Analysis of the Impact of Macroeconomics on the Cryptocurrency Market and Market Linkage

Kaixun Wu

Business Administration, FOM Hochschule für Oekonomie & Management, 45127, Essen, Germany
wukaixun@ldy.edu.rs

Abstract. Nowadays, the influence mechanism of macroeconomic variables on traditional investment targets has been fully studied, but few scholars have studied the impact of macroeconomic variables on the crypto market. Therefore, this paper uses the daily frequency data from July 31, 2023 to July 26, 2024, and explores the impact of macroeconomic variables (taking the US dollar index DXY as an example) on cryptocurrencies (taking BTC and ETH as examples) and the dynamic relationship between the prices of BTC and ETH through the establishment of a vector autoregressive (VAR) model. The results show that the impact of Bitcoin price on Ethereum price has a negative impact on the price of Ethereum during the bull and bear junction period of the crypto market, which covers the key time node of the BTC halving and the Fed continues to raise interest rates. In addition, the study also found that the U.S. dollar index has no significant impact on the volatility of cryptocurrency prices. These findings are crucial for investors and policymakers seeking to understand the interconnectedness of financial markets.

Keywords: BTC, ETH, DXY, VAR model, Cryptocurrency.

1 Introduction

With the further development of the economy, people have a higher demand for the security and privacy of assets, and blockchain technology has attracted extensive attention and attention from the government, scholars from all walks of life, financial institutions and capital markets. As a product of the new era, cryptocurrencies represented by Bitcoin (BTC) and Ethereum (ETH) meet the requirements of the market, and have gradually entered people's investment vision and become an indispensable part of today's financial market.

Cryptocurrencies have been around for less than 20 years, but in recent years, their investment attributes have become more and more similar to those of traditional financial targets, and scholars around the world have increasingly studied them. Specifically, the current research on the crypto market is mainly divided into four categories: Firstly, the effectiveness of the crypto market: Wei Zhang et al. have studied the information efficiency of various cryptocurrencies such as Bitcoin and Ethereum [1]; Secondly, Crypto Market Currency Pricing and Price Prediction: Dehua

J. Lu (ed.), *Proceedings of the International Workshop on Navigating the Digital Business Frontier for Sustainable Financial Innovation (ICDEBA 2024)*, Advances in Economics, Business and Management Research 315,
https://doi.org/10.2991/978-94-6463-652-9_54

Shen et al. examined the relationship between social media activity, specifically Twitter, and Bitcoin price volatility. They evaluated whether the sentiment and volume of Twitter posts were able to predict Bitcoin's short-term price fluctuations, and the study found that certain Twitter metrics did have a predictive effect on Bitcoin prices. This research is part of a broader effort to understand how non-traditional data sources can be leveraged for cryptocurrency pricing and forecasting [2]; thirdly, Irrational Investment Behavior and Market Anomalies in the Market: Ajaz Taufeeq explored herd behavior in the cryptocurrency market in a 2018 paper with Elie Bouri et al. in 2019 [3]. These studies analyze the performance of the herd effect in the cryptocurrency market, which can distort prices and lead to market inefficiencies [4]. These two studies contribute to the understanding of market anomalies and irrational behavior in the cryptocurrency market; fourthly, Cryptocurrency Investment Allocation Management: Ruixue Jing and Luis E.C. Rocha's 2023 paper focused on the best strategies for cryptocurrency portfolio management and proposed a web-based strategy to manage cryptocurrency portfolios by analyzing price correlations [5]. Their approach aims to construct portfolios with relatively high yields and minimal risk by taking advantage of the unique nature of cryptocurrency price fluctuations.

