When Crypto Sneezes: Forecasting US Macroeconomic Indicators using Cryptocurrency Volatility

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Introduction

Studies have shown that U.S. monetary policy announcements and macroeconomic shocks influence cryptocurrency volatility [1, 2, 3]. However, the reverse effect of crypto volatility on US macroeconomic indicators is largely unexplored.

Our Research Question: To what extent volatility in major cryptocurrencies, including stablecoins and non-stablecoins, can help improve forecasts of key U.S. macroeconomic indicators?

Data Processing

We collected data for 8 macroeconomic variables and 8 cryptocurrencies between 2017-09 and 2025-01. The macroeconomic variables were selected based on existing literature and cryptocurrencies based on market cap by 2025-01 and time availability [2].

Table 1. Macro variables.

Variable	Description	Source
LFPR	Labor Force Participation Rate	BLS
CPI	Consumer Price Index	FRED
r	Federal Funds Rate	FRED
M1	M1 Money Supply	FRED
GDP	Real GDP Index	S&P Global
IM	Imports	FRED
EX	Exports	FRED
CC	Consumer Confidence Index	FRED

Table 2. Crypto variables (*stablecoins).

Variable	Description	Source
BTC	Bitcoin	Bloomberg
ETH	Ethereum	Investing.com
DOGE	Dogecoin	Investing.com
ADA	Cardano	Investing.com
LTC	Litecoin	Investing.com
XRP	XRP	Investing.com
USDT*	Tether	Investing.com
USDC*	USD Coin	Investing.com

Log Volatility for Cryptocurrencies. For cryptocurrencies, we log-transformed the monthly volatility.

$$LV_m = \ln\left(\sqrt{V_m}\right), \quad V_m = \sum_{p=1}^{N_m} R_{p,m}^2$$

Methodology

SARIMAX

To assess the predictive power of cryptocurrency, we compared two models:

- **Baseline SARIMA**: no exogenous variables:

$$Y_t = c + \sum_{i=1}^{p} \phi_i Y_{t-i} + \sum_{j=1}^{q} \theta_j \varepsilon_{t-j} + \sum_{s=1}^{P} \Phi_s Y_{t-sS} + \sum_{r=1}^{Q} \Theta_r \varepsilon_{t-rS} + \varepsilon_t$$

- **SARIMAX**: use lagged cryptocurrency volatility as exogenous regressors:

$$Y_t = c + \sum_{i=1}^{p} \phi_i Y_{t-i} + \sum_{j=1}^{q} \theta_j \varepsilon_{t-j} + \gamma X_{t-l} + \sum_{s=1}^{P} \Phi_s Y_{t-sS} + \sum_{r=1}^{Q} \Theta_r \varepsilon_{t-rS} + \varepsilon_t$$

We followed these steps:

1. **Order Selection.**

Table 3. SARIMA(X) parameters.

Parameter	Method	Criterion
d	ADF Test	$p < 0.05$
p	AIC	AR Order
q	AIC	MA Order

Table 4. Seasonal orders

Parameter	Method	Criterion
D	Canova-Hansen	Seasonal root
P	AIC	Seasonal AR
Q	AIC	Seasonal MA

The seasonal period S is set to $S = 3$ month (quarterly marker).

