The Impact of China's Monetary Policy on Cryptocurrency Volatility-Taking BTC, ETH, and USDT as Examples

Tianyu Zheng
School of Law/School of Statistics, Capital University of Economics and Business, China

Abstract: This study aims to explore the impact of China's monetary policy on the volatility of three cryptocurrencies. Empirical analysis is conducted using vector autoregression (VAR), time-varying parametric VAR, and the DY2012 spillover index model. The study finds that while China's monetary policy is a Granger cause of cryptocurrency volatility, its static average effect is statistically insignificant. Dynamic analysis indicates that this effect is time-varying and heterogeneous, with Bitcoin showing the highest sensitivity, while the stablecoin USDT is primarily affected by interest rates. Furthermore, the cryptocurrency market exhibits strong internal volatility correlations. However, the study explicitly states that the conclusions should be interpreted with caution, as the models have limited explanatory power and the results are highly sensitive to model specifications, suggesting that the main drivers of cryptocurrency volatility may not be traditional monetary policy variables.

Keywords: China's Monetary Policy; Cryptocurrency Volatility; Multi-Currency Comparison

1. introduction

1.1 Introduction

This study aims to explore the impact of China's monetary policy on the volatility of BTC, ETH, and USDT. Existing research focuses on factors such as price bubbles and regulatory events but lacks systematic testing on the impact of macroeconomic monetary policy, especially that of China, a major economy. [1] Although cryptocurrency trading is strictly prohibited in China, its monetary policy, through global entities and financial channels, may have a "China shock" to cryptocurrencies as global risk assets. [2] Understanding this mechanism is of great significance for expanding the theoretical boundaries of monetary policy and assessing cross-border financial risks.

Therefore, this study selects China's M2 growth rate and government bond yield as core policy variables, and constructs an empirical framework including a static VAR model, a dynamic TVP-VAR model, and a DY2012 volatility linkage model to systematically examine the average relationship, time-varying characteristics, and internal transmission structure of the impact, providing empirical evidence from a Chinese perspective on the interaction between centralized policies and decentralized financial markets.

1.2 Research Content and Framework

1.2.1 Research content

This study aims to systematically explore the impact of China's monetary policy on cryptocurrency market volatility. To achieve this research objective, the content will be divided into the following four progressively deeper core parts.

First, a VAR model will be used for testing. The independent variables of the model will include the M2 money supply growth rate and the benchmark interest rate, representing China's monetary policy, while the dependent variable will be the volatility of three cryptocurrencies. The study will systematically conduct stationarity tests, Granger causality tests, impulse response function analysis, and variance decomposition using this model, aiming to explore the average direction and strength of the impact of Chinese monetary policy shocks on cryptocurrency volatility.

Considering that the transmission effect of monetary policy may change over time, this study will further employ the TVP-VAR model to capture the time-varying characteristics of the relationship between variables. This model allows the impulse response function to change with different points in time, enabling a more detailed characterization of how the impact of China's monetary policy on cryptocurrency volatility dynamically evolves at different macroeconomic stages, thereby identifying structural breakpoints and nonlinear characteristics influencing the effect. [3]

To deeply analyze the risk transmission and linkage structure within the cryptocurrency market under the influence of monetary policy, this study applies the dynamic conditional correlation coefficient model proposed by Diebold & Yilmaz. The core of this model is to estimate the time-varying dynamic conditional correlation coefficients among the volatility of three cryptocurrencies: BTC, USDT, and ETH. Through model fitting, the aim is to quantify the linkage and persistence characteristics of market volatility. [4]

2. A Study on the Impact of Monetary Policy on Cryptocurrency Price Volatility

2.1 Sample Selection and Data Sources

This study selects the monthly broad money supply M2 and the average monthly yield of government bonds to represent China's monetary policy, based on both price and quantity factors. M2 represents the broad money supply and reflects the stance of monetary policy in terms of total supply and liquidity injection. It is a key quantitative indicator for measuring aggregate demand and potential inflationary pressure. [5] Regarding the price-type indicator, this study chooses the yield of government bonds instead of the reserve requirement ratio, mainly for the following reasons: Firstly, with the deepening of China's interest rate marketization reform, the core role of the policy interest rate system in the transmission of monetary policy has become increasingly prominent. According to the transmission mechanism proposed by the People's Bank of China in the "2023 Fourth Quarter Report on China's Monetary Policy", market interest rates represented by the yield of treasury bonds have become more direct and crucial benchmarks for reflecting the price signals of monetary policy and influencing the pricing of various assets. [6] Secondly, the yield of government bonds is widely regarded as China's risk-free benchmark interest rate. It not only embeds the market's expectations for the future trend of policy interest rates but also serves as the basis for risk pricing and valuation of various assets, including financial assets. [7] Therefore, it can more sensitively and comprehensively reflect the price dimension of monetary policy and its impact on the financial market. In contrast, the reserve requirement ratio is more regarded as a quantitative or structural tool for adjusting the liquidity of the banking system, with a lower adjustment frequency and a relatively indirect price signal function. Thus, choosing the yield of government bonds can more effectively capture the price transmission effect of monetary policy and its impact on the volatility of emerging assets such as cryptocurrencies.

Due to the extremely low prices and minimal value fluctuations of the three cryptocurrencies before January 1, 2016, and the absence of value data for some cryptocurrencies, the sample period is set from January 1, 2016 to January 1, 2026, covering a 10-year period. Considering the high volatility of cryptocurrency values and their 24-hour trading, the frequency of cryptocurrency value fluctuations is inconsistent with the values used to measure monetary policy. Therefore, the daily volatility is calculated based on the daily trading prices of the three cryptocurrencies, and then the monthly volatility is calculated. The processing method for the yield of government bonds is similar. Information on the money supply M2 and the yield of government bonds is obtained from the official website of the People's Bank of China, while data on BTC, USDT, and ETH are sourced from the CoinMarketCap website.

