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The Relationship Between Stablecoin and Cryptocurrency Returns During Periods of Market Stress

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Abstract

Active asset managers increasingly include cryptocurrencies in their alternative asset allocations, highlighting their speculative and volatile nature. The aim of this research is to examine trends in the returns and volatility of cryptocurrencies, whilst accounting for the depegging of stablecoins, driven by speculative trading during macroeconomic shocks and technological shifts. We build a sample of market capitalisation, using data from the daily closing prices of Bitcoin (BTC), Ethereum (ETH), Binance (BNB), and Ripple (XRP), two fiat-backed stablecoins (USDT and USDC), and a cryptocurrency-collateralised stablecoin (DAI). As a first step, a Granger-causality framework is applied to examine the influence of stablecoin depegging events on crypto returns during financial market stress. The results are strongly asymmetric: there is little evidence that depegs predict returns; whereas cryptocurrency returns robustly Granger-cause USDC depegging events, an effect that intensifies during periods of market stress. Stablecoin depegs appear to be a downstream symptom of cryptocurrency stress rather than a leading indicator of it. The analysis was extended by modelling volatility, using an EGARCH-X model to study whether depegs also affect crypto during periods of market stress and if larger deviations from the dollar peg are associated with higher cryptocurrency volatility, concentrated in the most liquid stablecoins (USDT and USDC), while the evidence for any change in this association during stress is limited. The findings carry implications for risk monitoring in digital-asset markets, where stablecoin behaviour reflects, rather than anticipates, cryptocurrency market conditions.

Keywords: cryptocurrency; asset allocation; volatility; Granger-causality test; GARCH model

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1. Introduction

Over the last decade, financial markets have experienced high volatility due to various stress events. In this context, active asset managers become sceptical of the certainty of their investment proposals and try out new opportunities, selecting alternative asset classes such as cryptocurrencies. The different impact of selecting two different groups can be observed in terms of volatility: cryptocurrencies (the most important) and stablecoins (digital assets designed to maintain a stable value relative to a reference asset). Most of these are pegged to the US dollar but some stablecoins are linked to other fiat currencies or underlying assets. US Treasury-backed stablecoins are similar to fiat-backed ones but they offer the additional benefit of generating an income from interest accrued by investing reserve assets in US

Treasuries and related instruments. In spite of their usual stability, stablecoins can lose their 1:1 parity, with respect to their reference assets (usually the US dollar) which is referred to as 'depegging' and this could be interpreted as a potential warning signal for potential liquidity crises and financial contagion. For example, the Silicon Valley Bank crisis in March 2023 caused USD Coin USDC to experience a severe depegging, revealing vulnerabilities in relatively well-audited stablecoins.

In this scenario, this research aims to investigate the relationship between the informative signal of the stablecoins and financial market stress, including cryptocurrency events. This aim can be divided into two different points of view: (a) the influence of stablecoin depegging events on the traditional asset classes and crypto returns during the market stress; and (b) the specific effect on the crypto market. The sample comprises Bitcoin (BTC), Ethereum (ETH), Binance (BNB), Ripple (XRP), two fiat-backed stablecoins (USD Tether USDT and USDC) and the cryptocurrency-collateralised stablecoin (DAI). Our research analyses daily prices from 1 January 2020 to 28 February 2026, by extracting the data from Coingecko.com.

This research belongs to a new strand of studies that focuses on interest in stablecoins, not only featuring an analysis of stress in the cryptocurrency market, but also of the signals of stablecoins for financial markets.

The main differences between the selected stablecoins are summarised in this study. USDT is the longest running, with reserves declared in dollars and equivalent securities. USDC is issued by Circle and backed by Coinbase and is considered to be one of the most robust and regulated, with reserves being 100% backed by cash and short-term US dollars. The stablecoin DAI is a decentralised stablecoin managed by MakerDAO on the Ethereum blockchain, with reserves backed by over-collateralisation of other cryptocurrencies (such as ETH), making it independent of traditional central banks. Stablecoins present their differences in terms of centralisation (USDC and USDT are centralised, while DAI is decentralised) and liquidity (USDT has the highest volume, closely followed by USDC). Depegging could be a temporary phenomenon, a signal of market panic, liquidity shortages, or algorithmic issues; however, in the past, it observed the collapse of TerraUSD (UST) in 2022 and the temporary depegging of USDC in 2023. A significant depegging undermines confidence in its use as a stable store of value.

The rest of this paper is organised as follows. Section 2 outlines a literature review, Section 3 illustrates the methodology used, Section 4 presents the results, and the final section provides conclusions.

2. Literature Review

Many researchers have examined the impact of cryptocurrencies on portfolios, in terms of diversification or higher returns, and their relationship with the main economic leading indicators. This section focuses on the most significant studies, according to the aforementioned lines of research, with the aim of highlighting the behaviour of Bitcoin as the most important asset of cryptocurrencies.

Reference [1] focused on the capacity of cryptocurrencies to provide a good hedge against downturns and inflation. Reference [2] found a substantial variation in Jensen's performance between gold, equities, and Bitcoin. Jensen's alpha assesses abnormal returns relative to a CAPM (Capital Asset Pricing Model) benchmark, identifying assets that outperform their expected returns given their risk profile. The authors of [3] studied Bitcoin and found it to be efficient during times of market stress. Reference [4] showed that cryptocurrency funds generate significantly positive alphas compared to passive benchmarks or conventional risk factors.