2 Method

2.1 Data Preprocessing

This article intercepts the daily trading data of BTC, ETH and DXY from July 31, 2023 to July 26, 2024 UTC, and the time range is at the bull and bear junction of the crypto market, and covers the key time nodes of the BTC halving and the passage of BTC and ETH spot ETFs. Source: (https://coinmarketcap.com/) and (https://www.investing.com/)

Although the crypto market is not closed without stopping, due to the lack of holiday data for the US dollar index, this article first cleanses its data, removing data on non-trading days such as weekends, New Year's Day, and Christmas. The stationarity test is then performed to present the results as shown in Table 1

Table 1. Augmented Dickey-Fuller Test Result

	Dickey-Fuller	Lag order	P-value
Bitcoin （btc_price_ts）	-1.8228	6	0.6505
Ethereum (eth_price_ts)	-2.2499	6	0.4707
US dollar （dxy_index_ts）	-2.1436	6	0.5154

As shown in Table 1, for all three-time series (btc_price_ts, eth_price_ts, dxy_index_ts), the p-value is much greater than 0.05 (the usual significance level). This means that the null hypothesis that these time series may have unit roots cannot be rejected. And the smaller the Dickey-Fuller statistic, the more likely the time series is to be stationary. However, in these results, all statistics are not small enough to indicate the acceptance of the null hypothesis that these time series are not stationary [6]. Therefore, first-order differential processing is required to turn it into a stationary sequence and make the data easier to model and analyze later. After performing the differential score, the ADF test was performed again, and the results are shown in Table 2:

Table 2. Augmented Dickey-Fuller Test

	Dickey-Fuller	Lag order	P-value
Bitcoin （diff_btc_price_ts）	-7.0828	6	0.01
Ethereum (diff_eth_price_ts）	-6.4932	6	0.01
US dollar（diff_dxy_index_ts）	-6.1471	6	0.01

The Dickey-Fuller statistic for the three post-differential sequences is significantly negative, suggesting that the post-differential sequences are more likely to be stationary, meaning that the series are stationary at a significance level of 0.01.

2.2 Cointegration Test

Then, the cointegration test is carried out to determine whether there is a long-term stable equilibrium relationship between the three nonstationary time series of BTC, ETH, and DXY, which is helpful to understand the long-term interaction between the three variables and facilitate more effective prediction and decision-making in the future, as shown in Table 3 [7].

Table 3. Phillips and Ouliaris Unit Root Test

	Estimate	Std. Error	t value	Pr(>|t|)
Intercept	-6.478e+04	1.507e+04	-4.298	2.44e-05***
z[, -1]eth_price_ts	2.050e+01	2.462e-01	83.260	< 2e-16***
z[, -1]dxy_index_ts	5.715e+02	1.443e+02	3.961	9.69e-05***
F-statistic=3477		p-value: < 2.2e-16		
Multiple R-squared=0.9644		Adjusted R-squared=0.9641		
Critical values of Pu	1%=53.8731	5%=40.5252		10%=33.6955
Value of test-statistic=27.0058				

Note: ***＜0.001; **＜0.5; *＜0.1

As shown in Table 3, the analysis showed that the R-squared was 0.9644, indicating that the model had a 96.44 degree of interpretation, indicating a good fit. The F-statistical value was 3477, and the p-value was less than 2.2e-16, indicating that the model was significant overall. However, in the long run, there is no significant cointegration relationship between these variables. This may mean that although these factors will have an impact on the price of Bitcoin in the short term, there is no long-term equilibrium or stable relationship between them.

2.3 Lag Selection

With the help of information criteria, a balance is found between goodness-of-fit and complexity of the model to determine the lag period [8]. From the outputs, the four criteria, Akaike Information Criterion (AIC), Hannan-Quinn Information Criterion (HQIC), Schwarz-Bayesian Information Criterion (BC), and Final Prediction Error Criterion (FPE) The consensus recommendation is that the optimal lag order is 1.

2.4 Granger Causality Test

In this section, the first-order lag is used for the three variables after the first-order difference [9]. In these two Granger causality tests, the results are shown in Table 4, and the US dollar index (diff_dxy_index_ts) does not show a significant causal relationship with the changes in the price of Bitcoin (diff_btc_price_ts) and the price of Ethereum (diff_eth_price_ts), and does not have the ability to predict the price changes of Bitcoin and Ethereum. This suggests that, contrary to traditional financial markets, changes in DXY cannot be used to predict price changes for Bitcoin and Ethereum.

Table 4. Granger causality of DXY-index on BTC and ETH prices

	F	P-value
on BTC	2.6969	0.1018
on EYH	1.0308	0.3109

As shown in Table 5, this result is contrary to the expectation (BTC has an effect on ETH), and the p-value of both sets of tests is greater than 0.05, which cannot reject the null hypothesis, indicating that BTC and ETH prices do not have the ability to influence each other's prices. This shows that in most cases, ETH falls at the same time as BTC, and it is not due to the rise or fall of BTC that guides the market.

