The Impact of Stablecoins on Bitcoin Returns: An Empirical Analysis Based on VAR Model

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Abstract. Bitcoin's price dynamics are influenced by both internal factors (e.g., supply shocks, investor sentiment) and external drivers, among which the stability of stablecoins has attracted increasing academic and regulatory attention. This paper investigates the effect of stablecoin peg deviations (USDT and USDC) on Bitcoin returns using daily data from January 2020 to August 2025. Based on a vector autoregression (VAR) framework, we conduct unit root tests, lag order selection, model estimation, Granger causality tests, and impulse response analysis. Results show that both Bitcoin returns and stablecoin deviations exhibit strong short-term inertia. USDT and USDC deviations significantly Granger-cause Bitcoin returns, whereas the reverse causality is weaker. Impulse responses indicate that stablecoin deviations first produce positive shocks to Bitcoin returns, followed by negative corrections that gradually stabilize. The effect of USDT is more pronounced and persistent, underscoring its central role in cryptocurrency markets. These findings highlight the importance of monitoring stablecoin market stability, especially USDT, for investors and regulators seeking to manage systemic risks in crypto markets.

Keywords: Bitcoin, Stablecoin, Peg deviation, VAR model.

1. Introduction

With the rapid development of blockchain technology and the continuous expansion of the cryptocurrency market, Bitcoin has become the most representative cryptocurrency and a central topic in both academic and industry research. However, its price exhibits substantial volatility, making risk management and forecasting challenging [1, 2]. Prior studies show that Bitcoin behaves more like a speculative asset than a medium of exchange, while also displaying partial hedging properties similar to gold [3]. Moreover, Bitcoin has become increasingly integrated with global financial markets, which makes its price dynamics more susceptible to macroeconomic shocks [4].

Among the external factors influencing Bitcoin prices, stablecoins have emerged as a key driver of market liquidity and trading activity. By design, stablecoins maintain a 1:1 peg to fiat currencies such as the U.S. dollar, providing a convenient medium of exchange and facilitating arbitrage across cryptocurrency exchanges [5, 6]. Nevertheless, stablecoins are not perfectly stable: "de-pegging" events occasionally occur, which may trigger liquidity shocks and amplify price fluctuations in the broader crypto market [7].

A growing body of empirical research explores the link between stablecoins and Bitcoin. Griffin and Shams demonstrated that Tether (USDT) issuance is positively associated with Bitcoin price increases, raising concerns about potential price manipulation [8]. Ante et al. and Saggu further found that Tether minting and burning events have statistically significant and asymmetric effects on Bitcoin returns, indicating that stablecoin shocks transmit rapidly to Bitcoin prices [9, 10]. Grobys et al. showed that the volatility of stablecoins is closely connected to Bitcoin volatility, while Wang et al. and Hatem et al. explored whether stablecoins function as diversifiers, hedges, or safe havens and found mixed evidence [11-13].

Beyond USDT, USD Coin (USDC) has gained prominence as a major stablecoin, emphasizing reserve transparency and regulatory compliance. However, the Silicon Valley Bank crisis in March 2023 caused USDC to experience a severe de-pegging, revealing vulnerabilities even in relatively well-audited stablecoins [14]. Lyons and Viswanath-Natraj analyzed the arbitrage mechanisms that normally maintain stablecoin pegs but emphasized that these mechanisms can fail under stressed market conditions [15].

From a methodological perspective, multivariate time-series models such as VAR provide a powerful tool to capture the dynamic and bidirectional relationships among financial variables. Katsiampa used GARCH-type models to examine Bitcoin's volatility dynamics, while Ji et al. employed VAR and connectedness approaches to analyze spillovers among cryptocurrencies and other asset classes [16, 17]. These approaches motivate the use of a VAR framework in this study to explore the dynamic interactions between Bitcoin returns and stablecoin peg deviations.

In sum, while prior research has offered valuable insights into the relationship between stablecoins and Bitcoin, two research gaps remain. First, most studies have focused on USDT, with limited systematic examination of USDC. Second, few studies use VAR models to analyze the dynamic effects of stablecoin de-pegging on Bitcoin returns. This paper addresses these gaps by employing a VAR model with daily data from January 2020 to August 2025, examining the short- and medium-term impact of USDT and USDC peg deviations on Bitcoin returns, and providing new evidence on risk transmission mechanisms in the cryptocurrency market.

