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

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Abstract

Active asset managers are increasingly including 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 while accounting for the depegging of stablecoins driven by speculative trading macroeconomic shocks, and technological shifts. It builds a sample, by 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, Granger causality tests were applied to examine the influence of stablecoin depegging events on crypto returns during financial market stress. The results indicate that DAI exhibits the most consistent Granger-causal relationship with cryptocurrency returns; whereas, the predictive power of USDT and USDC depegging events varies across assets. The analysis was extended by modelling volatility using an EGARCH-X model to study whether depegs also affect crypto during periods of market stress. In this case, the evidence for statistically significant effects is limited. Nevertheless, in the instances where significance is detected, the results are consistently linked to USDC.

Keywords: cryptocurrency; asset allocation; volatility; granger causality test; GARCH model

JEL Classification: G1, G11, G12

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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. In this context, 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 an early 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 predictive capacity 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 turmoil; b) the specific effect on the crypto market. The sample comprises Bitcoin (BTC), Ethereum (ETH), Binance (BNB), Ripple (XRP), two fiat-backed stablecoins (USDTether USDT and USDC) and the cryptocurrency-collateralised stablecoin (DAI). Our research analyses the daily prices from January 1, 2020, to February 28, 2026 by extracting the data from Coingecko.com.

This research belongs to a new strand of studies that focus on interest in stablecoins, featuring an analysis not only of stress in the cryptocurrency market but, also, of the predictive capacity 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 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 the Literature review, Section 3 illustrates the methodology, 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.

Borri (2019) focused on the capacity of cryptocurrencies to provide a good hedge against downturns and inflation. Lumbantobing and Sadalia (2021) 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 expected returns given their risk profile. Wu et al. (2021) studied Bitcoin and found it to be efficient during times of market stress. Bianchi and Babiak (2022) showed that cryptocurrency funds generate significantly positive alphas compared to passive benchmarks or conventional risk factors

Białkowski (2020), Fang et al. (2021), and Almeida and Gonçalves (2023) focused on the cryptocurrency market, which has experienced rapid development, being amongst the fastest growing world financial markets. Hardiyanto et al. (2023) found that crypto price volatility is very high, with drastic changes in value occurring within short time periods. Widiawira and Akbar (2023) demonstrated that stocks often outperform Bitcoin and gold, in terms of Jensen Alpha, suggesting better risk-adjusted returns. Bianchi et al. (2023) 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. Kurniawati et al. (2024) 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. Ante et al. (2021) 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. Hoang and Baur (2021) maintained a collateralised peg and full reserves, and showed that stablecoins are much less volatile than other cryptocurrencies, equities, and commodities. Kristoufek (2021) and Grobys and Huynh (2022) highlighted stablecoin's instability, as shown by its large dependence on other cryptocurrencies, including Bitcoin. Arner et al. (2020) and Catalini et al. (2022) 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. De Blasis et al. (2023) 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. Łęt et al. (2023) showed that Bitcoin and Ethereum are correlated with stablecoins. Jayawardhana and Colombage (2024) 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.

Al-Afeef et al. (2024) 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 an innovative financial products and services, like decentralised finance (DeFi) platforms. Lee et al. (2025) 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 January 1, 2022 to December 31, 2023. They found that significant fluctuations in the cryptocurrency market influence stablecoin depegging. Napari et al. (2025) 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 spillover of return shocks from the EMDE currencies to the stablecoin market. Eichengreen et al. (2025) 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. Naifar (2025) studied systemic tail dependence within the crypto-asset ecosystem 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 reduce the risk during downturns. Fantazzini (2025) 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 have the predictive capacity to anticipate the possible impact on asset-class prices.

3. Methodology

Data on the daily closing prices of cryptocurrencies and stablecoins were obtained for the interval 1 January, 2020 to 28 February, 2026, from Coingecko.com. 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 as in Equation (1). The stablecoin depeg $D_{j,t}$ for stablecoin j was calculated from Equation (2).