Table 5. Granger causality between BTC and ETH prices

	F	P-value
diff_eth_price_ts Granger relationship to diff_btc_price_ts	2.6969	0.1018
diff_btc_price_ts Granger relationship to diff_eth_price_ts	1.0308	0.3109

2.5 VAR Model Estimation

The results shown in Table 6 show that the Roots of the Characteristic Polynomial of the model is less than 1, indicating that the VAR model is systematic. The residual correlation matrix shows the correlation of the residuals between the three time series [10]. It can be seen that the residual correlation between the Bitcoin price and the Ethereum price is high (0.8223), indicating that they have a strong positive linear relationship, and the error of the two variables tends to increase or decrease at the same time, while the correlation with the DXY index is low.

Table 6. Model Parameter Estimates

	BTC-price	ETH-price	DXY-index
Roots of the Characteristic Polynomial	0.9947	0.9492	0.9317

Estimation results for equations			
	BTC Pr(>|t|)	ETH Pr(>|t|)	DXY Pr(>|t|)
btc_price_ts.l1	<2e-16 ***	0.0215 *	0.6002
eth_price_ts.l1	0.372	<2e-16 ***	0.5885
dxy_index_ts.l1	0.486	0.3105	<2e-16 ***
Correlation matrix of residuals			
	btc_price_ts	eth_price_ts	dxy_index_ts
btc_price_ts	1.0000	0.8223	-0.1344
eth_price_ts	0.8223	1.0000	-0.1608
dxy_index_ts	-0.1344	-0.1608	1.0000

Summarizing the results, it is concluded that first, the Bitcoin price has a significant lag effect on itself, but has no significant impact on the Ethereum price and DXY index. Second, the lag effect of the Ethereum price on itself is significant, which has a certain impact on the price of Bitcoin, but does not affect the DXY index. Thirdly, the DXY index has a significant lagging effect on itself, but it is not significantly affected by the prices of Bitcoin and Ethereum.

From these results, it can be inferred that while the Bitcoin price is considered to have a significant influence on the cryptocurrency market, its impact on other variables is not significant in this model. On the contrary, the price of Ethereum has had a certain impact on Bitcoin, and the author speculates that there may be the following two reasons: First, the entire crypto market was in a bear market during the first half of the data interception period, and BTC had a weak guiding role in the overall crypto market. Second, in the second half of the data interception, although the overall crypto market entered a bull market, there was a hype expectation that the spot ETF of ETH would be passed, which played a great role in guiding the market.

2.6 Impulse Response Analysis

The impulse response of the model was analyzed to determine the response of one variable to the other variables over the next 10 periods after being impacted by one standard deviation [10]. Visualize and output the results as shown in Figures 1-3.

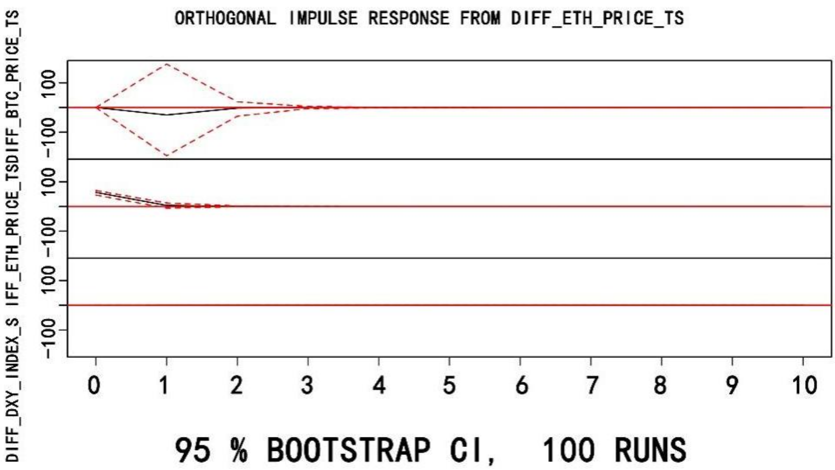

Fig.1 Impulse Response Function Analysis Results (diff_eth_price_ts)