2.2.1 Descriptive statistics

A descriptive statistical analysis was conducted comparing the money supply M2, the average monthly yield of Chinese government bonds, and the monthly yields of three cryptocurrencies. The results are shown in the figure 1, figure 2 and figure 3 below.

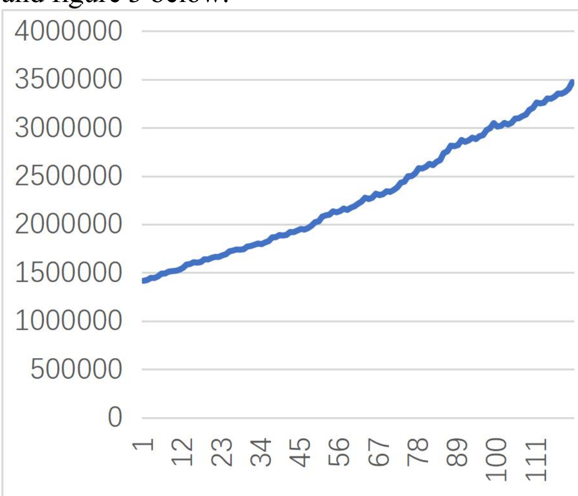


Figure 1. Money Supply M2

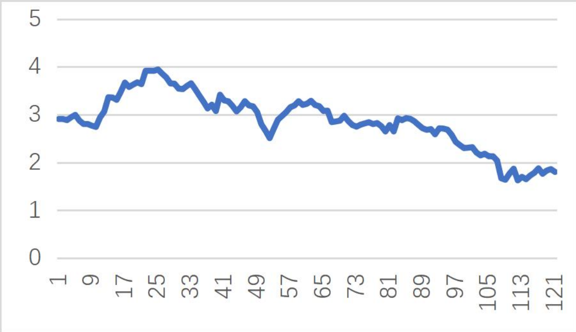


Figure 2. Monthly Average Yield of Government Bonds

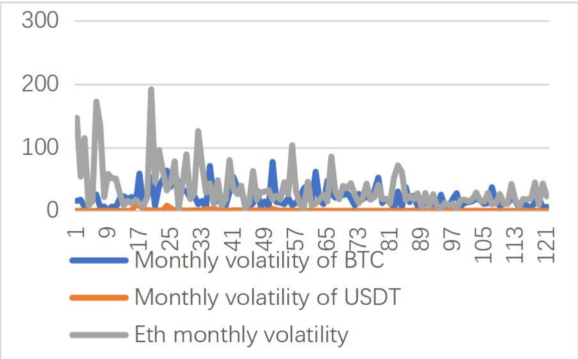


Figure 3. Monthly Volatility of BTC,USDT and ETH

It can be concluded that BTC has a larger standard deviation, a higher mean, and the largest extreme values compared to the other two cryptocurrencies. The monthly volatility of BTC and ETH both exhibit significant right skewness and leptokurtic distributions. USDT shows extremely high skewness and kurtosis, indicating its volatility instability.

2.2.2 Stationarity test

By comparing the monthly volatility of BTC, USDT, and ETH with the average monthly yield of Chinese government bonds over the past nine years. The ADF test results are shown in figure 4 below. The p-values of all four variables are less than 0.05, indicating that they are all stationary series.

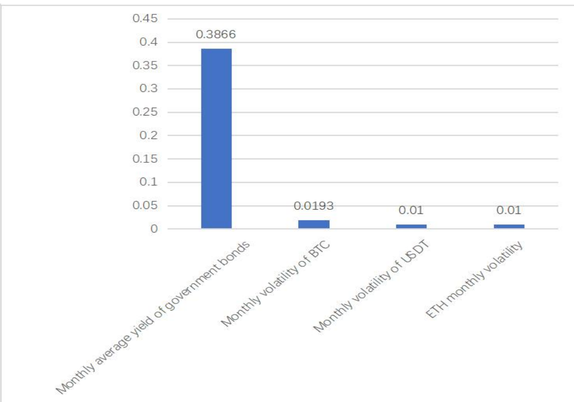


Figure 4. P-value

2.2.3 Residual normality test

Based on this, normality tests were performed on the monthly volatility of BTC, USDT, and ETH, as well as the average monthly yield of Chinese government bonds over the past nine years. These tests included the Jarque - Bera test, skewness test, and kurtosis test. As shown in the Table 1 below, the p-values are all close to 0. This indicates that the residual distribution exhibits significant asymmetry and has extremely thick tails.

Table 1. JB-Test (Multivariate)

JB-Test (multivariate)		
Chi-squared	df	p-value
6371.9	10	0

2.2.4 Autocorrelation test

Next, Ljung -Box autocorrelation tests were conducted on the monthly average yields of China's money supply M2, government bonds, BTC currency, USDT currency, and E TH volatility over the past 10 years. The specific results are shown in the following figure 5. The Ljung -Box test determines whether the sequence is white noise by testing whether the autocorrelation coefficients of a series of lags are jointly zero**. [8]** The null hypothesis H0 is that each value in the sequence is independent, and the alternative hypothesis H1 is that the sequences are not independent and are correlated. If the p-value of the test is less than the significance level, the null hypothesis is rejected, and the sequence is considered to have significant autocorrelation. The results are shown in the table above. According to the autocorrelation test results, the p-value of BTC monthly volatility is greater than 0.05, which means that it is not autocorrelated with the other variables. The p-values of the other variables are all less than the significance level of 0.05, the sequence is not white noise, and there may be autocorrelation.