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

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

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 of the CBOE Volatility Index (VIX) and daily closing prices of the S&P500 from the Federal reserve bank of St. Louis (fred.stlouisfed.org). 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 was required. A day of market stress was defined as a day on which either the CBOE Volatility Index (VIX) was greater or equal to 30 or the S&P 500 experienced a drawdown of at least −10%. A VIX threshold greater or equal to 30 was chosen, motivated by the findings of Whaley (2009). 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. A subsample was then created where only the observations of log-returns and stablecoin depegs were kept if the stress variable was equal to one on the respective day. This process resulted in a reduction from 2251 observations to 635 observations. 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.

After cleaning the data, Granger causality tests (Granger, 1969) were performed with $R_{i,t}$ as the dependent variable and $D_{j,t}$ as the independent variable. The regression model was specified as:

$$R_{i,t} = \alpha + \sum_{k=1}^{p} \beta_k R_{i,t-k} + \sum_{k=1}^{p} \gamma_k D_{j,t-k} + \varepsilon_t \tag{3}$$

where ε_t represents the error term on day t. It should be noted that this implicitly tests whether the stablecoin depegs observed during the previous stress event retained predictive power for crypto volatility in the current stress event.

Prior to estimation, an Augmented Dickey–Fuller (ADF) test was performed to check for stationarity of all log-returns $R_{i,t}$ and stablecoin depeg variables $D_{j,t}$ (Dickey & Fuller, 1979). The optimal lag length p was then determined using Akaike (AIC) (Akaike, 1998), Bayesian (BIC) (Schwarz, 1978), Hannan–Quinn (HQ) (Hannan & Quinn, 1979), and Akaike's final prediction error (FPE) (Akaike, 1970) information criterion, all constrained to a maximum of ten lags. If different optimal lags were proposed by the different information criteria, AIC was used as the primary criterion, followed by rechecking the results using the other information criteria to ensure robustness.

To investigate the predictive power 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) (Bollerslev, 1986; Nelson, 1991). 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 (Nelson, 1991).

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:

$$R_{i,t} = \mu_i + \varepsilon_{i,t} \quad (4)$$

Variance Equation:

$$\ln(\sigma^2_{i,t}) = \omega_i + \beta_i \ln(\sigma^2_{i,t-1}) + \alpha_i(|z_{i,t-1}| - E[|z_{i,t-1}|]) + \gamma_i z_{i,t-1} + \delta_1 D_{j,t} + \delta_2 S_t + \delta_3(D_{j,t} \times S_t) \quad (5)$$

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 (5): $D_{i,t}$ describes the magnitude of the depegging event of stablecoin i 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 $D_{j,t} \times S_t$ describes an interaction term representing the simultaneous occurrence of a depeg and a day of market stress.

Table 1.

Statistic	*BTC*	*ETH*	*BNB*	*XRP*	*USDT*	*USDC*	*DAI*
Mean (%)	−0.07	−0.19	−0.16	−0.06	0.05	0.02	0.26
Std Error	0.15	0.19	0.17	0.18	0.01	0.01	0.03
Median (%)	−0.04	−0.09	0.06	−0.01	0.04	0.02	0.05
Std Dev (%)	3.74	4.90	4.35	4.65	0.17	0.22	0.68
Variance	14.00	24.04	18.88	21.65	0.03	0.05	0.46
Kurtosis	29.59	28.16	44.76	23.10	14.02	96.17	15.16
Skewness	−2.53	−2.46	−3.69	0.07	0.27	−6.47	3.04
Min (%)	−43.37	−56.31	−55.90	−42.04	−1.27	−3.44	−3.30
Max (%)	13.77	18.12	18.01	42.34	1.23	0.69	5.85

Table 1 Descriptive Statistics

In this analysis, the focus is on the three key coefficients: δ_{i,j_1}, δ_{i,j_2} and δ_{i,j_3}. The first coefficient, δ_{i,j_1} indicates how much a stablecoins' depeg affects cryptocurrency volatility on its own. The second, δ_{i,j_2}, measures the general impact of market stress. However, this research is most interested in the effects of δ_{i,j_3}, which represents the interaction between the two. In the case of δ_{i,j_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 δ_{i,j_3}, this needs to interpreted with respect to δ_{i,j_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 %) during periods of market stress. On average, all cryptocurrencies' daily returns were slightly negative, while showing standard deviations ranging from 3.74% (BTC) to 4.90% (ETH). The extremely high Kurtosis, ranging from 23.10 (XRP) to 44.76 (BNB), indicated heavy tails in the distributions, which means that extreme fluctuations in returns were more common. The negative Skewness and, therefore, longer left-sided tails of BTC, ETH and BNB indicated that, during market stress, negative returns were more frequent than positive ones, while for XRP the opposite was the case ($skewness\ XRP = 0.07$), although only marginally.