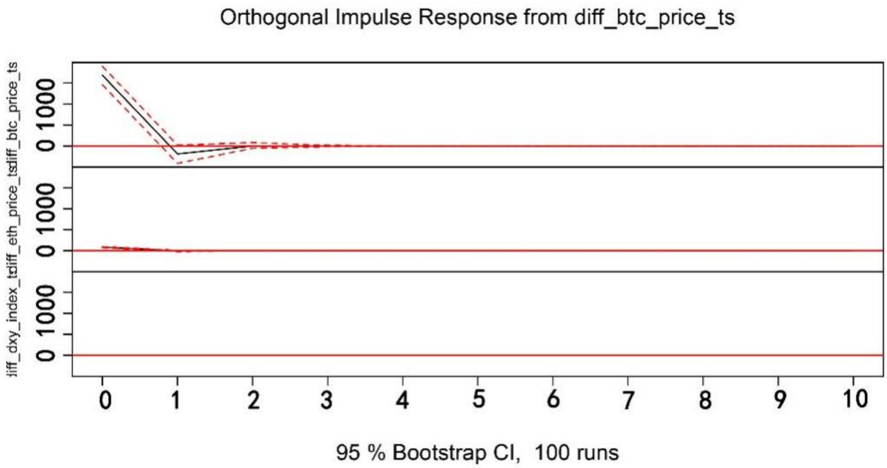

Fig.2 Impulse Response Function Analysis Results (diff_btc_price_ts)

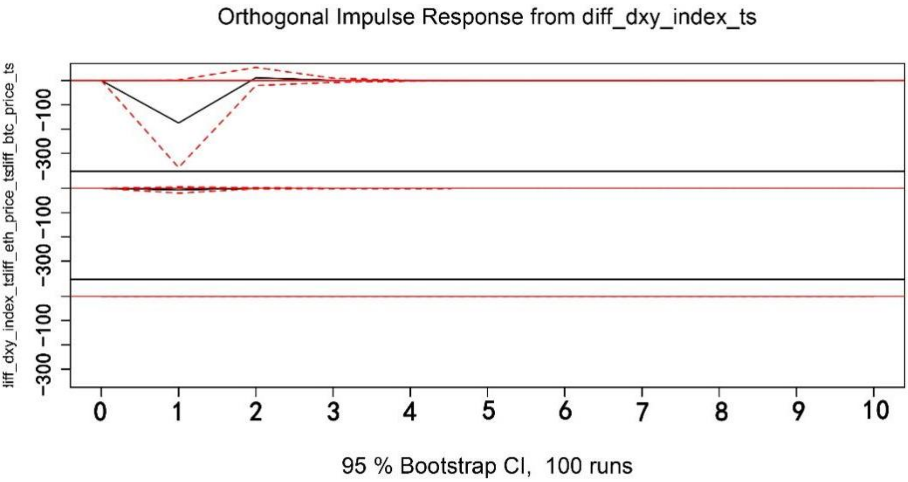

Fig.3 Impulse Response Function Analysis Results (diff_dxy_index_ts)

According to the results, the BTC price has a strong response to its own shock, indicating that it has a self-inertia effect, that is, it has a strong dependence on its past price changes, and the market gradually digests the information after the shock, and the impact gradually declines. However, the reaction of BTC price to the Ethereum shock is negative, and it first strengthens and then weakens over time, which indicates that the shock of ETH price may have a negative impact on BTC price in the short term, which means that there is a certain market competition and substitution effect, BTC and ETH both belong to the cryptocurrency market, and the liquidity of the crypto market is limited, and there is a competitive relationship between the two in some cases. When the price of ETH rises suddenly, investors may transfer funds from

BTC to ETH in pursuit of higher returns. This flow of funds could lead to a drop in the price of BTC, resulting in a negative response from Bitcoin to the Ethereum shock. In addition, the cryptocurrency market is highly speculative. When the market expects that ETH may make greater progress in technological innovation (e.g., the Ethereum Cancun upgrade during the data period, the success of DeFi projects, etc.) or market acceptance, investors may be more inclined to hold ETH rather than BTC due to public opinion and sentiment, which may trigger a decline in the price of BTC in the short term.