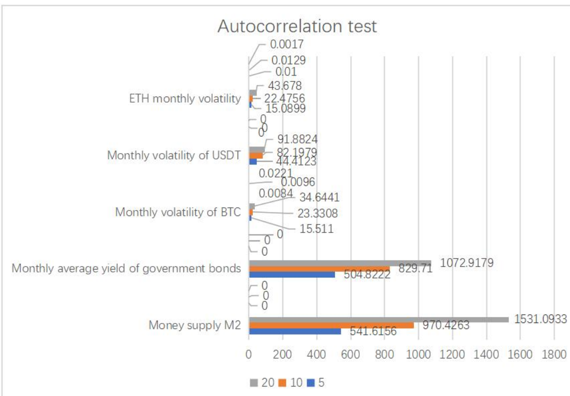


Figure 5. Autocorrelation Test

2.2.5 Granger causality test

Granger causality test is a statistical method based on time series data, used to determine whether one variable has predictive power for another variable. [9] In this test, the null hypothesis (H0) is that the money supply M2 and the average monthly yield of government bonds are not Granger causes of the monthly volatility of BTC, USDT, and ETH. The specific results are shown in the following Table 2. The test results reject the null hypothesis (H0), indicating that there is a significant Granger causal relationship between the average monthly yield of M2 government bonds and the monthly volatility of BYC, USDT, and ETH. This means that, statistically, changes in the average monthly yield of M2 government bonds help predict changes in the monthly volatility of these three cryptocurrencies.

Table 2. Granger Causality Test

Granger causality test			
F-Test	df1	df2	p-value
6.9589	6	570	0.000000374

2.2.6 Vector autoregression model analysis

This analysis uses a vector autoregressive (VAR) model with 600 observations, including money supply M2, average monthly yields on government bonds, and monthly volatility of three major cryptocurrencies. The model's explanatory power varies significantly across the equations. The model strongly explains changes in money supply and government bond yields. However, the opposite is true for the explained variables; the equation for cryptocurrency volatility has a relatively weak explanatory power. The specific details are shown in figure 6 below.

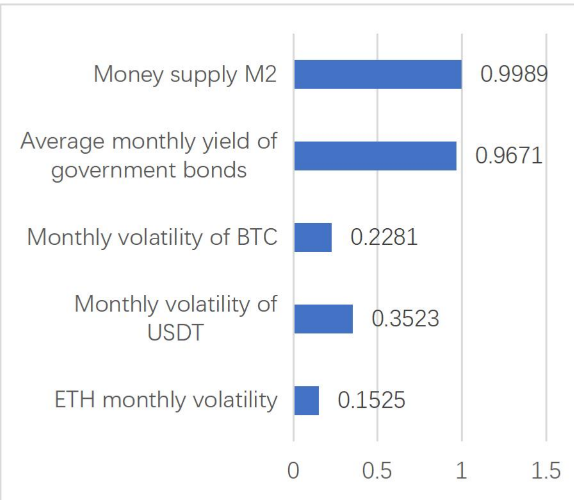


Figure 6. Adjusted R-squared

The impact of China's monetary policy on cryptocurrency volatility, which is reflected to some extent by China's money supply M2 and government bond yields, the impact is not statistically significant. The following figure 7 illustrates the impact of money supply M2 on three cryptocurrencies.

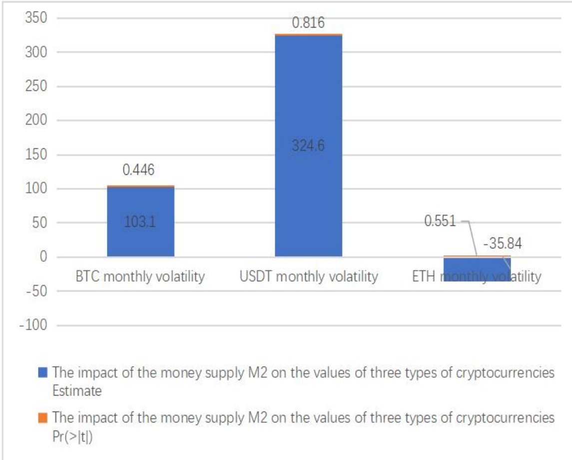


Figure 7. The Impact of the Money Supply M2 on the Values of Three Types of Cryptocurrencies

Data shows that the p-values for the impact of M2 on the volatility of various cryptocurrencies are all greater than 0.1 and are statistically insignificant. This indicates that during the studied period, changes in the money supply did not significantly affect the volatility of the cryptocurrency market. A similar conclusion can be drawn regarding the yields reflected in government bond yields, as illustrated in the following figure 8.

The results show that government bond yields only have a significant negative impact on BTC volatility, which may reflect the substitution relationship between traditional financial assets and crypto assets among investors. From the above tests, it can be concluded that the distribution of the three cryptocurrencies does not conform to a normal distribution throughout the research period. Since all parameters of the vector autoregressive (VAR) model are assumed to remain constant throughout the sample period, it characterizes a stable average dynamic relationship between variables. However, due to the inherent volatility and instability of the three cryptocurrencies, such a model is difficult to reflect the true situation of the data. Therefore, a time-varying parametric VAR model is needed for further analysis of this data. This model is an extension of VAR, allowing all or some of its parameters to change smoothly or abruptly over time.

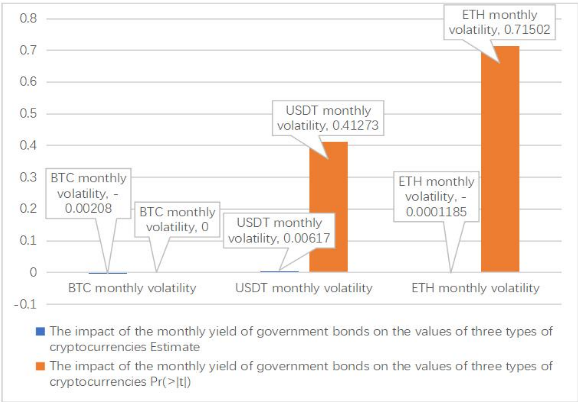


Figure 8. The Impact of the Monthly Yield of Government Bonds on the Values of Three Types of Cryptocurrencies