The sample mean of our stablecoin depegs were all positive, with DAI having the highest (0.26%). All three stablecoins exhibited standard deviations lower than 1%, which aligns with their fundamental purpose of tracking the value of the US dollar. The high Kurtosis of USDT (14.02), DAI (15.16) and USDC (96.17) indicated heavy tails, while the latter demonstrated extremely heavy tails. USDT and DAI were both somewhat right-skewed, while USDC showed severe 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, XRP) and for the stablecoins USDT and USDC. DAI depegging events were found to be stationary at the 5% significance level. Stationarity is a necessary requirement for Granger causality tests, as applying them to non-stationary variables yields unreliable results (Granger, 1979).

Table 2.

Asset	*ADF-Statistic*	*p-Value*	*Significance*
USDT	−5.94	<0.01	***
USDC	−7.44	<0.01	***
DAI	−3.91	0.0133	**
BTC	−8.78	<0.01	***
ETH	−8.51	<0.01	***
BNB	−9.10	<0.01	***
XRP	−9.06	<0.01	***

Table 2 Unit root tests using Augmented Dickey–Fuller

***, ** and* denote significance levels 1%, 5% and 10%, respectively.

4.3. Lag Length Selection

Optimal lag lengths were obtained using four information criteria: Akaike (AIC), Schwarz (BIC), Hannan–Quinn (HQ), and Final Prediction Error (FPE).

The results showed different optimal lags across stablecoins as independent variables, as shown in Table 3. The optimal lag length was selected where the majority of information criteria agreed, otherwise the AIC was preferred. In the latter case, robustness checks were performed using alternative lag specifications based on the BIC and HQ criteria. For USDC, most information criteria selected a lag length of one, across cryptocurrencies. For USDT, substantially higher lag orders of four to eight lags were proposed, with respect to the AIC. However, for DAI, lag lengths of either five or six were preferred, with respect to the AIC.

Table 3.

Dependent	Independent	AIC	BIC	HQ	FPE
BTC	USDT	5	1	3	5
BTC	USDC	2	1	1	2
BTC	DAI	5	3	4	5
BNB	USDT	8	1	3	8
BNB	USDC	1	1	1	1
BNB	DAI	6	4	5	6
XRP	USDT	4	1	4	4
XRP	USDC	2	1	1	2
XRP	DAI	6	3	4	6
ETH	USDT	4	1	3	4
ETH	USDC	1	1	1	1
ETH	DAI	5	3	4	5

Table 3 Optimal lag lengths

4.4. Granger Causality Results

Granger causality tests were performed to examine the null hypothesis $H_0: D_{i,t}\ does\ not\ Granger\text{-}cause\ R_{i,t}\ during\ periods\ of\ market\ stress$. The results provided heterogeneous evidence regarding the predictive power of stablecoin depegs for cryptocurrency returns and these are presented in Table 4.

Among the three stablecoins, DAI exhibited the most consistent predictive relationships. Specifically, DAI deppeging events were found to Granger-cause BTC and BNB returns during market stress regimes at the 5% significance level, with p-values of 0.0426 and 0.0155, respectively. XRP and ETH returns were Granger-caused by DAI depegging events at the 10% significance level.

The results also showed that both USDT and USDC depegging events Granger-cause BTC returns during market stress regimes at the 5% significance level. While there was a Granger-causal relationship between USDC depegs and ETH returns, with an F-statistic of 3.91, insufficient evidence was gathered to be able to infer a Granger-causal relationship between USDC depegs and XRP and BNB returns, respectively. However, evidence was found for USDT causing depegging events to Granger-cause XRP with a p-value of 0.0269 at the 5% level. Finally, the null hypothesis of USDT depegging events Granger-causing BNB and ETH returns was not rejected.

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 4.