The reaction of ETH price to the BTC shock is almost zero, which is inconsistent with the common sense expectation that BTC will have a price guide for ETH. Although there is a correlation between the two, the Ethereum and Bitcoin markets are independent to a certain extent. The price volatility of Bitcoin is mainly driven by the global macro economy, the movements of institutional investors, and market sentiment, while the price of Ethereum is more likely to be affected by technological innovations such as decentralized finance (DeFi) and smart contracts. In addition, the results may not fully reflect the correlation between the two due to data frequency and time span limitations.

In addition, the BTC price responded negatively to the US dollar index shock, which first strengthened and then weakened over time, which is related to the risk aversion in the market and the direction of capital flows, confirming the value of Bitcoin as digital gold or a safe-haven asset for a long time. However, the response of ETH price to the impact of the dollar index is almost zero, which reflects that Ethereum is more regarded as a technology platform currency, less connected to traditional financial markets, and its price reflects more of the prospect of technology application than safe-haven attributes. Therefore, when the DXY is volatile, the market's demand for Ethereum may not change significantly, resulting in a weaker response to the DXY shock.

2.7 Variance Decomposition

The dynamic impact of different variables on the system is measured by variance decomposition to quantify the contribution of each variable in the model to the prediction error of other variables in the system, and how these contributions change over time [10].

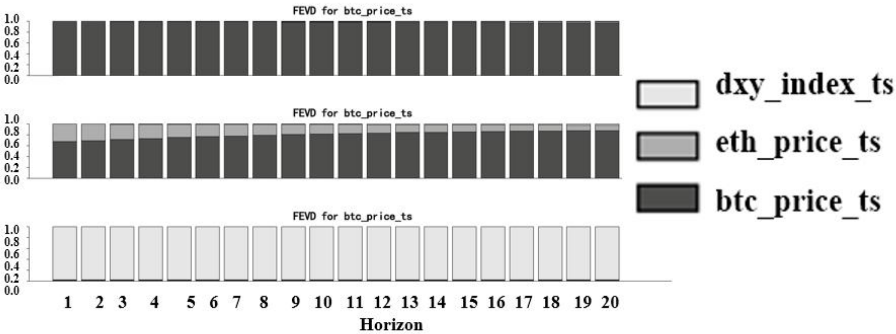

Fig. 4 Variance Decomposition Results

From Figure 4, it can be concluded that the variance of Bitcoin is mainly contributed by its own historical value, while the contribution of Ethereum and the US dollar index is relatively small, and its contribution to its own variance remains above 80%, showing the persistence of its impact. The variance decomposition of Ethereum is relatively uniform, and although this variable also has a great impact on itself, Bitcoin's contribution to it is more obvious, and Bitcoin's contribution has become more significant over time.

3 Further Discussion

3.1 The Results Guide Investment Decisions

This time series data is predicted for the next 10 periods and the results are visualized to produce results such as Figure 5 [11].

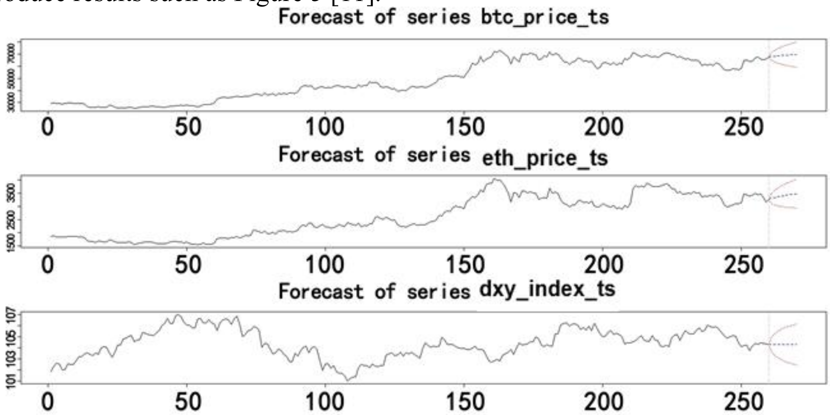

Fig. 5 Predicted Results of Time Series

In Figure 5, in the forecast area near the right, the price of Bitcoin is slightly rising or fluctuating, the price of Ethereum is trending upward, and the US dollar index series shows the strength of the US dollar relative to other currencies, with signs of decline or correction. The results of this study have implications for investment portfolios and investment decisions, and investors can buy cryptocurrencies accordingly. However, it should be noted that the confidence interval widens with the extension of the prediction period, and the reliability of the prediction decreases.