2.3 Empirical Study of Time-Varying Parameter Vector Autoregressive Model

2.3.1 Significance test of coefficients

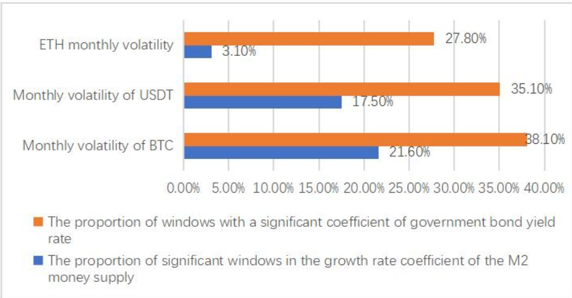


Figure 9. Coefficient significance test

The core idea of the significance test of the coefficients of the time-varying parameter vector autoregression model is whether the coefficient estimate is significantly non-zero at each specific time point. [10] As shown in figure 9 above, the impact of the government bond yield is generally stronger than that of the M2 growth rate: for the volatility of the three cryptocurrencies, the proportion of the window where the government bond yield coefficient is significant is significantly higher than that of the M2 growth rate. This indicates to some extent that the change in interest rates in the traditional financial market has a more sustained and stable impact on the volatility of the cryptocurrency market than the growth rate of the money supply.

In addition, different cryptocurrencies exhibit significant differences in their sensitivity to macroeconomic factors. BTC shows the highest sensitivity to both macroeconomic factors, confirming its role as a "bellwether" for the crypto market and a mainstream asset allocation target, and demonstrating a relatively closer connection with the traditional financial system. ETH is extremely insensitive to changes in the M2 growth rate. USDT, as the most important stablecoin, also shows high sensitivity to changes in government bond yields, which may reflect systemic changes in market demand for stablecoins during periods of risk aversion or tightening.

2.3.2 Robustness test based on changing window width

The purpose of the M2 money supply growth rate and the average monthly interest rate of government bonds on cryptocurrency volatility are fundamentally altered by different choices of the rolling regression window length. In terms of specific testing methods, in addition to the baseline 24-month window, shorter 18-month and longer 30-month windows were used to re-perform rolling regressions on the three cryptocurrencies, and the median of the M2 growth rate coefficient was calculated over the entire period. The specific results are shown in the figure 10, figure 11,figure 12, figure 13, figure 14 and figure 15 below.

This suggests that the volatility of the three cryptocurrencies responds robustly to the money supply M2. The coefficient estimates for BTC and ETH to the M2 growth rate show high consistency across different window widths. Whether considering trends or absolute values, the three window lines almost overlap or move in perfect sync, indicating that the estimated relationship of "excessive money supply driving up price volatility in major cryptocurrencies" is very stable. For USDT, its coefficient to the money supply M2 also tends to converge after 2022, but the estimates differ across earlier windows. This suggests that the relationship between USDT and M2 has also stabilized over time, especially in recent years.

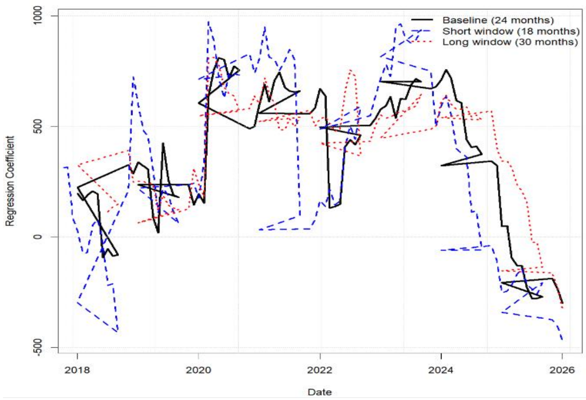


Figure 10. Robustness Test: BTC - M2 Growth Coefficient (Different Window Widths)

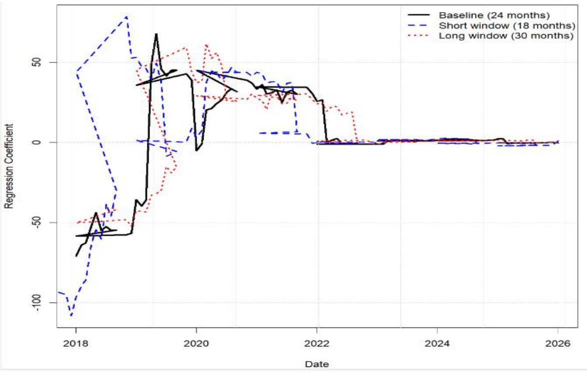


Figure 11. Robustness Test: USDT - M2 Growth Coefficient (Different Window Widths)

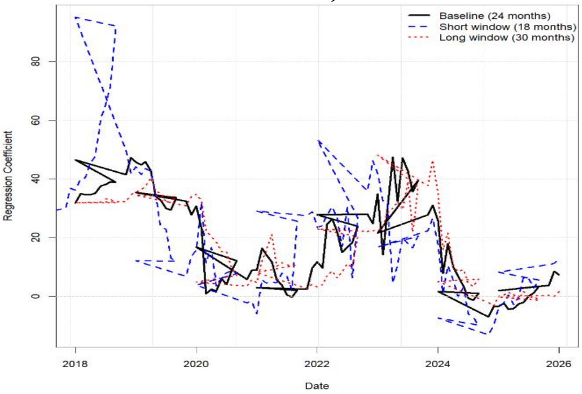


Figure 12. Robustness Test: BTC-Bond Yield Coefficient (Different Window Widths)