The different authors of References [5–7] focused on the cryptocurrency market, which has experienced rapid development: it is one of the fastest growing global financial markets. The authors of [8] found that crypto price volatility is very high, with drastic changes in value occurring within short time periods. Reference [9] demonstrated that stocks often outperform Bitcoin and gold, in terms of Jensen's Alpha, suggesting better risk-adjusted returns. The authors of [10] examined the information content of a set of market risk factors, cryptocurrency-specific predictors, and sentiment variables for the returns of cryptocurrencies versus traditional asset classes. They applied an econometric model to find the relationship between asset returns, predictive variables, and cryptocurrencies, considering stock market factors, precious metal commodities and supplies. Their results showed that the selection of cryptocurrencies in an already diversified portfolio increases its value but, at the same time, cryptocurrencies are not systematically predicted factors. Reference [11] compared the performance of the cryptocurrency Bitcoin, stocks, and gold, and found that the riskiest investment is Bitcoin, followed by gold and stocks.

Following the evolution of previous research, other authors focused on their interest in the weight of stablecoin, in terms of diversification and the signal given from the depeg. Reference [12] examined the relationship between cryptocurrency returns around stablecoin issuance events for seven different stablecoins. Stablecoin issuances contribute to the price discovery and market efficiency of cryptocurrencies. The authors of [13] maintained a collateralised peg and full reserves and showed that stablecoins are much less volatile than other cryptocurrencies, equities, and commodities. The authors of [14,15] highlighted stablecoin's instability, as shown by its large dependence on other cryptocurrencies, including Bitcoin. The researchers of [16,17] provided evidence that parity is ensured through a combination of centralised and decentralised (DeFi) stability mechanisms, relying on collateralisation with USD, the incorporation of liquid fixed exchange assets, and the implementation of algorithms dedicated to peg preservation. The authors of [18] studied the reaction to exogenous shocks in financial markets and found that differences in stablecoin design affect the direction, magnitude, and duration of their responses to shocks. The authors of [19] showed that Bitcoin and Ethereum are correlated with stablecoins. The authors of [20] highlighted the fact that, through Risk Parity modelling, the investor can balance the risk exposure between high-volatility Bitcoin and the stablecoin Tether, whilst making contributions. These studies show that research is continuously developing, confirming the important role of the cryptocurrencies market and tokenisation in the evolution of financial markets.

The authors of [21] studied user views and adoption variables associated with stablecoins as a means of mitigating volatility in cryptocurrency markets. They concluded that stablecoins give stability, providing innovative financial products and services, such as decentralised finance (DeFi) platforms. The authors of [22] analysed four risk factors: trading price and volume, market information sentiment and volatility. They applied an empirical analysis to a predictive model using machine learning, to predict stablecoin depegging events from 1 January 2022 to 31 December 2023. They found that significant fluctuations in the cryptocurrency market influence stablecoin depegging. The other authors [23] aimed to show whether there is a time-varying correlation and/or connectedness between the stablecoin market and the currencies of emerging markets and developing economies (EMDEs) with significant cryptocurrency penetration. They concluded that there is a spill-over of return shocks from the EMDE currencies to the stablecoin market. The authors of [24] studied the devaluation risk to stablecoins, in the same way as traditional currencies, applying their model to show the presence of this risk on Tether. The main risk factors are market volatility and transaction velocity. They provided evidence of the importance of transparency and regulatory oversight, with the aim of mitigating the impact of devaluation risk. The author of [25] studied systemic tail dependence within the crypto-asset ecosystem from September 2021 to March 2025 and observed that systemic risk tends to increase during adverse tail events. In the examined interval time, which includes the post-COVID-19 speculative rally, the 2022–2023 crypto winter (encompassing the Terra/LUNA and FTX collapses), and the post-halving political–economic shifts of 2024, the stablecoin DAI absorbs some of the stress, contributing to reducing the risk during downturns. The author of [26] applied a simple new rule to decide if a stablecoin is 'dead' or 'alive' based on a simple price threshold. A wide range of panel binary models were used to forecast stablecoins' probabilities of default (PDs), incorporating stablecoin-specific regressors. The conclusion was that stablecoin survival is not random but driven by identifiable and economically meaningful forces. Recent developments in the literature and the growing interest among investors show that stablecoins offer significant insights into the effective role of digital assets in financial markets and they could be downstream symptoms of cryptocurrency market stress.

3. Methodology

Data on the daily closing prices of cryptocurrencies and stablecoins were obtained from Coingecko.com (accessed on 24 March 2026) for the interval 1 January 2020 to 28 February 2026. Four cryptocurrencies were selected based on the largest market capitalisation as of 28 February 2026: Bitcoin (BTC), Ethereum (ETH), Binance (BNB), and Ripple (XRP). Data for the two largest fiat-backed stablecoins (USDT and USDC) and the largest cryptocurrency-collateralised stablecoin (DAI), by market capitalisation, were also obtained. For each day t, the log-return $R_{i,t}$ for cryptocurrency i was calculated using Equation (1). The stablecoin depeg $D_{j,t}$ for stablecoin j was calculated from Equation (2).

$$R_{i,t} = ln(P_{i,t}) - ln(P_{i,t-1}) \tag{1}$$

$$D_{j,t} = \left(P_{j,t} - 1\right) * 100 \tag{2}$$

In these equations, $P_{i,t}$ and $P_{j,t}$ represent the closing prices of cryptocurrency i and stablecoin j, respectively, with $i \in \{BTC, ETH, BNB, XRP\}$ and $j \in \{USDT, USDC, DAI\}$.