Dependent	Independent	F-Statistic	p-Value	Significance
BTC	USDT	2.44	0.0332	**
BTC	USDC	3.26	0.0389	**
BTC	DAI	2.31	0.0426	**
BNB	USDT	1.26	0.2644	
BNB	USDC	1.48	0.2236	
BNB	DAI	2.64	0.0155	**
XRP	USDT	2.76	0.0269	**
XRP	USDC	0.92	0.3989	
XRP	DAI	1.91	0.0775	*
ETH	USDT	1.18	0.3169	
ETH	USDC	3.91	0.0484	**
ETH	DAI	2.10	0.0635	*

Table 4 Granger causality tests, testing
$H_0: D_{i,t}$ *does not Granger-cause* $R_{i,t}$ *during periods of market stress*

***, ** and* denote significance levels 1%, 5% and 10%, respectively.

4.5. Cryptocurrency Returns Granger-Causing Stablecoin Depegs

In the reverse direction, by testing the null hypothesis $H_0: R_{i,t}$ *does not Granger-cause* $D_{i,t}$ *during periods of market stress*, the results revealed significant relationships across all cryptocurrencies. Cryptocurrency returns consistently Granger-caused stablecoin deppeging events, with particularly strong evidence for BTC, ETH and BNB. For these three, the null hypothesis of no Granger causality was rejected at the 1% significance level across all stablecoins. The only inconsistency, where the p-value was greater than 0.01, was found for XRP returns Granger-causing USDT and USDC depegging events. Here, the null hypothesis was rejected at the 10% and 5% significance level, respectively.

Table 5.

Dependent	Independent	F-Statistic	p-Value	Significance
USDT	BTC	5.68	<0.01	***
USDC	BTC	5.17	<0.01	***
DAI	BTC	4.52	<0.01	***
USDT	BNB	4.15	<0.01	***
USDC	BNB	7.40	<0.01	***
DAI	BNB	8.07	<0.01	***
USDT	XRP	2.35	0.0528	*
USDC	XRP	4.08	0.0174	**
DAI	XRP	4.30	<0.01	***
USDT	ETH	5.58	<0.01	***
USDC	ETH	8.58	<0.01	***
DAI	ETH	6.52	<0.01	***

Table 5 Granger causality tests, testing
$H_0: R_{i,t}$ *does not Granger-cause* $D_{i,t}$ *during periods of market stress*

***, ** and* denote significance levels 1%, 5% and 10%, respectively.

4.6. Results EGARCH

Tables 6–17 report the estimation results of the EGARCH(1,1) models for BTC, ETH, XRP and BNB, examining the effects of individual stablecoin depegging events on cryptocurrency volatility. The findings revealed that the interaction term δ_{i,j_3} was statistically significant in only two instances, while the depegging effect δ_{i,j_1}, which included every depegging value in the observation period regardless (whether it occurred on a stress day or not), was significant in a larger number of cases.

The constant term $\omega_{i,j}$ was negative and statistically significant at either the 1% or the 5% level for all models, except for the model of DAI depegs in relation with BTC returns. The significant results for $\omega_{i,t}$ are consistent with the logarithmic formulation of the EGARCH variance equation. β_{i,j_1}, the lagged variance term, was close to the value of one and significant at the 1% level in all cases. This indicates that shocks to volatility only decay gradually over time.

The term $\alpha_{i,j}$, which captures the effect of the size of past shocks, was statistically insignificant across all cryptocurrencies and model specifications. This suggests that the absolute size of shocks, relative to their expected magnitude, does not play a key role in explaining future volatility.

In contrast, the asymmetry parameter $\gamma_{i,j}$ was positive and statistically significant at the 1% level across all assets, except for DAI depegging events in relation to BTC returns. This indicates the presence of asymmetric volatility dynamics; whereby, positive shocks exert a stronger influence on conditional volatility than negative shocks of equal magnitude. This confirms that the EGARCH model was a more fitting choice, compared to the conventional GARCH model, where this effect could not have been measured.

The estimated shape parameter $\nu_{i,j}$ of the student-t distribution was significant across all models, with values consistently indicating high kurtosis.

4.6.1. Effect of $\boldsymbol{\delta_{i,j_1}}$ (Stablecoin Depegging Events Explanatory Power on Crypto Returns)

Heterogeneous results were obtained using no filter for stress days on the stablecoin depegging vectors (all periods). USDT was identified as the primary predictor, showing weakly significant positive effects on BTC and ETH volatility and significant effects on XRP; whereas, DAI only weakly predicted BNB whilst USDC remained insignificant.