3.2 An Understanding of Financial Interconnection

Financial interconnectivity refers to the relationships and interactions between different financial markets, assets, and economies. High interconnectivity means that changes in one market or asset can have a significant impact on other markets or assets [12]. This connection is especially evident in the context of economic globalization, especially between digital currencies, stock markets and foreign exchange markets.

The first is the relationship within the cryptocurrency market, where the price fluctuations of Bitcoin and Ethereum show a certain degree of linkage. From the above analysis, it can be concluded that at that stage, when the price of Ethereum rises, it will cause the price of bitcoin to fall, which shows the interaction of the current overall trend of the cryptocurrency market and investor sentiment. The second is the correlation between cryptocurrencies and the forex market, and the movement of the US dollar index may affect the performance of cryptocurrencies. When the dollar strengthens, some investors may choose to sell digital assets, putting downward pressure on Bitcoin and Ethereum prices.

4 Conclusion

4.1 Key Findings of the Study

In the study, it was found that the impact of the Bitcoin price on the price of Ethereum was negatively affected, and this phenomenon is not common in the cryptocurrency market. Typically, the prices of mainstream assets in the cryptocurrency market tend to exhibit a strong positive correlation, especially when the market is exposed to external shocks, such as policy changes or global events. However, at that stage, there was an inverse interaction mechanism between the prices of Bitcoin and Ethereum, which was manifested as: Firstly, Capital Liquidity and Market Sentiment: Due to the Fed's long-term high interest rate and lack of liquidity in the crypto market, when the price of Ethereum rises, some investors may withdraw their funds from Bitcoin and invest in Ethereum instead, causing the price of Bitcoin to fall in the short term. This phenomenon suggests that although both are part of the cryptocurrency market, at certain stages, the liquidity of capital in the market and investor sentiment may trigger a rivalry between Bitcoin and Ethereum. Secondly, technological competition: Bitcoin and Ethereum are somewhat competitive in technological innovation. For example, Ethereum's Cancun upgrade and spot ETF speculation are expected to attract more attention and funding, resulting in a temporary drop in demand for Bitcoin, which is reflected in the decline in price. This inverse relationship may be related to the market's expectations for different technical paths.

In addition, the influence mechanism of the volatility of the US dollar index and gold prices, as representatives of traditional safe-haven assets, on the price of cryptocurrencies can be understood from the following aspects: Traditionally, the rise of the dollar index is usually accompanied by a fall in the price of gold, and vice versa. However, while Bitcoin has responded to the US Dollar Index to some extent, the impact is not significant, indicating that Bitcoin has not yet completely replaced gold as a safe-haven asset, so its price is less sensitive to the US Dollar Index. In the study, it was observed that the Ethereum price barely reacted to changes in the U.S. dollar index, reflecting that Ethereum and other cryptocurrencies are still largely driven by market intrinsic factors such as technological developments, market demand, etc.

4.2 Recommendations for Practice

Provide Valuable Information to Investors

From the perspective of investment strategy, the research results provide some valuable suggestions and inspirations for cryptocurrency investors.

The first is to understand the market dynamics of Bitcoin and Ethereum. The study found that the inverse interaction mechanism between the prices of Bitcoin and Ethereum has emerged at certain stages, which suggests the following for investors: First, Diversification Strategy: When developing a cryptocurrency portfolio, investors should take into account that in some special market conditions, BTC and ETH will exhibit opposing price movements. Therefore, proper asset allocation and risk diversification can provide investors with better protection in market volatility. Second, Daily Trading Opportunities: Due to the inverse price relationship between Bitcoin and Ethereum, daily investors can capture potential trading opportunities by carefully monitoring market sentiment and capital flows. For example, when the price of Ethereum rises, shorting Bitcoin may become a strategy in the short term.