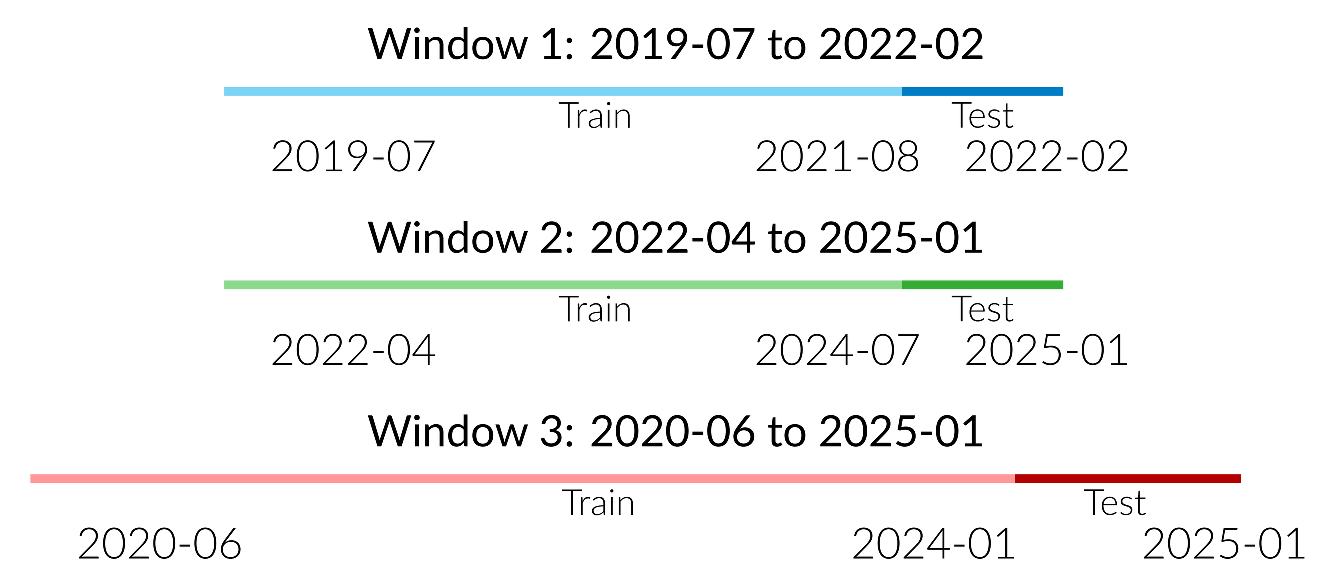
2. **Model Fitting.** We generated 0–6 month lags for each crypto asset, selected variables with p-value < 0.05, and ranked them by MAPE improvement.
3. **Model Evaluation.** We evaluated model performance using p-values and MAPE (Mean Absolute Percentage Error):

$$\text{MAPE} = \frac{100}{n} \sum_{t=1}^{n} \left| \frac{y_t - \hat{y}_t}{y_t} \right|$$

Methodology

Window Classification

Based on the volatility of our macroeconomic variables, we defined 3 windows to capture periods of high volatility [including the COVID shock], low volatility [without significant shock], and a more holistic, medium volatility period.



Results

MAPE Improvement

Combining all significant MAPE percentage changes across the three windows, we found improvement ranging from 2% to 93%, with an average improvement of 32%. Since MAPE measures the average prediction error as a percentage of actual values, larger MAPE percentage improvement indicated better model forecast accuracy in forecasting macroeconomic indicators when crypto is considered.