2. Research Framework

To investigate the impact of stablecoin peg deviations on Bitcoin returns, this study selects Bitcoin log returns and stablecoin peg deviations as variables and employs a vector autoregression (VAR) model. VAR models capture dynamic relationships among multiple variables without assuming prior causality, making them suitable for analyzing the interaction between stablecoins and Bitcoin.

Daily time-series data from January 2020 to August 2025 are used. The Bitcoin return btc_ret_t is calculated as the log difference of Bitcoin prices, as shown in Equation (1):

$$btc\_ret_t = \ln(P_t) - \ln(P_{t-1}) \tag{1}$$

Where P_t is the closing price of Bitcoin on day t.

The peg deviations of stablecoins are calculated as percentage deviations from the 1:1 peg, as shown in Equations (2) and (3):

$$usdt\_dev_t = \frac{P_t^{USDT} - 1}{1} \times 100 \tag{2}$$

$$usdc\_dev_t = \frac{P_t^{USDC} - 1}{1} \times 100 \tag{3}$$

Where P_t^{USDT} is the observed daily market price of USDT, P_t^{USDC} is the observed daily market price of USDC.

After conducting stationarity and unit root tests, these variables are confirmed to be stationary and included in the VAR model. The general VAR model is specified in Equation (4):

$$Y_t = A + B_1 Y_{t-1} + B_2 Y_{t-2} + \cdots + B_k Y_{t-k} + U_t,\ U_t \sim IID(0, \Omega) \tag{4}$$

Where $Y_t = (btc\_ret_t, stablecoin\_dev_t)$, A is the constant term vector, B_j are the parameter matrices, U_t is the disturbance vector, t denotes time, and k is the lag order determined by information criteria.

3. Data and Descriptive Statistics

Data are sourced from CoinMarketCap's official website, covering daily values from January 1, 2020 to August 20, 2025. The descriptive statistics for btc_ret, usdt_dev, and usdc_dev are presented in Table 1.

Table 1. Descriptive statistics of Bitcoin returns and stablecoin deviations

Variable	Min	Max	Mean	Std.Dev	Skewness	Kurtois
btc_ret	-17.1821	46.473	-0.1343	3.2996	1.3613	21.8477
usdt_dev	-2.5752	5.3585	0.0363	0.2006	8.9390	276.2484
usdc_dev	-2.9876	4.4029	0.0376	0.3162	5.1676	74.9076

On average, Bitcoin daily returns are slightly negative (mean = −0.13%), reflecting its volatile and risky nature. The standard deviation of 3.30 indicates substantial daily price fluctuations, consistent with Bitcoin being a highly volatile asset. Its skewness is positive (1.36), suggesting that extreme positive returns occur more often than extreme negative ones, while the kurtosis (21.85) shows heavy tails and frequent large shocks.

For stablecoins, both USDT and USDC display very small average deviations from their pegs (≈ 0.03), confirming that they generally maintain their $1 target. However, their distributions are not perfectly symmetric: USDT has a very high skewness (8.94) and extremely high kurtosis (276.25), implying occasional large positive deviations, while USDC also shows fat tails (kurtosis = 74.91) but with less extreme skewness (5.17). These patterns suggest that, although rare, significant depegging events do occur and may have meaningful impacts on Bitcoin returns—justifying further dynamic analysis.

4. Empirical Analysis

4.1. Pre-estimation Tests

Before constructing the VAR model, it is necessary to test the stationarity of each variable in order to avoid spurious regression problems. This paper applies the Augmented Dickey-Fuller (ADF) unit root test to Bitcoin returns (btc_ret), USDT deviations (usdt_dev), and USDC deviations (usdc_dev) to examine their time-series properties. The results are presented in Table 2.

