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Bubbles, Crashes and Contagion: Evidence on Volatility Forecasting in Cryptocurrencies and Stablecoins

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INTRODUCTION & AIM

Periodically collapsing bubbles (PCB) and **crashes** are a recurrent feature of **cryptocurrency** markets and represent a major challenge for volatility forecasting and risk management. While these dynamics have been widely investigated for traditional cryptocurrencies, their role in **stablecoin** markets remains comparatively underexplored.
Although stablecoins are designed to preserve a stable value relative to a reference asset, temporary departures from the peg may convey relevant information about liquidity pressures and confidence in the peg mechanism.

The aim is to propose a framework called **Bubble Crash-GARCH model**. The framework is implemented in three steps:

1. PCB and crashes are detected through **Phillips, Shi and Yu test**, a real-time monitoring procedure, that is applied to daily log-prices (defining the bubble as a deviation of the price from the fundamental value);
2. Thei intensity of PCB and crashes is quantified by including bubble-crash indicators in the **conditional mean** equation of daily log-returns;
3. Their contribution to one-step-ahead return volatility forecasting is evaluated using the **Clark–West (CW) test** over the period from January 1, 2019, to February 28, 2026, with August 31, 2025, as the cutoff date. The test is conducted against a carefully selected benchmark, chosen from a set of competing models that includes **asymmetric GARCH specifications** and **different distributional assumptions**.

The analysis is conducted from both an **idiosyncratic** (denoted by "OWN") and a **contagion** (denoted by "CO") perspective, and particular attention is devoted to the **Bitcoin–USDT channel**.

METHOD

$$\Delta p_t = u_{r1,r2} + \rho_{r1,r2} p_{t-1} + \sum_{j=1}^{l} \phi_{j,r1,r2} \Delta p_{t-j} + \nu_t$$

PCB

$$p_t = g_T + p_{t-1} + u_t$$
$$H_0: u_{r1,r2} = g_T \text{ and } \rho_{r1,r2} = 0$$
$$H_1: u_{r1,r2} = 0 \text{ and } \rho_{r1,r2} > 0$$

CRASHES

$$p_t = -L_t + p_{t-1} + u_t$$
$$H_0: u_{r1,r2} = g_T \text{ and } \rho_{r1,r2} = 0$$
$$H_1: u_{r1,r2} = K \text{ and } \rho_{r1,r2} = 0$$