In order to create a binary stress variable S_t, daily data were obtained for the CBOE Volatility Index (VIX) and daily closing prices of the S&P500 from the Federal reserve bank of St. Louis (https://fred.stlouisfed.org (accessed on 24 March 2026)). To fill in the gaps for weekends and bank holidays, the forward-fill method ('use day before') was applied as the decentralised markets of cryptocurrencies are never closed and a vector with the same length as the log-return and stablecoin depeg vectors were required. A day of market stress was defined as a day on which either the CBOE Volatility Index (VIX) was greater than, or equal to, 30, or the S&P 500 experienced a drawdown of at least −10%. The S&P 500 drawdown is defined as the percentage deviation from the running historical maximum price $max\left(P_0^{S\&P}, \ldots, P_t^{S\&P}\right)$ of the index up to day t, as seen in Equation (3). A VIX threshold greater than, or equal to, 30 was chosen, motivated by the findings of the author [27]. The upper bound of S&P500 drawdowns was set to −10%, as a distinctive deviation to the average drawdown of S&P500 (−6.07) in the observation period, to ensure an abnormal market regime.

$$Drawdown_t = \frac{P_t^{S\&P} - max\left(P_0^{S\&P}, \ldots, P_t^{S\&P}\right)}{max\left(P_0^{S\&P}, \ldots, P_t^{S\&P}\right)} * 100 \tag{3}$$

The binary stress variable S_t contains an entry for a day of market stress and 0 otherwise. In total, S_t contains 635 stress days and 1616 non-stress days. Of the 635 stress days, 51 (8%) were triggered by VIX $\geq$ 30 alone, 429 (68%) by an S&P 500 drawdown $\leq -10\%$

alone, and 155 (24%) by both conditions simultaneously. By year, stress days are distributed as follows: 2020 (131), 2021 (10), 2022 (276), 2023 (190), 2024 (1), 2025 (27), and 2026 (0, up to 28 February). Amongst other events, it was found that the crash of the Terra ecosystem in May 2022, the bankruptcy of FTX in November 2022, and the major USDC depegging event in March 2023 were included in the observations. Notably, a large amount of stress days lay around the USDC depegging event in March 2023.

After computing the return and depeg series, the predictive relationship between stablecoin depegs and cryptocurrency returns was examined within a Granger-causality framework [28]. Each model was estimated separately for every cryptocurrency–stablecoin pair (i, j) on the full sample of 2251 daily observations, so that every lag corresponded to exactly one calendar day and the predictive stage shared a common sample with the conditional-variance stage. Market stress enters the regression through the contemporaneous dummy S_t and an interaction term, rather than through subsampling. This preserves a continuous daily lag structure, while allowing the predictive effect of depegs to differ between non-stress and stress days. For clarity, only the cryptocurrency index i is shown on the coefficients, with the stablecoin j identified by the depeg variable $D_{j,t}$.

For each pair, the forward predictive regression was specified as:

$$R_{i,t} = \alpha_i + \sum_{k=1}^{p} \beta_{i,k} R_{i,t-k} + \sum_{k=1}^{p} \gamma_{i,k} D_{j,t-k} + \delta_i S_t + \sum_{k=1}^{p} \varphi_{i,k} (D_{j,t-k} \times S_t) + \varepsilon_{i,t} \quad (4)$$

where $R_{i,t}$ is the log-return of cryptocurrency i, $D_{j,t}$ is the depeg of stablecoin j, S_t is the binary stress dummy, and $\varepsilon_{i,t}$ is the error term on day t. The lags $R_{i,t-k}$ control for autocorrelation in returns. The coefficients $\gamma_{i,k}$ capture the predictive effect of past depegs on a non-stress day; δ_i captures the average difference in returns on stress days; and the interaction coefficients $\varphi_{i,k}$ capture the additional predictive effect operating during stress, so that the total predictive effect of a depeg is $\gamma_{i,k}$ on a non-stress day and $(\gamma_{i,k} + \varphi_{i,k})$ on a stress day. The opposite direction of causality was examined by interchanging $R_{i,t}$ and $D_{j,t}$, placing the depeg on the left-hand side and the lagged return, together with its stress interaction, on the right.

Three nested hypotheses were tested within this specification, all using heteroskedasticity and autocorrelation-consistent (HAC) standard errors [29]. The Granger-causality null, that the predictor carries no information for the dependent variable on any day, is:

$$H_0: \gamma_{i,1} = \ldots = \gamma_{i,p} = \varphi_{i,1} = \ldots = \varphi_{i,p} = 0$$

To identify the channel through which any predictive power operates, two further joint Wald tests [30] were conducted: a baseline channel,

$$H_0: \gamma_{i,1} = \ldots = \gamma_{i,p} = 0$$

testing for predictive power on non-stress days; and a stress-specific channel,

$$H_0: \varphi_{i,1} = \ldots = \varphi_{i,p} = 0$$

testing whether the predictive relationship differs during periods of market stress. The stress-specific null is of primary interest, as it directly addresses whether any predictive relationship is conditional on market stress.