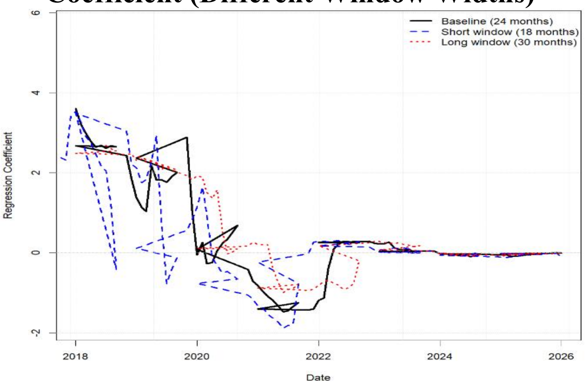


Figure 13. Robustness Test: USDT-Bond Yield Coefficient (Different Window Widths)

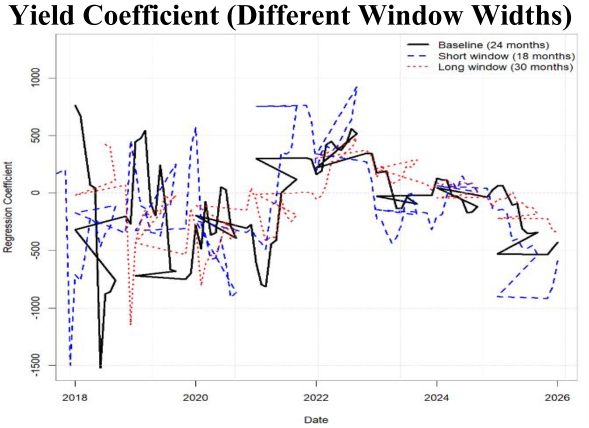


Figure 14. Robustness Test: ETH-M2 Growth Coefficient (Different Window Widths)

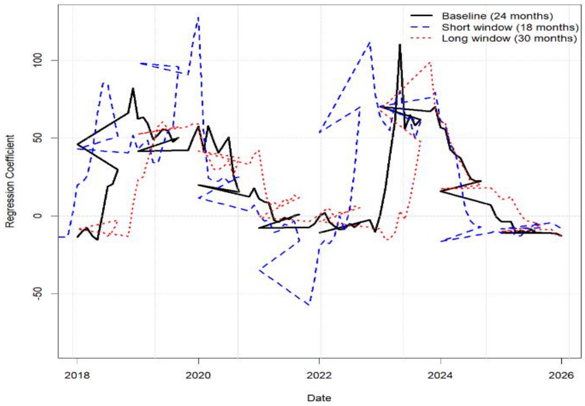


Figure 15. Robustness Test: ETH-M2 Growth Coefficient (Different Window Widths)

The volatility of the three cryptocurrencies showed relatively weak robustness in response to government bond yields, and there were significant differences between the cryptocurrencies. The coefficient estimates for BTC and ETH in relation to government bond yields were sensitive to window width. Visible differences were observed in the coefficient values and volatility details obtained from different windows. This indicates that the estimation results of the impact of interest rate changes on the volatility of these two cryptocurrencies depends to some extent on the choice of window length. USDT , as a stable coin, exhibited unique characteristics.

2.3.3 Out- of-sample predictive power test

Sample predictive power test is to compare the performance of the rolling window model with that of the traditional fixed-parameter model in predicting future cryptocurrency volatility, in order to evaluate the actual predictive power of the rolling window method. At the methodological level, the data is first divided into two parts according to time: the first 80% is used as the training set, and the latter 20% as the test set. At each time point in the test set, the model is retrained using data from a fixed-length (24-month) window up to the previous period, and predictions are made for the current period. The specific results are shown in the figure 16, figure 17, figure 18 below.

BTC volatility was around 15 in early 2024, peaking at around 25 in July 2024, before declining and stabilizing around 15, exhibiting high volatility and oscillating characteristics without a clear trend. The rolling window prediction more closely reflects actual volatility, although it still underestimates the magnitude of the volatility, it represents a significant improvement over the fixed model.