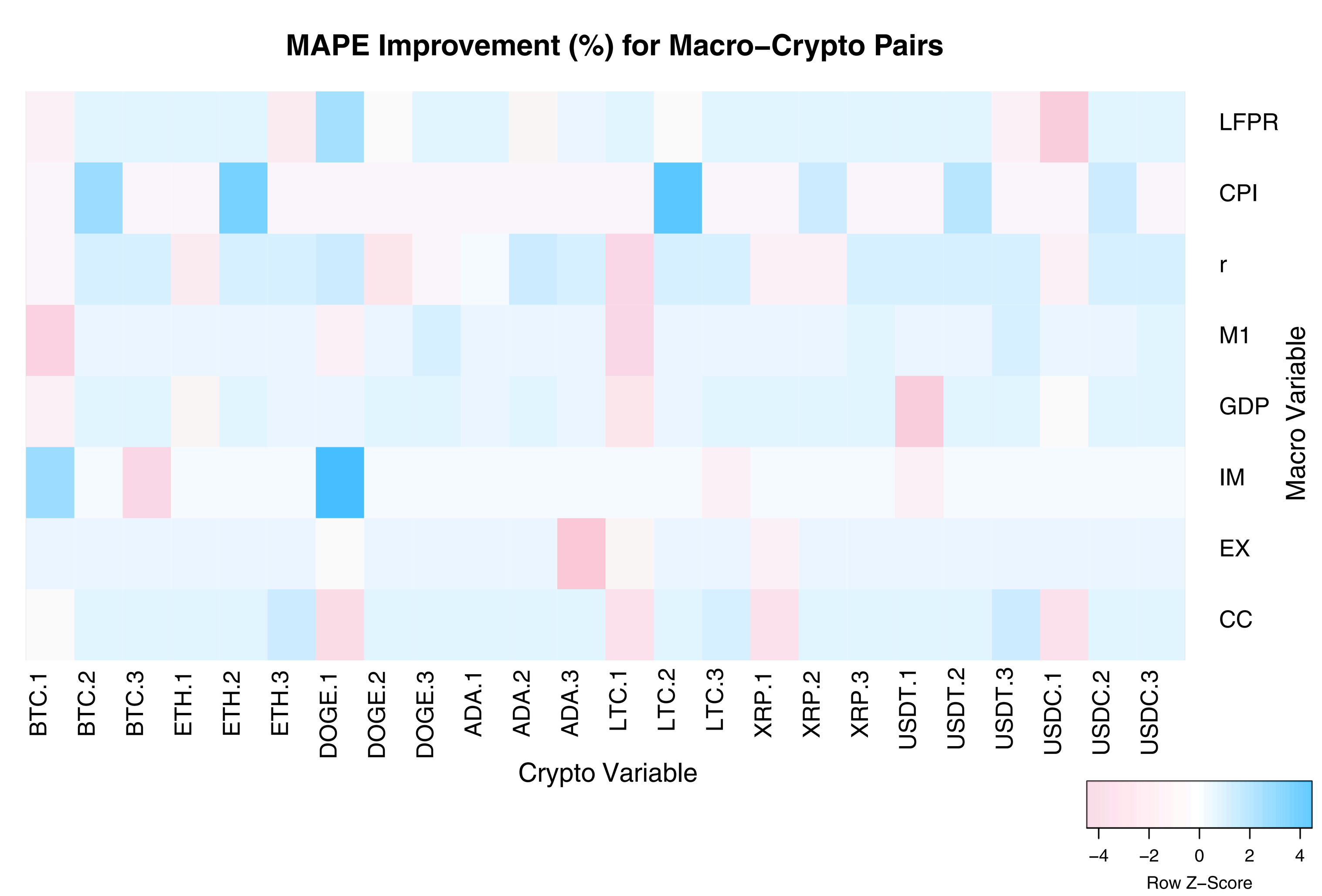


Figure 1. SARIMAX vs. SARIMA MAPE improvement(%) for macro-crypto pairs, windows 1-3 using heatmapper [4]

Across Windows

For each of the windows 1-3, we found that only certain cryptocurrencies helped improve the forecast of different macroeconomic indicators.

- In **Window 1** (high volatility), incorporating *Dogecoin* volatility with a two-month lag improved predictions for LFPR, r, and IM, with MAPE reductions of 69.65%, 45.63%, and 65.48%, respectively.
- In **Window 2** (low volatility), LTC, ETH, BTC, USDT, USDC, and XRP reduced forecast error for CPI. *Cardano* at a three-month lag yielded the greatest improvement in this window, reducing the MAPE for r forecasting by 19.91%.

Results

- In **Window 3** (moderate volatility), forecasts of the M1 money supply benefited the most from incorporating cryptocurrency volatility, with *Dogecoin* at a two-month lag reducing the MAPE by a substantial 93.39%.