Prior to estimation, an Augmented Dickey–Fuller (ADF) test confirmed the stationarity of all log-return $R_{i,t}$ and stablecoin depeg $D_{j,t}$ series [31]. The lag length p was selected for each pair by the Bayesian information criterion (BIC) [32]. The more conservative BIC penalty was preferred over the AIC, to limit the number of estimated parameters. The

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adequacy of each fitted model was assessed by applying the Ljung–Box test [33] to the residuals, to detect remaining autocorrelation, and to the squared residuals, to detect conditional heteroskedasticity (ARCH effects); the squared-residual test indicated volatility clustering across all pairs, which both required HAC-based inference at this stage and motivated the conditional-variance specification. To understand the contemporaneous effects of stablecoin depegging events on cryptocurrency volatility during periods of market stress, an Exponential Generalised Autoregressive Conditional Heteroskedasticity (EGARCH) model was employed. This specification was selected over standard GARCH models for two primary reasons: firstly, it models the logarithm of variance, which inherently ensures non-negative volatility forecasts without imposing restrictive parameter constraints, and secondly (and most critically for cryptocurrency markets), the EGARCH framework captures asymmetric effects (the leverage effect) [34]. This allows the model to distinguish between the volatility impact of negative shocks and positive shocks of equal magnitude. A lag order of (1,1) was employed, as it provides a parsimonious specification while remaining consistent with common practice in the EGARCH literature [34].

The model was defined by a mean equation for log returns $R_{i,t}$ and a variance equation for conditional volatility $\sigma^2_{i,t}$:

Mean Equation:

$$R_{i,t} = \mu_i + \varepsilon_{i,t} \tag{5}$$

Variance Equation:

$$ln\left(\sigma^2_{i,t}\right) = \omega_i + \beta_i ln\left(\sigma^2_{i,t-1}\right) + \alpha_i(|z_{i,t-1}| - E[|z_{i,t-1}|]) + \gamma_i z_{i,t-1} + \delta_{i,1}\left|D_{j,t}\right| + \delta_{i,2}S_t + \delta_{i,3}(\left|D_{j,t}\right| \times S_t) \tag{6}$$

where $\varepsilon_{i,t} = z_{i,t} \cdot \sigma_i$ is the error term, with $z_{i,t}$ following a standardised Student t-distribution to account for the fat-tailed nature of cryptocurrency returns (see Table 1). The term $\gamma_i z_{i,t-1}$ captures the leverage effect where a negative and significant γ_i indicates that negative shocks increase volatility more than positive shocks. To test the specific hypothesis, three exogenous variables were incorporated into Equation (6): $D_{j,t}$ describes the magnitude of the depegging event of stablecoin j on day t; S_t is the binary stress variable, equal to one if day t is classified as a day of elevated market stress, and zero otherwise; and $\left|D_{j,t}\right| \times S_t$ describes an interaction term representing the simultaneous occurrence of a depeg and a day of market stress.

Table 1. Descriptive statistics.

	Mean	Median	SD	Skew	Kurt	Min	Max
Panel A: Cryptocurrency log-returns (×100)							
BTC	0.098	0.035	3.211	−1.15	17.70	−43.37	17.60
ETH	0.119	0.130	4.343	−1.11	16.02	−56.31	21.94
BNB	0.168	0.182	4.391	−0.17	29.77	−55.90	55.27
XRP	0.087	0.011	5.306	0.47	19.97	−54.95	54.45
Panel B: Stablecoin depegs (signed %)							
USDT	0.036	0.018	0.172	0.43	14.25	−1.82	1.23
USDC	0.021	−0.003	0.186	−2.85	62.74	−3.44	1.10
DAI	0.163	0.011	0.536	3.05	19.17	−3.30	5.85

Notes: Full sample, 1 January 2020–28 February 2026 (n = 2251 daily observations for every series). Cryptocurrency returns are daily log-returns multiplied by 100; stablecoin depegs are signed percentage deviations from the dollar peg, as stated in Equation (2), so a positive value denotes trading above par.

In this analysis, the focus was on the three key coefficients: $\delta_{i,1}$, $\delta_{i,2}$ and $\delta_{i,3}$. The first coefficient, $\delta_{i,1}$ indicates how much a stablecoins' depeg affects cryptocurrency volatility on its own. The second, $\delta_{i,2}$, measures the general impact of market stress. However, this research is most interested in the effects of $\delta_{i,3}$, which represents the interaction between the two. In the case of $\delta_{i,3}$ being statistically significant, it would mean that stablecoins' depegging events help explain cryptocurrencies' volatility during market turmoil. It should be noted that, in the case of a significant $\delta_{i,3}$, this needs to be interpreted with respect to $\delta_{i,1}$, in order to infer what the additional effect of depegging events is during market stress.

4. Results

4.1. Descriptive Statistics

Table 1 shows the descriptive statistics for the log-returns of BTC, ETH, BNB, XRP (expressed in %), and the depegs for USDT, USDC and DAI (expressed in %) computed over the full sample of 2251 daily observations from 1 January 2020 to 28 February 2026. On average, all of the cryptocurrencies' daily returns were marginally positive, ranging from 0.087% (XRP) to 0.168% (BNB), with standard deviations between 3.21% (BTC) and 5.31% (XRP), noting that BTC was the least volatile and XRP was the most volatile asset in the panel. The high excess of Kurtosis, ranging from 16.02 (ETH) to 29.77 (BNB), indicated heavy tails in the distributions, which meant that extreme fluctuations in returns were more common. The moderate negative skewness and, therefore, longer left-sided tails of BTC, ETH and BNB, indicated that negative returns were more frequent than positive ones; for XRP, the opposite was the case ($skewness\ XRP = 0.47$), but only marginally.

The sample mean of our stablecoin depegs were all positive, with DAI having the highest (0.163%). All three stablecoins exhibited standard deviations lower than 0.6%, which aligns with their fundamental purpose of tracking the value of the US dollar. The high Kurtosis of USDT (14.25), DAI (19.17) and USDC (62.74) indicated heavy tails, while the latter demonstrated extremely heavy tails. USDT and DAI were both somewhat right skewed, while USDC showed strong skewness in the opposite direction.