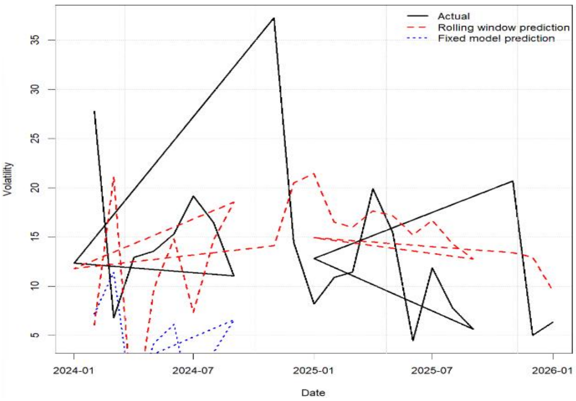


Figure 16. BTC Volatility: Out-of-Sample Prediction Comparison

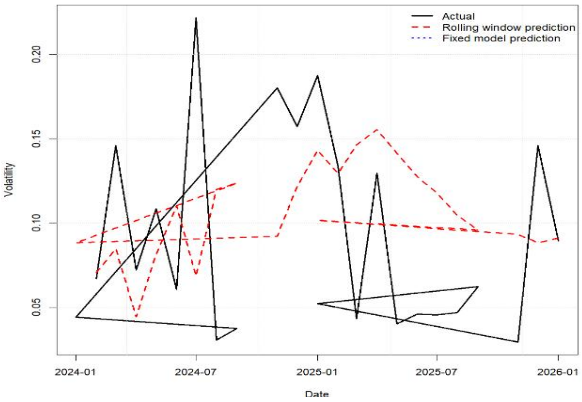


Figure 17. USDT Volatility: Out-of-Sample Prediction Comparison

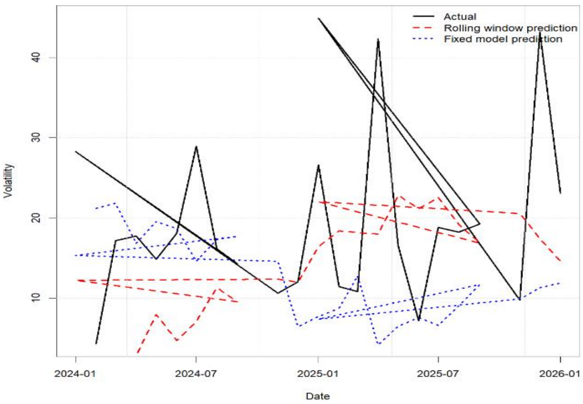


Figure 18. ETH Volatility: Out-of-Sample Prediction Comparison

USDT volatility is extremely stable, consistently remaining at a low level of 0.05 with almost no change, consistent with its characteristics as a stable coin. The prediction lines of both forecasting models completely overlap and are almost identical to the actual values. The three lines essentially overlap at the 0.05 level. For the extremely stable USDT, both models produce identical and excellent predictions. This indicates that USDT volatility is minimally affected by macroeconomic factors or has a stable relationship with them, eliminating the need for complex time-varying models.

Comparison of ETH volatility predictions. ETH volatility shows a clear upward trend, rising steadily from 10 in January 2024 to 30 in January 2026, demonstrating a trend of growth. Both prediction models are highly consistent with actual values, with the three lines almost completely overlapping. Both models successfully captured the upward trend of ETH volatility. For ETH with a clear trend, both models perform well, indicating that the relationship between ETH volatility and explanatory variables is relatively stable, or that the upward trend dominates.

These results validate the value of the rolling window regression method in predicting cryptocurrency volatility, especially for assets with high volatility and potentially time-varying relationships with traditional financial variables.

2.3.5 Time-varying parameter vector autoregressive model analysis

R-squared values of the three cryptocurrencies are all low. Among them, BTC: 22.18%, USDT: 18.11% , ETH: 10.35%. This indicates that the M2 growth rate and the yield of government bonds can only explain part of the changes in cryptocurrency volatility. Most of the remaining changes may be driven by other factors, such as investor sentiment and market fear index, macroeconomic policies other than monetary policy, technical factors, etc. [11] The specific statistical results are shown in the Table 3 upon.

Table 3. Time-varying Parameter Vector Autoregressive Model Analysis

	BTC volatility	USDT volatility	ETH volatility
M2 growth rate coefficient range	-300.1859 810.0681	-70.9101 67.7454	-1521.928 762.7046
Range of Treasury bond yield coefficients	-7.0148 47.4489	-1.4704 3.6053	-15.2006 110.1427
Mean R squared	0.2218	0.1811	0.1035
The percentage of time when the M2 coefficient is positive	84.5%	60.8%	42.3%
Percentage of time during which the yield coefficient of government bonds is positive	88.7%	54.6%	61.9%

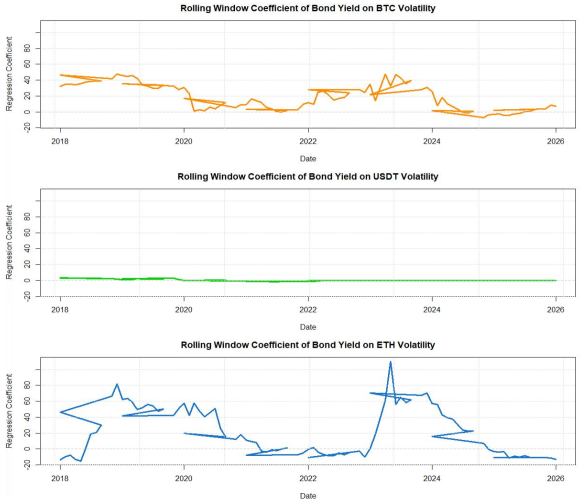


Figure 19. Rolling Window Coefficient of Bond Yield on BTC, USDT and ETH Volatility

As shown in the figure 19 1 above. The impact of the government bond yield coefficient on BTC and ETH is positive most of the time which was shown in figure 19 upon. However, for USDT, another cryptocurrency, the coefficient is almost evenly balanced between positive and negative values, indicating that the impact of government bond yields on USDT volatility is the least clear. This further confirms USDT 's characteristic as a " stablecoin, " where its volatility is more driven by factors other than monetary policy.

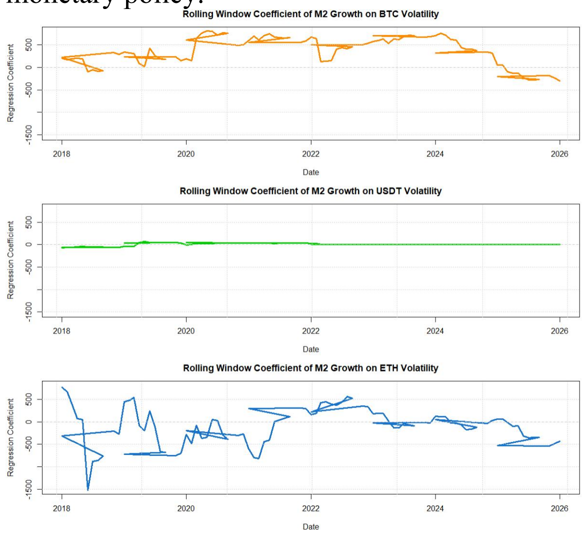


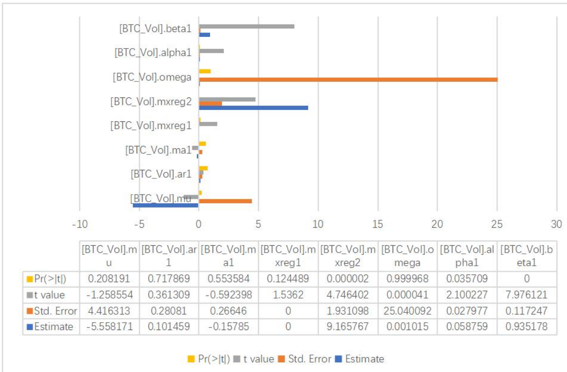
Figure 20. Rolling Window Coefficient of Bond Yield on BTC,USDT and ETH Volatility

The money supply M2, its coefficient for BTC's volatility ranges extremely wide, indicating a very strong and sustained positive driving effect of M2 growth on BTC volatility which was shown in figure 20 above. In terms of the impact of M2 on ETH 's volatility, its coefficient range is the most extreme, but its positive timeframe is the lowest. This reveals that ETH's relationship with M2 is the most complex and unstable, potentially more influenced by specific industry cycles, leading to its fluctuating response to macro liquidity. Finally, for USDT, its coefficient range is the smallest, positive 60.8% of the time. As a stable coin, USDT is designed to be pegged to the US dollar, and its volatility should theoretically be low. The relatively weak positive impact of M2 on its volatility may be because USDT serves more as a medium of exchange than a speculative asset.