Table 2. Results of Unit Root Tests for Variables

Variables	T-statistic	1% Critical Value	5% Critical Value	10% Critical Value	P-Value
btc_ret	–17.571	–3.43	–2.86	–2.57	0
usdt_dev	–17.337	–3.43	–2.86	–2.57	0
usdc_dev	–8.343	–3.43	–2.86	–2.57	0

As shown in Table 2, the ADF test statistics for the three variables are all significantly smaller than the critical values at the 1%, 5%, and 10% levels, with corresponding p-values close to 0. This indicates that the null hypothesis of a unit root can be rejected, implying that all variables are stationary in their level forms. Therefore, it is appropriate to directly use the raw time series for VAR modeling without the need for further differencing.

After confirming the stationarity of the variables, the next step is to determine the optimal lag length for the VAR model. To this end, several commonly used information criteria—including AIC (Akaike Information Criterion), SC (Schwarz Criterion), HQ (Hannan-Quinn Criterion), and FPE (Final Prediction Error)—are employed. These criteria balance model fit and parsimony, ensuring that the chosen lag length avoids both underfitting and overfitting.

Table 3. Results of Lag Selection

	USDT-BTC model	USDC-BTC model
AIC(n)	5	4
HQ(n)	5	4
SC(n)	4	4
FPE(n)	5	4

As shown in Table 3, for the USDT–BTC model, the AIC, HQ, and FPE criteria all suggest a lag length of 5, while the SC criterion leans toward a lag length of 4. Considering that most criteria converge on 5 and that longer lags may better capture dynamic interactions, a lag length of 5 is ultimately selected as the optimal lag for the USDT–BTC system.

For the USDC–BTC model, all four information criteria (AIC, SC, HQ, and FPE) consistently recommend a lag length of 4. Given this unanimity, the lag length of 4 is directly adopted as the optimal specification for the USDC–BTC system.

In summary, subsequent VAR estimations are conducted with a lag length of 5 for the USDT–BTC system and a lag length of 4 for the USDC–BTC system. This selection ensures that the models are both statistically robust and capable of effectively capturing the dynamic relationships between Bitcoin returns and stablecoin deviations.

4.2. Model Estimation

Based on the time series data of Bitcoin returns and the de-anchoring deviation of stablecoins (USDT, USDC), a VAR model is constructed to estimate the coefficients. The results are shown in Tables 4 and 5.

From the USDT–BTC system (Table 4), it can be seen that the VAR model with 5 lags reveals some significant relationships. The coefficient of Bitcoin returns at lag 1 is negative (-0.0472), showing a mean-reversion characteristic. Meanwhile, USDT deviations at lag 1 have a significantly positive impact on BTC returns (2.8603), but turn negative at lag 3 (-0.9258). This indicates that shocks in the USDT market deviations exert a short-term amplifying effect on Bitcoin returns, followed by a medium-term corrective response, showing a dual effect.

In the USDT equation, the coefficient of BTC returns at lag 1 is significantly positive (0.0025), suggesting that Bitcoin return fluctuations can partly transmit to the stablecoin market. Furthermore, multiple lag terms of USDT itself are significant, indicating that its de-anchoring deviations exhibit relatively strong self-persistence.

Table 4. VAR Model Estimation Results (USDT–BTC system, p=5)

Variable(Lag)	btc_ret equation	usdt_dev equation
btc_ret.l1	-0.0472* (-2.131)	0.0025 (1.908)
btc_ret.l2	0.0400 (1.801)	-0.0026* (-2.001)
btc_ret.l3	-0.0022 (-0.097)	0.0006 (0.489)
btc_ret.l4	0.0563* (2.540)	-0.0023 (-1.786)
btc_ret.l5	0.0160 (0.729)	0.0007 (0.583)
usdt_dev.l1	2.8603*** (7.543)	0.2268*** (10.270)
usdt_dev.l2	-0.7591 (-1.941)	0.0756*** (3.320)
usdt_dev.l3	-0.9258* (-2.369)	0.1000*** (4.395)
usdt_dev.l4	-0.3408 (-0.868)	0.1270*** (5.560)
usdt_dev.l5	-0.3549 (-0.921)	-0.0930*** (-4.145)
Constant	-0.1460(-1.941)	0.0203*** (4.640)
Adjusted R-squared	0.03349	0.1135

From the USDC–BTC system (Table 4), it can be observed that in the VAR model with lags 1 to 4, several variables show significant effects (P<0.05) on Bitcoin returns or USDC deviations. Specifically, the first lag of Bitcoin returns is significantly negative (–0.0581), indicating a certain mean-reversion effect in BTC returns. At the same time, USDC deviations at lag 1 exert a strong positive impact on BTC returns (2.1828), while lags 3 and 4 show significant negative effects (–0.8005, –0.6812), suggesting that deviations in the USDC market relative to Bitcoin prices have both short-term positive shocks and medium-term negative corrections, but with asymmetric effects.