For BTC, the coefficient on USDT depegging was positive and weakly significant. In contrast, no statistically significant effects were observed for USDC or DAI. Identical results were obtained by replacing BTC with ETH.

For XRP, the results also indicated statistically significant effects for USDT at the 5% significance level, although no significant relationship was found for DAI and USDC.

For BNB, only DAI depegging showed weak statistical significance with a positive coefficient, while USDT and USDC remained insignificant.

4.6.2. Effect of Market Stress Variable $\boldsymbol{\delta_{i,j_2}}$

The coefficient on the market stress variable was not found to be statistically significant across all of the models, with the exception of the model which included USDC depegging events and XRP. In the named model, a significant $\delta_{XRP,USDC_2}$ (−0.029) was found at the 10% level.

4.6.3. Effect of Variable of Greatest Interest $\boldsymbol{\delta_{i,j_3}}$

The term δ_{i,j_3} captures the additional effect of stablecoin depegging on cryptocurrency volatility during periods of market stress. Testing the null hypothesis H_0: $\delta_{i,j_3} = 0$, the H_0 was not rejected in all but two cases, indicating limited evidence of differential effects during market stress. It should be noted that δ_{i,j_3} must always be interpreted with the respective value and significance of δ_{i,j_1}. In cases of δ_{i,j_1} and δ_{i,j_3} both being significantly greater than zero, it can

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be inferred that depegging events of stablecoin j exert a positive effect on the volatility of cryptocurrency i which intensifies during periods of market stress.

The first of the two significant cases was the model of USDC to BTC, where the H_0 was rejected at the 5% significance level with an estimate of $\delta_{BTC,USDC_3} = -0.202$. As insufficient evidence was found for $\delta_{BTC,USDC_1}$ being significantly different from zero, one can conclude that depegging events of USDC reduce BTC volatility during market stress.

The second of the two significant cases was the model of USDC to BNB where $\delta_{BNB,USDC_3} = -0.288$ at the 10% significance level. As an insignificant $\delta_{BNB,USDC_1}$ was found, one can conclude the same as for the model of USDC and BTC. It is noteworthy that only two instances of a statistically significant interaction effect δ_{i,j_3} were observed, both associated with USDC.

Table 6.

Variable	*Estimate*	*p-Value*	*Significance*
μ	0.001	0.089	*
ω	−0.108	0.000	***
α_1	−0.010	0.517	
β_1	0.984	0.000	***
γ_1	0.153	0.000	***
δ_1 (Depeg)	0.060	0.069	*
δ_2 (Stress)	−0.010	0.343	
δ_3 (Interaction)	−0.075	0.453	
v	2.995	0.000	***

Table 6 EGARCH(1,1) estimation results for BTC volatility with USDT depegging

Table 7.

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Variable	*Estimate*	*p-Value*	*Significance*
μ	0.001	0.017	**
ω	−0.111	0.000	***
α_1	−0.013	0.422	
β_1	0.983	0.000	***
γ_1	0.160	0.000	***
δ_1 (Depeg)	0.019	0.643	
δ_2 (Stress)	−0.009	0.310	
δ_3 (Interaction)	−0.202	0.048	**
v	3.020	0.000	***

Table 7 EGARCH(1,1) estimation results for BTC volatility with USDC depegging

Table 8.

Variable	*Estimate*	*p-Value*	*Significance*
μ	0.001	0.086	*
ω	−0.061	0.498	
α_1	−0.005	0.815	
β_1	0.990	0.000	***
γ_1	0.146	0.587	
δ_1 (Depeg)	0.000	0.999	
δ_2 (Stress)	−0.011	0.370	
δ_3 (Interaction)	−0.008	0.694	
v	2.986	0.000	***

Table 8 EGARCH(1,1) estimation results for BTC volatility with DAI depegging

Table 9.