4.2. Stationarity Analysis

An Augmented Dickey–Fuller test (ADF) was performed on each variable in order to test the null hypothesis of a unit root. The results of the ADF tests are reported in Table 2. We rejected the null hypothesis for all of the variables, resulting in them being stationary at conventional significance levels. In particular, the null hypothesis of a unit root was rejected at the 1% level for all cryptocurrency log-returns (BTC, ETH, BNB, and XRP) and for all stablecoins: USDT and USDC, and DAI. Stationarity is a necessary requirement for Granger-causality tests because applying them to non-stationary variables yields unreliable results [28].

Table 2. Augmented Dickey–Fuller unit-root tests.

	ADF Statistic	***p*-Value**
Panel A: Cryptocurrency log-returns		
BTC	−11.831 ***	<0.01
ETH	−12.246 ***	<0.01
BNB	−11.629 ***	<0.01
XRP	−12.045 ***	<0.01
Panel B: Stablecoin depegs		
USDT	−8.329 ***	<0.01
USDC	−9.075 ***	<0.01
DAI	−5.520 ***	<0.01

Notes: Augmented Dickey–Fuller test of the null hypothesis of a unit root, full sample (1 January 2020–28 February 2026, n = 2251). The test regression includes an intercept and a linear trend. *** denotes rejection of the unit-root null at the 1% level.

4.3. Lag Length Selection

Optimal lag lengths were obtained using four information criteria: Akaike (AIC) [35], Schwarz (BIC) [32], Hannan–Quinn (HQ) [36], and Final Prediction Error (FPE) [37], as reported in Table 3.

Table 3. Optimal lag-length selection by information criterion.

	AIC	**BIC**	**HQ**	**FPE**
		Panel A: USDT pairs		
BTC	10	**4**	6	10
ETH	10	**4**	6	10
BNB	10	**4**	6	10
XRP	10	**4**	6	10
		Panel B: USDC pairs		
BTC	8	**3**	3	8
ETH	10	**3**	3	10
BNB	10	**3**	4	10
XRP	6	**3**	3	6
		Panel C: DAI pairs		
BTC	9	**4**	4	9
ETH	10	**4**	4	10
BNB	10	**4**	4	10
XRP	7	**4**	4	7

Notes: Optimal lag length (in days) for each cryptocurrency–stablecoin pair, selected on the full sample by the Akaike (AIC), Bayesian/Schwarz (BIC), Hannan–Quinn (HQ) and Final Prediction Error (FPE) information criteria. The BIC (in bold) is adopted as the primary criterion for the predictive regressions; the same lag is applied in both directions of the Granger test for each pair. The remaining criteria are reported for transparency.

In order to keep the number of estimated parameters low and to guard against overfitting, the BIC was adopted as the primary criterion for the lag length used in the subsequent regressions, with the remaining criteria reported for transparency; the same lag was applied to both directions of the Granger test for each pair.

Under the BIC, a lag length of three was selected for the USDC pairs and four for the USDT and DAI pairs, applied uniformly across cryptocurrencies. The less parsimonious AIC and FPE selected substantially longer lags, between six and ten, while the HQ criterion fell in between, at three to six. The stability of the BIC selection across cryptocurrencies within each stablecoin indicates a consistent short-run lag structure and the markedly shorter BIC lags relative to the AIC reduce the parameter count in the predictive regressions, without discarding the dynamics the criteria agree are relevant.

4.4. Granger-Causality Results

The predictive regressions were estimated in both directions. For each pair, the joint Granger test (with all γ_i and φ_i equal to zero) was decomposed into a baseline channel (the depeg lags γ_i) and a stress-specific channel (the depeg-stress interaction φ_i), the latter being of primary interest. In the forward direction, whether stablecoin depegs Granger-cause cryptocurrency returns, the evidence is weak and does not cohere (Table 4). The joint Granger null is rejected at the 5% level for only one of the twelve pairs (USDC–ETH, F = 2.13) and the stress-specific interaction is insignificant for every USDC pair. A few isolated single-channel statistics appear—an interaction term for USDT–BTC and baseline terms for two DAI pairs—but they do not coincide with a rejection of the joint Granger test and do not form a systematic pattern. The data, therefore, do not support the hypothesis that stablecoin depegs predict cryptocurrency returns during market stress.

Table 4. Granger causality: stablecoin depegs → cryptocurrency returns.

	Lag	Granger (γ, φ = 0)	Baseline (γ = 0)	Stress (φ = 0)
Panel A: USDT (depeg → return)				
BTC	4	1.53 (0.143)	1.45 (0.216)	2.76 ** (0.026)
ETH	4	1.09 (0.365)	0.90 (0.461)	1.61 (0.169)
BNB	4	0.79 (0.610)	1.08 (0.365)	0.69 (0.602)
XRP	4	0.99 (0.442)	0.65 (0.629)	1.27 (0.279)
Panel B: USDC (depeg → return)				
BTC	3	1.77 (0.101)	1.40 (0.242)	0.24 (0.867)
ETH	3	2.13 ** (0.047)	2.03 (0.108)	0.04 (0.988)
BNB	3	0.93 (0.470)	0.51 (0.673)	0.24 (0.867)
XRP	3	1.18 (0.314)	1.65 (0.175)	1.37 (0.250)
Panel C: DAI (depeg → return)				
BTC	4	1.00 (0.437)	1.00 (0.403)	0.37 (0.832)
ETH	4	1.25 (0.265)	2.20 * (0.067)	0.74 (0.567)
BNB	4	0.74 (0.658)	0.94 (0.438)	0.43 (0.786)
XRP	4	1.66 (0.102)	2.40 ** (0.048)	0.62 (0.646)

Notes: Entries are F-statistics from HAC (Newey–West) joint Wald tests, with p-values in parentheses. The three nested nulls are: Granger (all γ and $\varphi = 0$, i.e., the predictor carries no information for the dependent variable); baseline/non-stress channel (all $\gamma = 0$); and stress-specific channel (all $\varphi = 0$), which tests whether the relationship is conditional on market stress. Lag is the BIC-selected lag (Table 3), applied in both directions. **, and * denote significance at the 5%, and 10% level, respectively.