In conclusion, the impact of M2 and Treasury yields on cryptocurrency volatility not only exists but also exhibits profound time-varying and structural characteristics. However, the reliability of such an impact warrants further investigation.

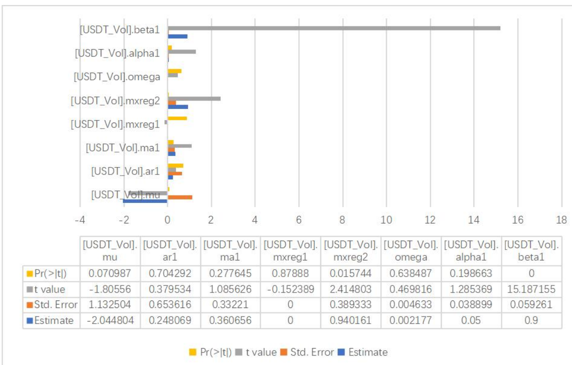
2.4 Empirical Study of the DY2012 Model

The DY2012 model typically refers to a specific application or variant of the dynamic conditional correlation coefficient model, with its core being the DCC-GARCH model. Proposed by Robert Engle et al., it is primarily used to analyze the dynamic correlations between multiple financial time series over time.



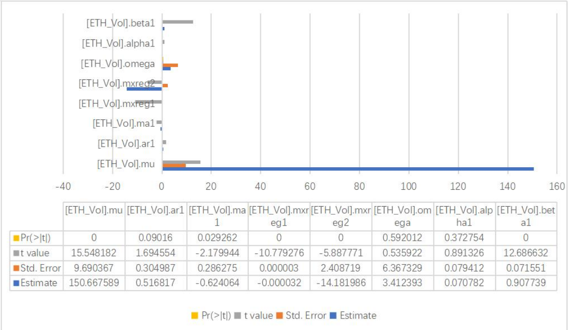
	[BTC_Vol].mu	[BTC_Vol].ar1	[BTC_Vol].ma1	[BTC_Vol].mxreg1	[BTC_Vol].mxreg2	[BTC_Vol].omega	[BTC_Vol].alpha1	[BTC_Vol].beta1
Pr(>|t|)	0.208191	0.717869	0.553584	0.124489	0.000002	0.999968	0.035709	0
t value	-1.258554	0.361309	-0.592398	1.5362	4.746402	0.000041	2.100227	7.976121
Std. Error	4.416313	0.28081	0.26646	0	1.931098	25.040092	0.027977	0.117247
Estimate	-5.558171	0.101459	-0.15785	0	9.165767	0.001015	0.058759	0.935178

Figure 21. DY2012 Model Analysis Results - BTC



	[USDT_Vol].mu	[USDT_Vol].ar1	[USDT_Vol].ma1	[USDT_Vol].mxreg1	[USDT_Vol].mxreg2	[USDT_Vol].omega	[USDT_Vol].alpha1	[USDT_Vol].beta1
Pr(>|t|)	0.070987	0.704292	0.277645	0.87888	0.015744	0.638487	0.198663	0
t value	-1.80556	0.379534	1.085626	-0.152389	2.414803	0.469816	1.285369	15.187155
Std. Error	1.132504	0.653616	0.33221	0	0.389333	0.004633	0.038899	0.059261
Estimate	-2.044804	0.248069	0.360656	0	0.940161	0.002177	0.05	0.9

Figure 22. DY2012 Model Analysis Results - USDT



	[ETH_Vol].mu	[ETH_Vol].ar1	[ETH_Vol].ma1	[ETH_Vol].mxreg1	[ETH_Vol].mxreg2	[ETH_Vol].omega	[ETH_Vol].alpha1	[ETH_Vol].beta1
Pr(>|t|)	0	0.09016	0.029262	0	0	0.592012	0.372754	0
t value	15.548182	1.694554	-2.179944	-10.779276	-5.887771	0.535922	0.891326	12.686632
Std. Error	9.690367	0.304987	0.286275	0.000003	2.408719	6.367329	0.079412	0.071551
Estimate	150.667589	0.516817	-0.624064	-0.000032	-14.181986	3.412393	0.070782	0.907739

Figure 23. DY2012 Model Analysis Results - ETH

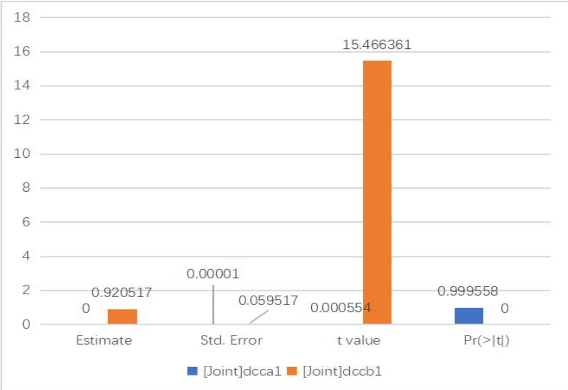


Figure 24. DY2012 model analysis results

The model estimates the individual volatility characteristics of three cryptocurrency volatility series-BTC, USDT, and ETH-and their dynamic correlations which was shown in figure 21, figure 22, figure23 and figure24. Results show that the volatility of each series exhibits strong persistence. The model type is a dynamic conditional correlation coefficient model, used to capture the time-varying correlations between multiple time series. Each [asset_Vol] part represents a separate GARCH (1,1) model. The ARCH coefficients measure the impact of previous volatility shocks on current volatility.