On the other hand, fluctuations in BTC returns also feed back into USDC deviations. For instance, btc_ret.l1 in the USDC equation is significantly positive (0.0029), indicating that changes in Bitcoin prices can amplify short-term price deviations of stablecoins. Overall, the results suggest a bidirectional and significant dynamic relationship between USDC and BTC.

Table 5. VAR Model Estimation Results (USDC–BTC system, p=4)

Variable (Lag)	btc_ret equation	usdc_dev equation
btc_ret.l1	-0.0581** (-2.635)	0.0029* (2.011)
btc_ret.l2	0.0396 (1.793)	-0.0041** (-2.806)
btc_ret.l3	0.0025 (0.115)	-0.0005 (-0.346)
btc_ret.l4	0.0586** (2.679)	-0.0028 (-1.948)
usdc_dev.l1	2.1828*** (6.514)	0.4115*** (18.702)
usdc_dev.l2	-0.5453 (-1.536)	0.0811*** (3.477)
usdc_dev.l3	-0.8005* (-2.255)	0.2626*** (11.264)
usdc_dev.l4	-0.6812* (-2.011)	0.0939*** (4.221)
Constant	-0.1375 (-1.888)	0.0056 (1.154)
Adjusted R-squared	0.0271	0.5434

Overall, the VAR estimations empirically demonstrate a significant and bidirectional dynamic relationship between Bitcoin returns and stablecoin peg deviations. The results underscore that stablecoin deviations exert a short-term amplifying effect on Bitcoin returns, which is subsequently followed by a medium-term corrective adjustment, reflecting partial mean reversion. Conversely, fluctuations in Bitcoin returns are found to significantly transmit into the stablecoin market, influencing peg stability. These findings highlight the pivotal role of stablecoin stability in cryptocurrency market dynamics and provide important implications for risk monitoring and price forecasting in digital asset markets.

4.3. Granger Causality Test

To further investigate the relationship between Bitcoin returns and the deviations of stablecoins (USDT and USDC), this study employs the Granger causality test. The results are presented in Table 6.

Table 6. Results of Granger Causality Test and Instantaneous Causality Test

H0	Statistics (F/Chi²)	P-value	Conclusion
btc_ret do not Granger-cause usdt_dev	F = 2.5256	0.0273	Reject H_0, causality exists
usdt_dev do not Granger-cause btc_ret	F = 12.396	5.85E-12	Reject H_0, causality exists
btc_ret do not Granger-cause usdc_dev	F = 4.2133	0.0021	Reject H_0, causality exists
usdc_dev do not Granger-cause btc_ret	F = 11.575	2.40E-09	Reject H_0, causality exists
No instantaneous causality between: btc_ret and usdt_dev	$Chi^2 = 9.0958$	0.0026	Reject H_0, causality exists
No instantaneous causality between: usdc_dev and btc_ret	$Chi^2 = 0.3228$	0.5699	Accept H_0

Table 6 reports the results of the Granger causality tests between Bitcoin returns and the peg deviations of USDT and USDC. The null hypotheses that Bitcoin returns do not Granger-cause USDT/USDC deviations are rejected at the 5% significance level, indicating that Bitcoin price fluctuations help predict subsequent changes in stablecoin deviations. Similarly, the null hypotheses that USDT and USDC deviations do not Granger-cause Bitcoin returns are also strongly rejected, suggesting that stablecoin de-anchoring contains predictive power for future Bitcoin returns.