Sample Forecast: CC With Tether

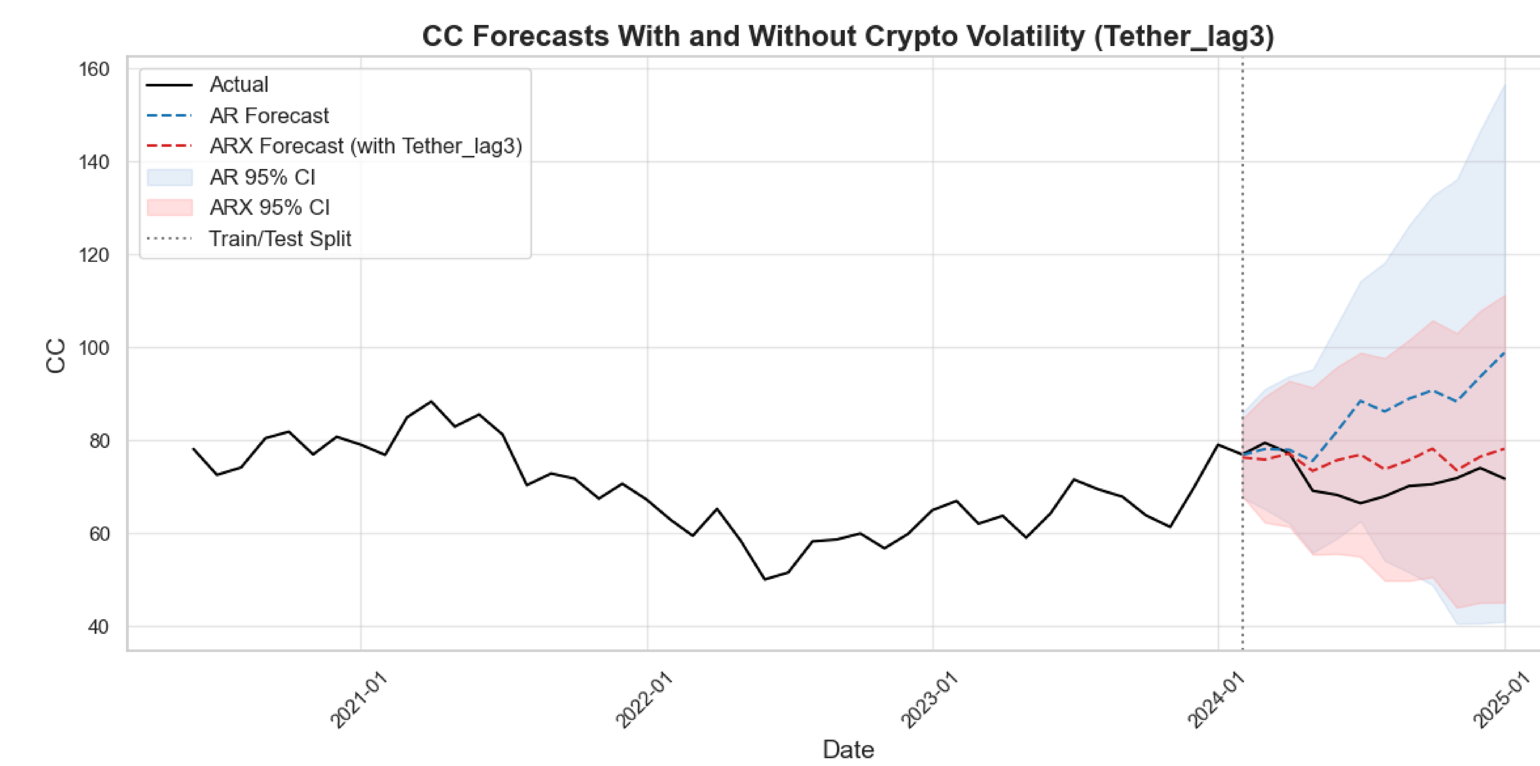


Figure 2. Consumer confidence index forecasts for window 3 with and without Tether volatility (3 months lag)

$$CC_t = -1.3806 \cdot USDT_{t-3} + 0.2807 \cdot \varepsilon_{t-1} - 0.3349 \cdot \varepsilon_{t-2} - 0.9010 \cdot \varepsilon_{t-3} + \varepsilon_t$$

$$\varepsilon_t \sim \mathcal{N}(0, \sigma^2 = 17.8967)$$

For Window 3, Tether, with a 3 month lag, proved significant in forecasting Consumer Confidence (p-value=0.01). Including Tether in the SARIMAX model improved the MAPE by 65.8% when compared to the benchmark SARIMA model. For every unit change in Tether log volatility, the forecast for CC volatility decreased by 1.38. This suggested that Tether, along with Ethereum and Litecoin, exhibited forecasting ability for Consumer Confidence during a moderately volatile period.

Conclusion

Our analysis revealed that cryptocurrencies can be used for forecasting macroeconomic variables across periods of different macroeconomic volatility. Notably:

- Dogecoin was a consistent predictor across all three time windows, suggesting that investor sentiment may be more closely linked to the broader economy than previously understood.
- In the low volatility regime, 6 crypto assets improved inflation rate (CPI) prediction, suggesting that during calm market phases, inflation may become more closely aligned with crypto dynamics.

While specific cryptocurrencies' predictive power proved to be conditional on the market regime, our model's performance suggests a potentially larger role in hybrid forecasting models that combine traditional assets with cryptocurrency. Future explorations could include non-linear models and also global macroeconomic indicators.

References

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