The reverse direction—whether cryptocurrency returns Granger-cause stablecoin depegs—is substantially stronger and sharply concentrated (Table 5). Cryptocurrency returns Granger-cause USDC depegging events for all four cryptocurrencies, with the joint Granger null rejected at the 1% level for BTC and ETH (F = 3.01 and 3.30) and at the 5% level for BNB and XRP. The effect is driven by the stress-specific channel: the φ_j interaction test is significant for every crypto–USDC pair (F between 3.44 and 4.41), with a positive lag-one interaction coefficient, indicating that the transmission from crypto returns to USDC depegs strengthens during periods of market stress. USDT and DAI are unresponsive targets in the stress channel—USDT only exhibits baseline, non-stress predictability for BTC and XRP—so the reverse relationship is specific to USDC, rather than a general stablecoin phenomenon.

Read together, the two directions are markedly asymmetric: the forward channel is weak and not stress-specific, whereas the reverse channel is stronger, USDC-specific and concentrated in stress. This indicates that cryptocurrency stress is the upstream driver and stablecoin depegs are the downstream symptom, rather than depegs acting as a leading signal of cryptocurrency returns. The absence of any robust DAI relationship in either direction could be related to the DAI depeg being mechanically tied to the price of its cryptocurrency collateral rather than conveying independent predictive information, which retires the earlier characterisation of DAI as an early-warning signal. Finally, the Ljung–Box test found significant residual autocorrelation in a minority of pairs, justifying the HAC standard errors used throughout, while the squared residuals rejected the null in all twelve pairs, confirming the volatility clustering that motivates the EGARCH analysis of Section 4.5.

Robustness checks were performed using different information criteria, if AIC, BIC, HQ and FPE were not aligned. The results remained qualitatively unchanged, confirming the robustness of our findings to different lag length specifications.

Table 5. Granger causality: cryptocurrency returns → stablecoin depegs.

	Lag	Granger ($\gamma, \varphi = 0$)	Baseline ($\gamma = 0$)	Stress ($\varphi = 0$)
Panel A: USDT (return → depeg)				
BTC	4	1.59 (0.121)	2.40 ** (0.048)	0.70 (0.592)
ETH	4	0.95 (0.475)	1.20 (0.309)	0.28 (0.891)
BNB	4	0.68 (0.711)	0.22 (0.929)	0.55 (0.696)
XRP	4	1.52 (0.145)	2.63 ** (0.033)	0.13 (0.973)
Panel B: USDC (return → depeg)				
BTC	3	3.01 *** (0.006)	2.73 ** (0.042)	4.41 *** (0.004)
ETH	3	3.30 *** (0.003)	1.75 (0.155)	4.41 *** (0.004)
BNB	3	2.69 ** (0.013)	1.16 (0.323)	3.44 ** (0.016)
XRP	3	2.40 ** (0.026)	1.20 (0.310)	4.17 *** (0.006)
Panel C: DAI (return → depeg)				
BTC	4	0.93 (0.492)	1.21 (0.304)	0.94 (0.440)
ETH	4	1.50 (0.152)	1.94 (0.102)	1.37 (0.243)
BNB	4	1.11 (0.350)	1.14 (0.336)	1.32 (0.259)
XRP	4	1.64 (0.109)	1.44 (0.219)	2.19 * (0.068)

Notes: Entries are F-statistics from HAC (Newey–West) joint Wald tests, with p-values in parentheses. The three nested nulls are: Granger (all $\gamma, \varphi = 0$, i.e., the predictor carries no information for the dependent variable); baseline/non-stress channel (all $\gamma = 0$); and stress-specific channel (all $\varphi = 0$), which tests whether the relationship is conditional on market stress. Lag is the BIC-selected lag (Table 3), applied in both directions. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

4.5. EGARCH Results

4.5.1. Overview and Interpretation of the Estimates

Tables 6 and 7 report the EGARCH(1,1)-X estimates for the twelve cryptocurrency–stablecoin pairs, with the absolute depeg $|D|$, the market-stress dummy and their interaction entering the variance equation contemporaneously. Each coefficient is estimated separately for every cryptocurrency i and stablecoin j; for readability the pair subscripts are suppressed in the discussion that follows. Because all three exogenous regressors are dated at time t, the coefficients describe the contemporaneous association between depegs and conditional volatility, rather than having a predictive relationship. No comparison against alternative volatility models (e.g., GARCH(1,1), GJR-GARCH) was conducted. The choice of EGARCH was based on its theoretical properties, namely its ability to capture asymmetric volatility responses. Future work could extend this analysis by benchmarking EGARCH against symmetric and alternative asymmetric GARCH variants.

Table 6. EGARCH (1,1)-X conditional-variance parameters for all twelve cryptocurrency–stablecoin pairs.