In addition, the instantaneous causality test shows a significant contemporaneous relationship between Bitcoin returns and USDT deviations ($Chi^2 = -9.0958$, $p = 0.0026$), implying that shocks in the USDT market and Bitcoin returns respond simultaneously within the same period. However, no instantaneous causality is found between USDC deviations and Bitcoin returns, suggesting that USDC reacts to Bitcoin price movements with a slight lag rather than immediately.

Overall, these results confirm a bidirectional and time-dependent causal linkage between Bitcoin and stablecoin markets, with USDT showing stronger and more immediate interactions compared to USDC.

4.4. Impulse Response Analysis

To explore the dynamic relationship between Bitcoin returns and the de-pegging premium of stablecoins (USDT and USDC), this study constructs impulse response functions based on the estimated VAR model.

For the impact of USDT de-pegging premium shocks on Bitcoin returns, the results shown in Figure 1 indicate that Bitcoin returns experience a significant positive shock in the first period, rising rapidly. By the second period, the effect reaches its peak before beginning to decline, and around the fourth period, the effect turns negative. Subsequently, the fluctuations gradually weaken and approach zero. This suggests that short-term volatility in the USDT market has a notable impact on Bitcoin prices, but the effect is temporary.

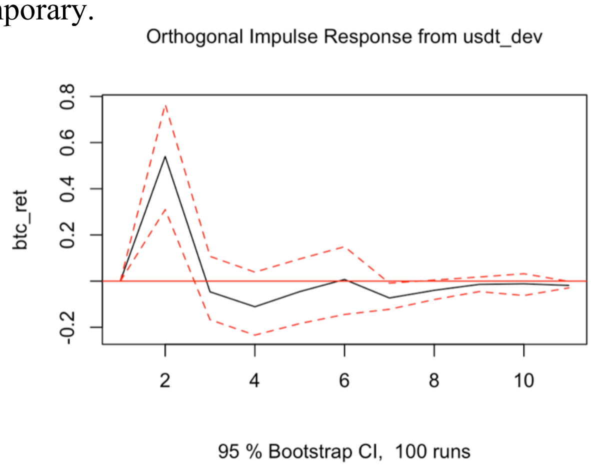

Figure 1. Impulse response analysis of btc_ret to usdt_dev

In contrast, as shown in Figure 2, the response of USDT de-pegging premium to shocks in Bitcoin returns is not significant. The response amplitude is relatively small, and the fluctuation bands hover closely around zero, indicating that Bitcoin has only a limited feedback effect on USDT deviations.

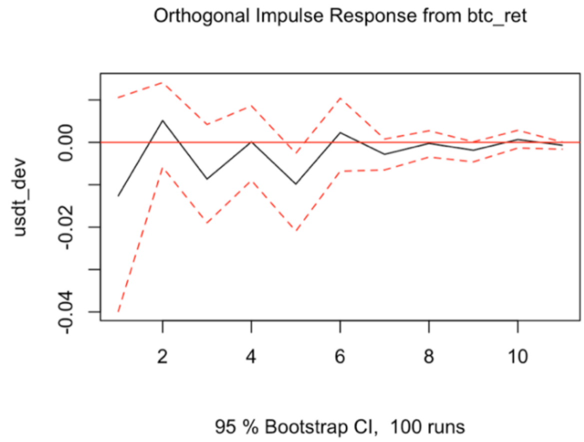

Figure 2. Impulse response analysis of usdt_dev to btc_ret

As shown in Figure 3, the impulse response of Bitcoin returns to a one-standard-deviation shock in USDC de-anchoring exhibits a clear short-run positive effect. The response peaks in period 2, indicating that USDC de-anchoring significantly amplifies Bitcoin returns in the immediate aftermath of the shock. This effect subsequently turns negative around periods 3–4, reflecting a partial mean-reversion in Bitcoin prices, and gradually converges toward zero in later periods. However, the overall amplitude of the impact is slightly lower than that of USDT. This indicates that while USDC's influence on Bitcoin is directionally consistent with USDT, its market transmission effect is weaker.