all GARCH coefficients are close to 1 and highly significant, indicating high persistence of volatility. BTC volatility is mainly driven by its previous volatility, and its response to previous shocks is relatively mild. USDT volatility is almost entirely driven by persistence. ETH, like USDT, exhibits significant persistence of volatility. The external variable mxreg2 has a highly significant impact on both BTC and ETH. For the DCC component, the estimated value of dcca1 coefficient a is 0 and completely insignificant. This means that the standardized residual product from previous periods has almost zero impact on the current dynamic correlation coefficient. The estimated value of dccb1 coefficient b is 0.9205 and highly significant. This means that the dynamic correlation coefficient from previous periods has a significant impact on the current value, and the correlation has extremely strong persistence.

3. Conclusion

This study uses a combination of VAR, TVP-VAR, and DY2012 models to systematically examine the impact of China's monetary policy on the volatility of mainstream cryptocurrencies.

Granger causality tests confirm that China's monetary policy variables are a statistical cause of cryptocurrency volatility. However, standard VAR models show that the static average coefficient of this impact is not statistically significant. Secondly, TVP-VAR dynamic analysis reveals the time-varying nature of the impact. The effect of monetary policy on cryptocurrency volatility is not fixed but fluctuates significantly over time. BTC is most sensitive to the two policy variables; ETH is extremely insensitive to changes in M2; and USDT's volatility is mainly affected by government bond yields. Finally, DY2012 model analysis shows that the dynamic conditional correlation coefficients among the volatility of BTC, ETH, and USDT have extremely strong persistence. This indicates that the internal volatility linkage structure of the cryptocurrency market is very stable, and its intrinsic correlation is stronger than the immediate impact of external monetary policy shocks.

In summary, this study confirms the complex and time-varying dynamic impact of China's monetary policy on the cryptocurrency market, but its volatility cannot be reliably predicted based on traditional macroeconomic variables. However, the study's conclusions should be viewed with caution. The main reason is the model's limited explanatory power , suggesting that the primary drivers of cryptocurrency volatility may not be traditional monetary policy, but rather other factors such as global sentiment, regulation, or technology. Furthermore, some results are highly sensitive to model parameter settings, indicating insufficient stability.

References

[1] Global Economy, (2026). [Academic Research • China's Monetary Policy] The Pulse of the Dragon and the Tides of the World: Deconstructing the Internal and External Mechanisms of China's Monetary

Policy Transmission and Global Restructuring: The Neglected Commodity Transmission Chain. https://mp.weixin.qq.com/s?src=11&timestamp=1771829414&ver=6559&signature=qVbNxwpT5u0zJndGe4395zUBjmlkV*PMwfI1VmkXrAouq*YrQZzj2HJJOFZQzLjuf8MtT2Ag*lQTYj3*w-JZpnC*54eMJmfHLZbl3LSf2X2HNu-hCZqGE98bCG9UrD9B&new=1

[2] Deng Wei. (2017) Bitcoin price bubble, evidence, causes and implications. Journal of Shanghai University of Finance and Economics, 19: 1-5.

[3] Ni Zhongxin, Lu Xing, Xue Wenjun. (2016) Can the "Belt and Road " strategy resolve China's excess steel production capacity? - Prediction based on the average of time-varying parameter vector autoregression model. International Trade Issues, 03:163-166.

[4] Liu Chao, Xu Junhui, Zhou Wenwen. (2017) Research on risk spillover effect in China's financial market - based on spillover index and complex network method. Systems Engineering Theory & Practice, 37:1-4.

[5] National Bureau of Statistics, (2025). Analysis of Money Supply. https://www.stats.gov.cn/zs/tjws/zytjzbqs/hbgyl/202502/t20250226_1958808.html

[6] Office of the Financial Committee of the Communist Party of Sichuan Provincial Committee, Financial Work Committee of the Communist Party of Sichuan Provincial Committee, Sichuan Provincial Local Financial Administration Bureau (2024). China's Monetary Policy Implementation Report for the Fourth Quarter of 2023. https://dfjrjgj.sc.gov.cn/scdfjrjgj/tjxx/2024/2/20/387f71a382244deba7a0e205572864a4.shtml

[7] Sina Finance, (2025). Central Bank: Attaches great importance to government bond yields and hopes the market can move steadily and sustainably. https://finance.sina.com.cn/jjxw/2025-01-14/doc-ineextzu1838487.shtml

[8] Nie Qiaoping, Sun Qiming (2022). A review of the development and application of the Ljung-Box test in time series models. Economic Theory and Practice, 04:1-3.

[9] Cao Yongfu , (2006). A Review of Granger Causality Tests, Quantitative Economics and Technological Research, 01: 156-158.

[10] Numerical Driven and Econometric Statistics, (2025). Introduction to Time-Variated Parametric Vector Autoregression (TVP-VAR) Models and Case Studies. https://mp.weixin.qq.com/s?__biz=MzIwOTM3MTE2Mg==&mid=2247483723&idx=1&sn=2f7b58469751aca82fd658787b260632&chksm=96cf739c0108caff87329e68dc5cdfce0e70c56877eb8b8730fde7298d1d2a4820096133115c#rd

[11] Liao Xiaoqiong, Zhao Huawei, Su Zhiwei, Xu Ruzhi, (2021). Dynamic Characteristics Analysis of Cryptocurrency Values-Taking Bitcoin, Ethereum, and Ripple as Examples, Finance and Economics, 02: 13-17.