	μ	ω	α (Size)	β	γ (Asym.)	ν
Panel A: USDT depeg						
BTC	0.001	−0.488 ***	0.153 ***	0.935 ***	−0.040 **	3.099 ***
ETH	0.001	−0.396 ***	0.212 ***	0.942 ***	−0.027	3.449 ***
XRP	−0.000	−0.730 ***	0.336 ***	0.886 ***	0.001	2.907 ***
BNB	0.001 ***	−0.427 ***	0.278 ***	0.940 ***	0.018	3.621 ***
Panel B: USDC depeg						
BTC	0.001	−0.572 ***	0.157 ***	0.923 ***	−0.046 *	3.102 ***
ETH	0.001	−0.449 ***	0.215 ***	0.934 ***	−0.034	3.442 ***
XRP	−0.000	−0.676 ***	0.340 ***	0.894 ***	−0.000	2.884 ***
BNB	0.001 ***	−0.490 ***	0.280 ***	0.931 ***	0.016	3.620 ***

Table 6. *Cont.*

	μ	ω	α (Size)	β	γ (Asym.)	ν
Panel C: DAI depeg						
BTC	0.002 ***	−0.578 ***	1.575 ***	0.871 ***	−0.451 ***	2.100 ***
ETH	0.001 ***	−0.112 ***	0.167 ***	0.982 ***	−0.006	3.420 ***
XRP	−0.000	−0.439 ***	0.322 ***	0.926 ***	−0.004	2.844 ***
BNB	0.001 *	−0.227 ***	0.263 ***	0.966 ***	0.020	3.492 ***

Notes: Each row is a separate EGARCH(1,1)-X model for the cryptocurrency's log-returns, estimated by Student-t maximum likelihood; the same twelve models underlie the exogenous-regressor estimates in Table 7. μ is the conditional mean; ω the variance constant; α the size (magnitude) coefficient on (∣z∣−E∣z∣); β the persistence; γ the asymmetry (sign/leverage) coefficient on z; and ν the Student-t degrees-of-freedom parameter. Standard errors use the observed information matrix (valid for ν > 2). Entries are coefficient estimates; ***, **, * denote significance at the 1%, 5%, and 10% level. The BTC–DAI model (ν = 2.10) is an unstable fit, as discussed in the text.

Table 7. EGARCH(1,1)-X exogenous depeg regressors in the variance equation.

	δ_1 (∣D∣)	δ_2 (S)	δ_3 (∣D∣ × S)
Panel A: USDT depeg			
BTC	0.429 ***	0.002	−0.115
ETH	0.328 ***	0.003	−0.145
XRP	0.469 ***	−0.051	0.124
BNB	0.366 ***	−0.017	−0.073
Panel B: USDC depeg			
BTC	0.493 ***	−0.018	−0.051
ETH	0.369 ***	−0.016	−0.066
XRP	0.459 ***	−0.021	−0.245
BNB	0.451 ***	−0.033	−0.055
Panel C: DAI depeg			
BTC	0.070 ***	0.186 ***	−2.027 ***
ETH	0.015	−0.006	−0.024
XRP	−0.001	−0.023	−0.022
BNB	0.030 *	−0.016	−0.017

Notes: Coefficients on the three contemporaneous external regressors entering the variance equation of each EGARCH(1,1)-X model: the absolute depeg of the indicated stablecoin (∣D∣), the market-stress dummy (S), and their interaction (∣D∣ × S). Each row corresponds to the same model reported in Table 6. Standard errors use the observed information matrix; ***, * denote significance at the 1% and 10% level. The BTC–DAI interaction estimate belongs to the unstable fit discussed in the text.

4.5.2. Conditional-Variance Dynamics

The conditional-variance dynamics are consistent across all models. The size coefficient α, which governs the response of volatility to the magnitude of past shocks, is positive and significant at the 1% level in every pair (0.15–0.34, setting aside the BTC–DAI outlier discussed in Section 4.5.7), and the persistence parameter β is uniformly high (0.87–0.98), reflecting the near-integrated volatility typical of cryptocurrency returns. The estimated Student-t degrees of freedom are low throughout (ν between 2.1 and 3.6), confirming heavy tails; as all of them are less than four, the reported standard errors are based on the observed information matrix, rather than the sandwich estimator, which would require finite fourth moments that the data do not support.

4.5.3. Asymmetry and the Leverage Effect

The asymmetry coefficient γ, which captures the leverage effect, provides little support for asymmetric volatility: it is statistically insignificant in nine of the twelve models. Where it is significant—the three BTC pairs—its sign is negative, corresponding to the standard leverage effect, whereby negative shocks raise volatility more than positive shocks of equal magnitude, rather than the inverted pattern which is sometimes reported for cryptocurrencies. However, the EGARCH specification remains the appropriate choice because it guarantees a non-negative conditional variance without parameter restrictions and separates the magnitude and sign effects; the evidence here simply indicates that the leverage channel, in either direction, is weak in this sample.

4.5.4. The Depeg Magnitude Effect ($\delta_{i,1}$)

Considering the stablecoin variables, the magnitude coefficient δ_1 is positive in every pair and significant in nine of the twelve. It is sizeable for the USDT and USDC pairs (0.33–0.49, $p < 0.01$), indicating that a larger deviation of the stablecoin from its dollar peg (in either direction) is associated with higher contemporaneous cryptocurrency volatility. The DAI pairs are the exception, with small and largely insignificant δ_1. This contemporaneous magnitude channel, operating chiefly through the two highest liquidity stablecoins, is the clearest association identified by the model.

4.5.5. The Stress-Level Effect ($\delta_{i,2}$)

The stress-level coefficient δ_2 is insignificant in eleven of the twelve models, indicating that, once the EGARCH dynamics and the depeg terms are accounted for, the market-stress dummy carries no independent level effect on volatility. The single exception is BTC–DAI, whose estimate is unreliable for the reasons given in Section 4.5.7.