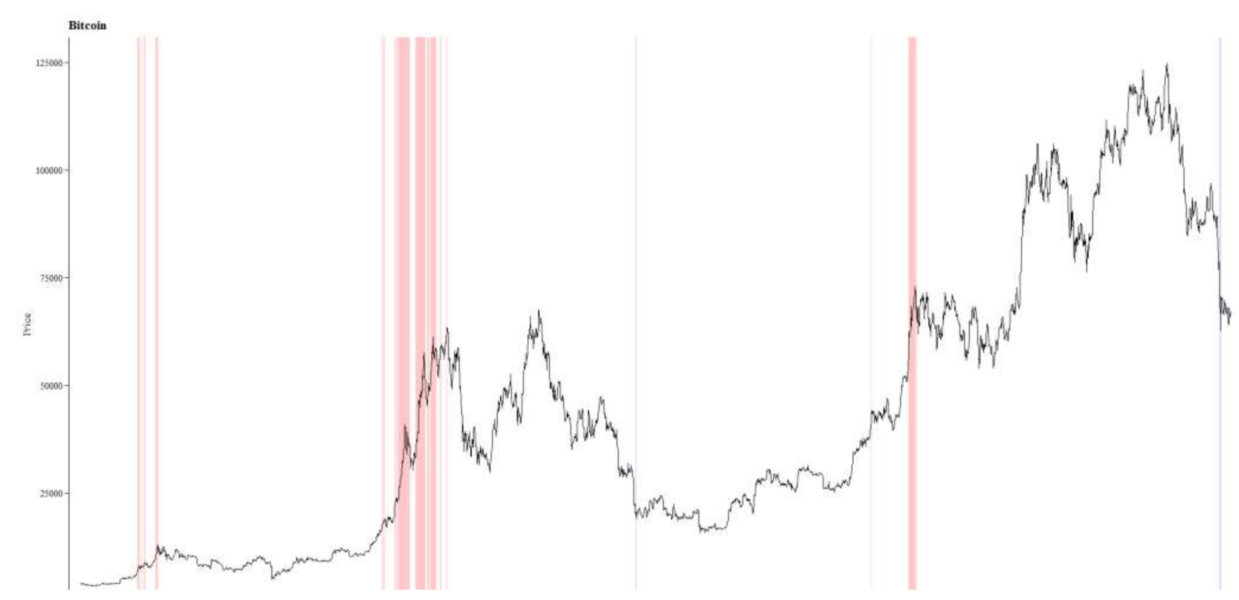
Date Stamping

$$\hat{r}_o = \inf_{r^* \in [r_0, 1]} \{ r^* : PSY_{r^*}(r_0) > cv_{r^*}(\beta_T) \}$$
$$\hat{r}_t = \inf_{r^* \in [\hat{r}_o, 1]} \{ r^* : PSY_{r^*}(r_0) < cv_{r^*}(\beta_T) \}$$

$$\boldsymbol{r_t = \mu + \theta_1^{OWN} B_t^{OWN} + \theta_2^{OWN} C_t^{OWN} + \theta_1^{CO} B_t^{CO} + \theta_2^{CO} C_t^{CO} + \varepsilon_t}$$
$$\varepsilon_t = \sigma_t z_t, \qquad z_t \sim D(0,1,\nu)$$
$$\sigma_t^2 = \omega + \sum_{j=1}^{q} \alpha_j \varepsilon_{t-j}^2 + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2$$