Second, the relationship of cryptocurrencies to traditional safe-haven assets is reassessed. Research shows a weak correlation between the dollar index and the price of Ethereum, suggesting a certain independence of the cryptocurrency market. This independence has the following implications in investment decisions: First, Separate Asset Class Considerations: The price action of cryptocurrencies does not exactly follow traditional safe-haven assets such as gold and the US dollar. Therefore, investors should consider cryptocurrencies as a separate asset class rather than a simple alternative to traditional safe-haven assets when allocating safe-haven assets. Second, Hedging Strategies: Given the low correlation between cryptocurrencies and traditional financial assets, investors can use cryptocurrencies as part of a hedging strategy to reduce the overall volatility of their portfolios. Especially in the case of underperforming traditional markets, cryptocurrencies may offer different sources of income.

Reference value for policy makers

Policymakers can use the results of this study to assess the potential impact of financial policy in multiple dimensions. For example, how adjustments in monetary policy affect the economy through multiple channels such as digital assets, stock markets, and foreign exchange markets. This can help policymakers develop more effective and precise policies.

For the fast-growing fintech and digital asset space, policymakers need to constantly adjust the regulatory framework. By studying financial interconnectivity, policymakers can better understand the impact of innovation on markets, so they can develop appropriate regulatory policies to protect investors and maintain market fairness.

4.3 Research Deficiencies and Future Prospects

The data used in this article is not long enough to adequately capture the changes and trends of the market in different economic cycles. This can lead to models that do not reflect long-term economic behavior and market dynamics, making forecasts less robust. The study relies on daily frequency data from the Bitcoin, Ethereum, and U.S. dollar indices. In the crypto market, which is more volatile, more sensitive to information, and accounts for a greater proportion of investment sentiment, only studying daily frequency data may mask important short-term fluctuations and cannot effectively capture rapidly changing market dynamics. Future research can capture long-term trends and changes in the cryptocurrency market by expanding the time frame of the data to account for the different market cycles that Bitcoin and Ethereum have gone through since their inception.

In addition to daily data, future research could consider using hourly or minute-level high-frequency data to capture short-term volatility and microstructure in the market. High-frequency data analysis can reveal the short-term reaction mechanism of the market, such as the impact of breaking news or instantaneous changes in market sentiment on prices, which is of great significance to high-frequency traders and market makers.

References

1. Zhang, W., Wang, P., Li, X., Shen, D.: The inefficiency of cryptocurrency and its cross-correlation with Dow Jones Industrial Average. Physica A: Statistical Mechanics and its Applications **510**, 658-670 (2018)
2. Shen, D., Urquhart, A., Wang, P.: Does twitter predict Bitcoin? Economics Letters **174**, 118-122 (2019)
3. Taufeeq, A., Kumar, A. S.: Herding in Cryptocurrency Markets. Annals of Financial Economics **13**(2), 1-15 (2018)
4. Bouri, E., Gupta, R., Roubaud, D.: Herding behaviour in cryptocurrencies. Finance Research Letters **29**, 216-221 (2019)
5. Jing, R., Rocha, L. E. C.: A network-based strategy of price correlations for optimal cryptocurrency portfolios. Finance Research Letters **58**, 52-66 (2023)
6. Banerjee, A., Urga, G.: Cointegration and Unit Root Tests. In: Handbook of Financial Time Series, 561-592. Springer, Berlin (2015)
7. Pesaran, M. H.: Time Series Econometrics: Empirical Approaches. Oxford University Press, Oxford (2015)
8. Lütkepohl, H.: New Introduction to Multiple Time Series Analysis. Springer-Verlag, Berlin (2005)
9. Kirchgässner, G., Wolters, J.: Introduction to Modern Time Series Analysis. 3rd edn. Springer, Berlin (2019) .
10. Lütkepohl, H.: Vector Autoregressive Models. In: Handbook of Economic Forecasting. Elsevier, Amsterdam, 273-327 (2017)
11. Karlsson, S.: Forecasting with Bayesian Vector Autoregressions. In: Handbook of Economic Forecasting. Elsevier, Amsterdam, 791-897 (2013)
12. Diebold, F. X., Yılmaz, K.: Financial and Macroeconomic Connectedness: A Network Approach to Measurement and Monitoring. Oxford University Press, Oxford (2015)