Variable	Estimate	p-Value	Significance
μ	0.001	0.133	
ω	−0.176	0.000	***
α_1	−0.010	0.557	
β_1	0.972	0.000	***
γ_1	0.191	0.000	***
δ_1 (Depeg)	0.096	0.061	*
δ_2 (Stress)	−0.002	0.910	
δ_3 (Interaction)	−0.198	0.105	
ν	3.450	0.000	***

Table 9 EGARCH(1,1) estimation results for ETH volatility with USDT depegging

Table 10.

Variable	Estimate	p-Value	Significance
μ	0.001	0.000	***
ω	−0.139	0.000	***
α_1	−0.007	0.658	
β_1	0.977	0.000	***
γ_1	0.185	0.000	***
δ_1 (Depeg)	0.030	0.565	
δ_2 (Stress)	−0.008	0.447	
δ_3 (Interaction)	−0.149	0.177	
ν	3.434	0.000	***

Table 10 EGARCH(1,1) estimation results for ETH volatility with USDC depegging

Table 11.

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Variable	*Estimate*	*p-Value*	*Significance*
μ	0.001	0.001	***
ω	−0.104	0.000	***
α_1	−0.004	0.784	
β_1	0.983	0.000	***
γ_1	0.167	0.000	***
δ_1 (Depeg)	0.011	0.322	
δ_2 (Stress)	−0.008	0.423	
δ_3 (Interaction)	−0.021	0.215	
ν	3.424	0.000	***

Table 11 EGARCH(1,1) estimation results for ETH volatility with DAI depegging

Table 12.

Variable	*Estimate*	*p-Value*	*Significance*
μ	0.000	0.567	
ω	−0.510	0.001	***
α_1	−0.002	0.945	
β_1	0.915	0.000	***
γ_1	0.329	0.000	***
δ_1 (Depeg)	0.184	0.041	**
δ_2 (Stress)	−0.025	0.300	
δ_3 (Interaction)	−0.207	0.547	
ν	2.859	0.000	***

Table 12 EGARCH(1,1) estimation results for XRP volatility with USDT depegging

Table 13.

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Variable	*Estimate*	*p-Value*	*Significance*
μ	0.000	0.564	
ω	−0.440	0.003	***
α_1	−0.005	0.882	
β_1	0.926	0.000	***
γ_1	0.323	0.000	***
δ_1 *(Depeg)*	−0.052	0.591	
δ_2 *(Stress)*	−0.029	0.099	*
δ_3 *(Interaction)*	0.014	0.941	
v	2.847	0.000	***

Table 13 EGARCH(1,1) estimation results for XRP volatility with USDC depegging

Table 14.

Variable	*Estimate*	*p-Value*	*Significance*
μ	0.000	0.585	
ω	−0.433	0.013	**
α_1	−0.004	0.905	
β_1	0.927	0.000	***
γ_1	0.320	0.000	***
δ_1 *(Depeg)*	0.002	0.931	
δ_2 *(Stress)*	−0.022	0.231	
δ_3 *(Interaction)*	−0.031	0.294	
v	2.843	0.000	***

Table 14 EGARCH(1,1) estimation results for XRP volatility with DAI depegging

Table 15.

Variable	Estimate	p-Value	Significance
μ	0.001	0.015	**
ω	−0.204	0.000	***
α_1	0.023	0.269	
β_1	0.969	0.000	***
γ_1	0.259	0.000	***
δ_1 (Depeg)	0.075	0.229	
δ_2 (Stress)	−0.004	0.787	
δ_3 (Interaction)	−0.255	0.130	
v	3.533	0.000	***

Table 15 EGARCH(1,1) estimation results for BNB volatility with USDT depegging

Table 16.

Variable	Estimate	p-Value	Significance
μ	0.001	0.004	***
ω	−0.205	0.000	***
α_1	0.024	0.253	
β_1	0.969	0.000	***
γ_1	0.263	0.000	***
δ_1 (Depeg)	0.066	0.350	
δ_2 (Stress)	−0.011	0.400	
δ_3 (Interaction)	−0.288	0.051	*
v	3.543	0.000	***

Table 16 EGARCH(1,1) estimation results for BNB volatility with USDC depegging

Table 17.