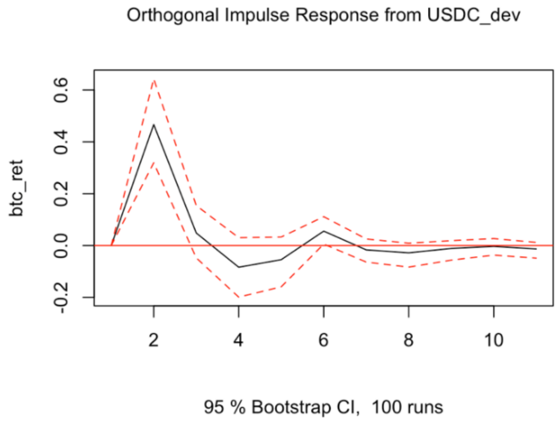

Figure 3. Impulse response analysis of btc_ret to usdc_dev

As illustrated in Figure 4, the impulse response of USDC deviations to a one-standard-deviation shock in Bitcoin returns remains statistically insignificant across all periods. The response oscillates narrowly around zero, with confidence intervals consistently covering the zero line. This indicates that Bitcoin return shocks exert only a weak and statistically negligible effect on USDC's peg deviations, suggesting limited feedback from Bitcoin price fluctuations to the USDC market.

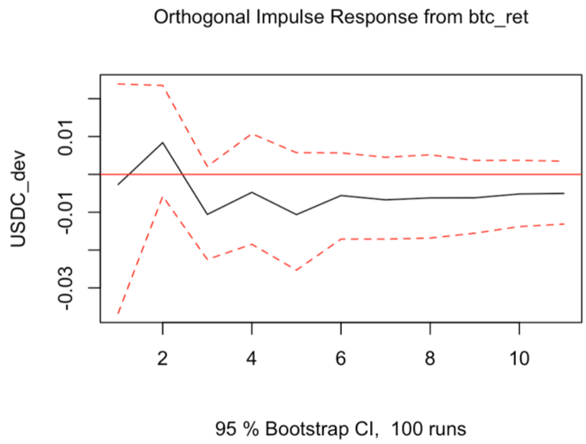

Figure 4. Impulse response analysis of usdc_dev to btc_ret

Overall, the price deviations of stablecoins—particularly USDT—exert a significant short-term impact on Bitcoin returns, characterized by an initial positive shock followed by a negative effect. In contrast, Bitcoin itself provides only a weak feedback response to stablecoin deviations. This suggests that the stablecoin market plays a certain leading role in Bitcoin's price formation mechanism, though its influence diminishes rapidly over time.

5. Conclusion

This paper provides a comprehensive empirical investigation of the dynamic interactions between Bitcoin returns and the de-anchoring premiums of major stablecoins, using daily data from January 2020 to August 2025 and a VAR modeling framework. Our results consistently show that both Bitcoin returns and stablecoin deviations exhibit strong short-term persistence, with Bitcoin's own lagged terms explaining most of its future volatility. More importantly, we find robust evidence that USDT and USDC deviations significantly Granger-cause Bitcoin returns, whereas the reverse causal relationship is weak and statistically insignificant. This asymmetry suggests that stablecoin markets act as a leading indicator rather than a passive follower of Bitcoin price fluctuations.

Impulse response analysis further reveals a clear dynamic pattern: de-anchoring shocks initially amplify Bitcoin returns, pushing prices in the same direction as the shock, followed by a negative adjustment that gradually stabilizes. This mean-reverting behavior highlights the transitory nature of stablecoin shocks, but also underscores their potential to exacerbate short-term volatility and create price overshooting. Moreover, the impact of USDT is found to be considerably stronger and more persistent than that of USDC, reflecting its dominant position in crypto trading volumes and liquidity provision. The stronger transmission from USDT may be linked to its wider adoption across centralized and decentralized exchanges, as well as its critical role in arbitrage and price discovery.

From a practical perspective, these findings carry significant implications for market participants and regulators. For investors, monitoring stablecoin market conditions—especially USDT's peg stability and liquidity dynamics—can improve portfolio allocation decisions and risk management strategies, particularly during periods of heightened volatility. For policymakers and regulators, the results point to the systemic importance of stablecoins, suggesting that enhanced oversight of their issuance, reserve management, and redemption mechanisms could help mitigate spillover risks and promote greater resilience in the cryptocurrency ecosystem.

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