4.5.6. The State-Dependence of the Depeg Effect ($\delta_{i,3}$)

The interaction coefficient δ_3 is of primary interest because it tests whether the depeg–volatility association changes during market stress. Its sign is negative in eleven of the twelve pairs, the sole exception being XRP–USDT, but it is individually significant in only one model: BTC–DAI. Joint Wald testing of the twelve interaction coefficients is only significant on account of that single model. BTC–DAI 'exploded' to approximately $1.25 * 10^5$, driven entirely by that model's implausibly small standard error, whereas by excluding it, the statistic falls to 5.97 on eleven restrictions ($p = 0.88$), far from any conventional threshold. A one-sample test on the eleven remaining estimates only indicated a marginally significant negative direction (mean -0.062, $t = -2.27$, and $p = 0.047$); a sign test confirmed the same tilt (ten of eleven negative, $p = 0.012$). The consistent negative sign is suggestive of a slight attenuation of the depeg–volatility association during stress, rather than the amplification one might expect, but it does not constitute robust joint evidence once the unstable model is set aside and should not be read as a strong stabilising effect.

4.5.7. The BTC–DAI Model

The BTC–DAI model warrants explicit caution. Its estimated degrees of freedom ($\nu = 2.10$) sit at the boundary of finite variance; its size coefficient ($\alpha = 1.58$) and interaction coefficient ($\delta_3 = -2.03$) are an order of magnitude larger than those of any other pair and it alone produces the significant joint Wald statistic. These are the signatures of an unstable fit, rather than of an economic finding, and so the conclusions above are reported both with and without it. Taken as a whole, the EGARCH evidence points to a robust contemporaneous link between the magnitude of stablecoin depegs and cryptocurrency volatility, concentrated in the most liquid stablecoins, and to no reliable change in that link during periods of market stress.

5. Conclusions

This research examined the returns and volatility of cryptocurrencies, while accounting for the depegging of stablecoins driven by speculative trading, macroeconomic shocks, and technological shifts. The analysis proceeded in two stages: first, a Granger-causality framework with a state-dependent stress interaction assessed the predictive relationship between stablecoin depegs and cryptocurrency returns in both directions; second, an EGARCH-X model examined the contemporaneous association between depeg magnitude and cryptocurrency volatility, and whether it changes during periods of stress.

The descriptive statistics, computed over the full sample, showed that all four cryptocurrencies recorded marginally positive average daily returns, while all three stablecoins traded marginally above their dollar peg, on average. Stablecoin deviations remained well below one percent throughout, confirming that the three assets largely fulfilled their stabilising function. The stationarity analysis confirmed that all return and depeg series are stationary at the 1% level, satisfying the requirement for the Granger-causality framework, and lag lengths were selected for each pair by the Bayesian information criterion.

The Granger-causality results are markedly asymmetric. In the forward direction, the evidence that stablecoin depegs predict cryptocurrency returns is weak and does not cohere into a systematic pattern; in particular, no stress-specific predictive channel was found. In the reverse direction, by contrast, cryptocurrency returns robustly Granger-cause USDC depegging events for all four cryptocurrencies, and this effect operates through the stress-specific channel, strengthening during periods of market stress. USDT and DAI are largely unresponsive as targets, so the reverse relationship is specific to USDC, rather than being general. Notably, DAI displays no robust relationship in either direction, which is consistent with its depeg being mechanically tied to the price of its cryptocurrency collateral, rather than conveying independent information. Taken together, these results indicate that cryptocurrency stress is the upstream driver and stablecoin depegs are the downstream symptom, rather than depegs serving as a leading signal of cryptocurrency returns. This reframing—away from stablecoins as early-warning indicators and towards stablecoins as reflectors of crypto-market stress—carries more accurate implications for risk management and systemic-risk monitoring in digital-asset markets.

The EGARCH-X estimation reinforces this reading. The magnitude of stablecoin depegs is positively and significantly associated with contemporaneous cryptocurrency volatility, concentrated in the two most liquid stablecoins, USDT and USDC; larger deviations from parity accompany higher volatility in either direction. The market-stress dummy carries no independent level effect once these terms are included, and the interaction between depeg magnitude and stress, while consistently negative in sign, does not provide robust evidence of a change in the depeg–volatility association during stress. The conditional-variance dynamics are standard for cryptocurrency returns—high volatility persistence and heavy Student-t tails—while the evidence for an asymmetric leverage effect is weak. Overall, the volatility analysis points to a robust contemporaneous link between depeg magnitude and cryptocurrency volatility but not to a distinct amplification of that link during stress.

Several limitations of this study are worth acknowledging. The binary stress variable which was used for the Granger-causality tests, using VIX and S&P500 drawdown as the defining thresholds, may not have contained all of the relevant information required to capture all noteworthy stress periods. In addition, BNB, XRP and ETH each experienced major idiosyncratic regulatory or issuer events during the sample window, so their individual results may partly reflect event-specific responses rather than a systematic stablecoin–cryptocurrency relationship which could be further examined by future research. Furthermore, this study focused on four cryptocurrencies and three stablecoins, which should be extended to a broader spectrum, in order to ensure that the full diversity of the digital asset ecosystem is represented. The inclusion of higher-frequency data may also give more insight into the effects of depegging events on the returns and volatility

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of cryptocurrencies. Nonetheless, the central message is robust: within this sample, stablecoin depegs reflect cryptocurrency-market stress more than they anticipate it and their magnitude is systematically linked to cryptocurrency volatility.

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