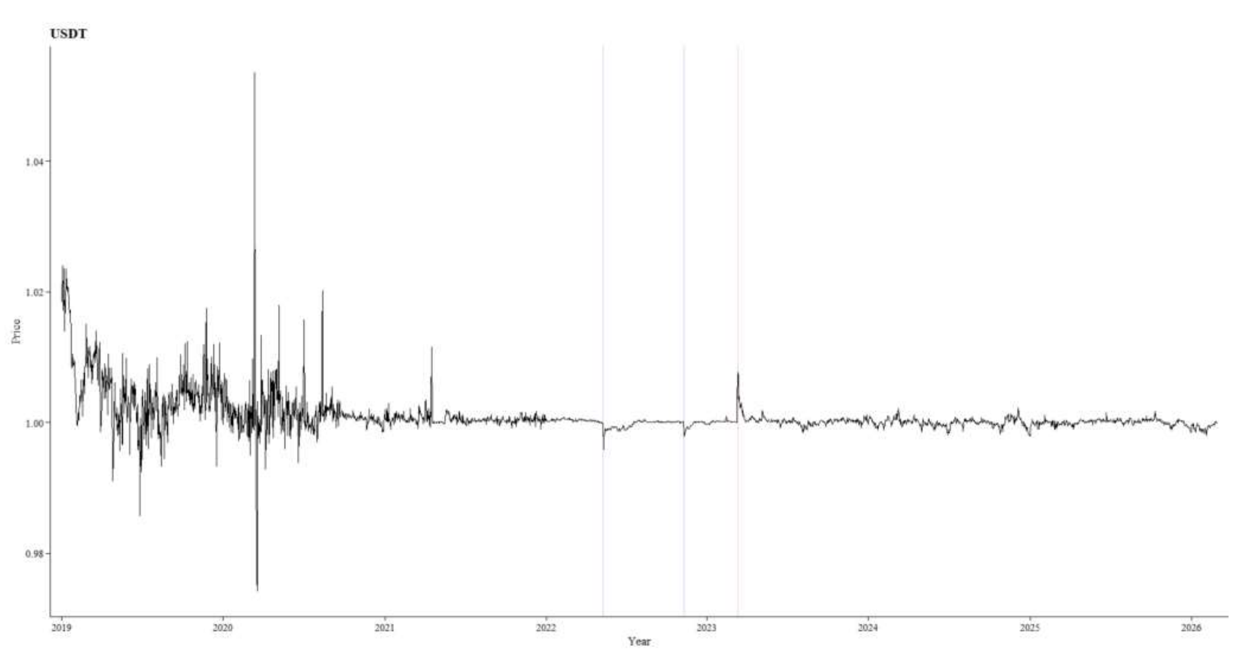
RESULTS & DISCUSSION

Bitcoin and **USDT** exhibit very different exposures to PCB (red lines) and crashes (blue lines) at 95% wild bootstrap critical value**.** In particular**,** Bitcoin records **125 events** (123 bubbles and 2 crashes) whereas USDT records only **4 events** (2 bubbles and 2 crashes), with evidence of a **bidirectional and asymmetric contagion**: while crashes in USDT have a strongly positive effect on the conditional mean returns of Bitcoin, bubbles in Bitcoin negatively affect the conditional mean returns of USDT. Moreover, the inclusion of extreme-event information from USDT significantly improves the forecasting performance of the volatility of Bitcoin.



Parameter / Statistic	GARCH	BC–GARCH^{OWN}	BC–GARCH^{USDT}
Mean equation			
μ	0.078*	0.051	0.049
θ_1^{OWN}	–	1.495***	1.492***
θ_2^{OWN}	–	-7.414**	-7.414**
θ_1^{USDT}	–	–	–
θ_2^{USDT}	–	–	8.405***
Variance equation			
ω	0.189**	0.190**	0.173**
α_1	0.074***	0.074***	0.069***
β_1	0.925***	0.925***	0.930***
shape (ν)	3.079***	3.082***	3.075***
Log-likelihood	-5708.577	-5696.761	-5695.091
CW p-value (vs. GARCH)	–	0.011	0.009

Estimation results for Bitcoin GARCH models. CW p-values refer to comparisons against the benchmark GARCH model. BC–GARCH^{OWN} includes Bitcoin own bubble and crash indicators, whereas BC–GARCH^{USDT} additionally includes the crash indicator associated with USDT. Statistical significance: *** 1%, ** 5%, * 10%.



Parameter / Statistic	ARMA–GARCH	ARMA–BC–GARCH^{OWN}	ARMA–BC–GARCH^{BTC}
Mean equation			
μ	0.000072	0.000097	0.000123
AR(1)	0.331***	0.316***	0.320***
MA(1)	-0.750***	-0.736***	-0.741***
θ_1^{OWN}	–	–	–
θ_2^{OWN}	–	-0.114***	-0.114***
θ_1^{BTC}	–	–	-0.004**
θ_2^{BTC}	–	–	–
Variance equation			
ω	0.000***	0.000***	0.000***
α_1	0.205***	0.193***	0.190***
β_1	0.794***	0.806***	0.809***
skew	1.062***	1.060***	1.060***
shape (ν)	4.195***	4.228***	4.178***
Log-likelihood	3524.468	3530.715	3532.470
CW p-value (vs. ARMA–GARCH)	–	0.123	0.098

Estimation results for USDT volatility models under the skewed Student-t distribution. All specifications include an ARMA(1,1) component in the mean equation to obtain well-specified residual dynamics. CW p-values refer to comparisons against the benchmark ARMA–GARCH skewed t distribution model. ARMA–BC–GARCH^{OWN} includes the USDT own crash indicator, whereas ARMA–BC–GARCH^{BTC} includes the USDT own crash indicator together with the Bitcoin bubble indicator. Statistical significance: *** 1%, ** 5%, * 10%.

CONCLUSIONS

The **Bubble Crash-GARCH framework** shows that Bitcoin and USDT have very different exposure to tail events, while also revealing asymmetric contagion between the two assets and a higher significant predictive gain in Bitcoin volatility forecasting when extreme-event information from USDT is included; although peg-deviation episodes in USDT are short-lived, they do occur and should therefore be monitored as potential early-warning signals for risk propagation in digital-asset markets.

FUTURE WORK / REFERENCES

- Extend the framework to the forecasting of Value-at-Risk and Expected Shortfall.

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