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Variable	*Estimate*	*p-Value*	*Significance*
μ	0.001	0.004	***
ω	−0.200	0.000	***
α_1	0.022	0.286	
β_1	0.969	0.000	***
γ_1	0.257	0.000	***
δ_1 *(Depeg)*	0.020	0.051	*
δ_2 *(Stress)*	−0.016	0.249	
δ_3 *(Interaction)*	−0.015	0.376	
ν	3.502	0.000	***

Table 17 EGARCH(1,1) estimation results for BNB volatility with DAI depegging

***, ** and* denote significance levels 1%, 5% and 10%, respectively.

5. Conclusions

The aim of this research was to examine trends in 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, Granger causality tests were applied to assess the directional predictive power of stablecoin depegs for cryptocurrency returns; second, an EGARCH-X model was employed to examine whether depegging events amplify cryptocurrency volatility specifically during periods of stress.

The descriptive statistics confirm that, during periods of market stress, all four cryptocurrencies exhibited slightly negative average daily returns, while all three stablecoins recorded positive average depegs, remaining below their dollar peg, on average. This is consistent with the notion that market stress simultaneously depresses cryptocurrency valuations and exerts upward pressure on stablecoin deviations from parity. Stablecoin volatility remained below one percent across all cases, confirming that even during market turmoil, the three assets largely fulfilled their stabilising function.

The stationarity analysis confirmed that all variables were stationary at conventional significance levels, satisfying the requirement for Granger causality testing. The lag length selection revealed notably higher optimal lags for USDT and DAI compared to USDC, for which a lag of one or two was consistently preferred. This pattern could suggest that USDC-related effects are very short-lived; whereas, USDT and DAI exhibit more persistent dynamics, requiring longer lag structures to capture their relationship with cryptocurrency returns, with respect to the AIC.

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The Granger causality results provided heterogeneous but meaningful evidence. Among the three stablecoins, DAI exhibited the most consistent predictive relationships, with depegging events found to Granger-cause returns of all four cryptocurrencies at either the 5% or 10% significance level. USDT and USDC depegging events were found to Granger-cause BTC returns at the 5% level, while their predictive power for other cryptocurrencies varied. These findings suggest that DAI, as a decentralised cryptocurrency-collateralised stablecoin, may serve as the most reliable early signal of cryptocurrency market stress, likely reflecting its structural dependence on the very assets whose returns it is found to predict. In the reverse direction, cryptocurrency returns were found to consistently Granger-cause stablecoin depegging events across all assets, with particularly strong evidence for BTC, ETH and BNB at the 1% significance level. This bidirectional relationship implies a feedback loop between cryptocurrency market conditions and stablecoin stability, which carries meaningful implications for risk management and systemic risk monitoring in digital asset markets.

The EGARCH-X estimation results revealed that the asymmetry parameter $\gamma_{i,j}$ was positive and statistically significant across virtually all model specifications, confirming the presence of leverage effects in cryptocurrency volatility. This validates the choice of the EGARCH framework over standard GARCH models, as it captures asymmetric volatility responses to positive and negative shocks of equal magnitude. The lagged variance term $\beta_{i,j}$ was close to unity across all models, indicating that volatility shocks only decay gradually over time, which is a commonly documented property of GARCH-family variance processes (Bollerslev, 1986; Nelson, 1991). Regarding the exogenous variables of primary interest, the depegging coefficient δ_{i,j_1} was found to be statistically significant in a limited number of cases, with USDT emerging as the primary predictor of BTC, ETH and XRP volatility. The market stress variable δ_{i,j_2} was largely insignificant, with the sole exception of the USDC–XRP model. Most notably, the interaction term δ_{i,j_3}, capturing the additional effect of depegging during stress periods, was statistically significant in only two instances. They both involved USDC, specifically in relation to BTC and BNB volatility, with negative coefficients. Given the simultaneous insignificance of δ_{i,j_1} in both cases, these results suggest that USDC depegging events reduce cryptocurrency volatility during periods of market stress, rather than amplifying it. This counterintuitive finding may reflect a dynamic whereby investors temporarily reallocate towards USDC during acute stress episodes, a mechanism discussed by Hoang and Baur (2021), which temporarily stabilises cryptocurrency prices. However, given that significant interaction effects were detected in only two out of twelve model specifications, the overall evidence for a systematic relationship contingent on stress between stablecoin depegging and cryptocurrency volatility remains rather limited.

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. 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 of cryptocurrencies.

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