is a prerequisite for verifying their ongoing compliance with established regulatory mandates concerning internal stability and operational market efficacy, thereby contributing directly to the maintenance of broader financial stability across the integrated market structure.

Recommendations for Portfolio Managers and Investors

Portfolio managers and institutional investors are strongly encouraged to cultivate a granular, empirically driven understanding of the inherent heterogeneity and sensitivity profiles across the diverse range of digital assets. This entails the rigorous development of an analytical comprehension regarding the distinct impulse response patterns and shock transmission dynamics characterising individual cryptocurrencies within varying market regimes. The resultant analytical clarity is pivotal in enabling investment professionals to significantly enhance the overall efficacy and risk-adjusted returns of their investment portfolios and to maximise allocative efficiency during the process of strategic asset deployment.

A key aspect of investment practice is the requirement for vigilant, continuous surveillance of overarching market trends and potentially consequential global events. This monitoring effort must encompass crucial external financial factors, including, but not limited to, the performance metrics of regional stock exchanges, fluctuations in the pricing of benchmark commodities such as West Texas Intermediate (WTI) crude oil futures, and established national exchange rate dynamics. Paramount attention must also be paid to significant geopolitical developments and macroeconomic shifts on a global scale, given their demonstrable and potent influence on the valuation and volatility of the cryptocurrency market, thereby necessitating the proactive and timely repositioning and strategic adjustment of existing investment mandates.

It is incumbent upon investors to meticulously manage the perpetual risk-return trade-off, exercising due prudence informed by quantitative analysis. Specifically, regarding digital stable assets, notably Tether (USDT), practitioners should remain cognizant of their characteristically modest impact coefficients on portfolio volatility alongside their inherent, albeit latent, vulnerabilities to systemic instability. Furthermore, a high degree of caution must be maintained concerning emergent risks stemming from unforeseen changes in regulatory frameworks and the potential for abrupt, high-magnitude market dislocations. Therefore, the implementation and consistent adherence to comprehensive and analytically sound risk management strategies are essential to optimally equate the prospect of competitive returns with systemic risk mitigation and capital preservation objectives.

However, it should be noted that while the results provide useful signals for portfolio diversification and hedging, investors should not rely solely on regional equity indicators when making allocation decisions. This is because cryptocurrency markets are influenced by multiple interacting factors like macroeconomic policy, liquidity conditions, technological developments, regulation, and behavioural dynamics beyond those included in the present model. The relationship between regional equity indices and cryptocurrencies is a complex and ongoing field of study, compounded by regional differences, changing regulatory environments, and the effect of control variables on this fluid relationship. So, the present findings should be interpreted cautiously.

Future Research

Future research may extend these findings by incorporating alternative frequencies of data. Additional data for recent years could also be added in future studies. Moreover, additional macro-financial variables and cross-country regulatory heterogeneity could also be implemented. For instance, Brent, additional exchange rates, and interest-rate indicators could be explored in future studies. Moreover, nonlinear time-varying models could also be implemented to further elucidate the evolving transmission mechanisms between cryptocurrencies and traditional financial markets.

ADDITIONAL INFORMATION

AUTHOR CONTRIBUTIONS

Conceptualization: *Mohd Azlan Shah Zaidi, Yuanyuan Wang*
Data curation: *Yuanyuan Wang*
Formal Analysis: *Yuanyuan Wang*
Software: *Yuanyuan Wang*
Resources: *Mohd Azlan Shah Zaidi*
Supervision: *Mohd Azlan Shah Zaidi*
Validation: *Mohd Azlan Shah Zaidi, Yuanyuan Wang*
Project administration: *Mohd Azlan Shah Zaidi*
Writing – review & editing: *Mohd Azlan Shah Zaidi, Yuanyuan Wang*
Writing – original draft: *Yuanyuan Wang*

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CONFLICT OF INTEREST

The Authors declare that there is no conflict of interest.

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ЗВ'ЯЗОК МІЖ КРИПТОВАЛЮТАМИ ТА РЕГІОНАЛЬНИМ ІНДЕКСОМ АКЦІЙ: ДОКАЗИ АНАЛІЗУ TVP-SV-VAR

Це дослідження аналізує зв'язок між основними криптовалютами (Bitcoin, Ethereum і Tether) та обраними регіональними фондовими ринками Америки, Азії та Європи, контролюючи при цьому глобальні фінансові фактори, включаючи ціни на сиру нафту й курс обміну EUR/USD. Основна мета полягає в ідентифікації та кількісному визначенні змінних у часі ефектів переливу й оцінці того, чи значно впливають регіональні фондові ринки на динаміку цін на криптовалюти протягом 2018–2023 років. Для цього дослідження використана модель векторної авторегресії зі змінними параметрами та стохастичною волатильністю (TVP-SV-VAR), запропонована Primiceri (2005) і розширена Nakajima (2011), що дозволяє спостерігати можливі зміни в економічній структурі. Дослідження показує, що ефекти переливу є найсильнішими в короткостроковій перспективі та зменшуються зі збільшенням часового горизонту. Серед регіональних ринків MSCI Asia найбільше впливає на Bitcoin і Tether, водночас MSCI Americas має найбільший вплив на Ethereum. Зокрема, у трьох ключових моментах спостереження в цьому дослідженні інтенсивність ринкової реакції Bitcoin та Ethereum завжди була послідовною, з більш вираженим відгуком під час спалаху COVID-19. Коефіцієнти впливу імпульсної реакції Tether загалом були нижчими, а його піковий відгук відбувся під час розподілу вакцини від COVID-19. Результати також показують, що шоки цін на нафту й зміни курсу обміну сприяють волатильності криптовалют, але з часом їхній вплив зменшується. Загалом, результати свідчать, що регіональні фондові умови є релевантними, але недостатніми для ухвалення рішень щодо портфеля, оскільки ціни на криптовалюти також залежать від макроекономічних, грошових і поведінкових факторів, які не повністю враховані в моделі. Це дає цінні висновки для портфельних менеджерів, інвесторів і навіть державних регуляторів.

Ключові слова: криптовалюти, регіональні фондові ринки, змінні в часі наслідки, TVP-SV-VAR, стохастична волатильність, динаміка валютного курсу, шоки цін на нафту, управління ризиками портфеля

JEL Класифікація: G100, G11, G15, G17, G18