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From zero to hero: Memecoins' spillover effects in cryptocurrency markets

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ABSTRACT

We analyze Trump's memecoin launch, showing heterogeneous volatility spillovers driven by sentiment and fundamentals. Political signals amplified speculative dynamics, underscoring how politics increasingly shapes cryptocurrency markets and investor behavior.

"I will make the United States the crypto capital of the planet."

[Donald Trump, Bitcoin Conference 2024]

1. Introduction

Political developments have increasingly shaped financial markets, with cryptocurrency markets becoming a notable arena where politics intersects with finance. The 2024 US presidential election brought this relationship into sharp focus, as Donald Trump, the Republican candidate, made an unprecedented pivot toward supporting digital assets. Declaring his intention to make the United States the "crypto capital of the planet", Trump positioned cryptocurrencies at the center of his economic agenda, creating expectations of a more favorable policy stance under his presidency.[1] These expectations materialized on January 18, 2025, when Trump introduced his official memecoin minted on the Solana blockchain ($TRUMP). Within 24 h, $TRUMP experienced an extraordinary surge of 900%, generating $18 billion in trading volume and surpassing DOGE, the largest existing memecoin, by $4 billion.[2] The following day, the launch of $MELANIA, a memecoin associated with the First Lady, further amplified market speculation. These events were not merely speculative in nature; they represented a significant exogenous shock that extended beyond financial speculation to signal a broader regulatory and political agenda.

The aim of this study is to examine how the launch of $TRUMP, as both a political signal and financial event, impacted cryptocurrency markets. Specifically, we investigate three critical questions: (1) How did the announcement of $TRUMP influence the returns and volatility of major cryptocurrencies? (2) Did this event generate financial contagion across the cryptocurrency market? (3) Were the effects heterogeneous, with responses varying based on the characteristics of individual cryptocurrencies, such as their technological infrastructure, use case, or speculative appeal?

To address these questions, we employ the Baba-Engle-Kraft-Kroner (BEKK) multivariate generalized autoregressive conditional heteroskedasticity (MGARCH) model from Engle and Kroner (1995), which is particularly suited for examining the relationships between volatilities and correlations dynamics over time. We examine a set of the 10 largest cryptocurrencies by market capitalization and find

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[1] Source: New York Post (https://nypost.com/2024/07/27/us-news/trump-pledges-to-make-us-the-crypto-capital-of-the-planet-during-speech-at-worlds-largest-bitcoin-conference).

[2] Source: CoinDesk (https://www.coindesk.com/markets/2025/01/19/solana-hits-275-lifetime-peak-as-official-trump-memecoin-surges-to-8-b).

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significant volatility spillover effects following the introduction of Trump's memecoin, which indicates the presence of financial contagion among other crypto-assets. The event triggered significant shifts in cryptocurrency market dynamics, with Solana and Chainlink recording the largest gains due to their infrastructural and strategic connections. Established cryptocurrencies such as Bitcoin and Ethereum, instead, demonstrated resilience as both their cumulative abnormal returns (CARs) and variance stabilized in the post-event period. Conversely, other memecoins, including Dogecoin and Shiba Inu, experienced declines as value likely migrated toward Trump's memecoin.

Indeed, the launch of the $TRUMP memecoin occurred amid a highly polarized political environment in the United States, characterized by intense partisan divisions. Trump's brand, inherently tied to strong political emotions, heightened investor sensitivity, amplifying market reactions. For some investors, Trump's endorsement symbolized a unique speculative opportunity, fueling a pronounced bandwagon effect. Others, however, perceived substantial political and regulatory risks associated with his controversial image, adopting a more cautious stance. This polarization explains the heightened volatility and differentiated market responses observed, as investor reactions ranged from enthusiasm based on anticipated political support for cryptocurrencies to skepticism driven by perceived reputational and political uncertainty.

The spillover effects in cryptocurrency markets have indeed gained increasing attention in recent years due to their implications for financial stability, risk management, and portfolio diversification (e.g., Symitsi and Chalvatzis, 2018; Elsayed and Sousa, 2024; Platanakis and Urquhart, 2019, among others). Existing studies primarily focus on spillovers within cryptocurrencies (e.g., Koutmos, 2018; Bouri and Jalkh, 2023; Moratis, 2021) or between cryptocurrencies and traditional financial assets (e.g., Corbet et al., 2018; Cao and Xie, 2022), revealing patterns of interconnectedness, contagion risks, and volatility transmission. While these studies have enriched our understanding of spillovers in cryptocurrency markets, they primarily focus on financial or technological drivers of contagion, such as market crashes, liquidity constraints, or blockchain innovations. The role of political signals, particularly in the context of politically connected tokens, remains largely unexplored.

To the best of our knowledge, this study is the first to analyze the effects of politically connected tokens on cryptocurrency markets. It expands the understanding of how political narratives influence decentralized financial markets. Furthermore, while previous research has focused predominantly on negative shocks such as Bitcoin's price crashes (e.g., Kalyvas et al., 2020), the Terra-Luna collapse (e.g., De Blasis et al., 2023), and the FTX (e.g., Galati et al., 2024a,b) or Silicon Valley Bank (e.g., Galati and Capalbo, 2024) bankruptcies, this study examines the market effects of a positive shock driven by political signals. This is particularly relevant given the evidence that positive shocks increase the volatility of cryptocurrencies more significantly than negative shocks (Baur and Dimpfl, 2018). Finally, it offers insights for scholars, practitioners, and policymakers by highlighting the heterogeneity in market responses to politically connected tokens, and emphasizing how asset-specific characteristics influence contagion dynamics.

2. Data and methodology

2.1. Data and sample selection

This study uses proprietary minute-by-minute close mid-price data for 10 cryptocurrencies among the most significant 20 by market capitalization[3]: Bitcoin (BTC), Ethereum (ETH), Ripple (XRP), Solana (SOL), Dogecoin (DOGE), Chainlink (LINK), Avalanche (AVAX), Shiba Inu (SHIB), Polkadot (DOT), and Litecoin (LTC). Data are collected from Gemini, a well-known US centralized exchange used in prior studies (e.g., Galati and De Blasis, 2024), and sourced from the LSEG Tick History database.[4] The dataset consists of 20,160 observations and spans from January 11, 2025, to January 25, 2025, allowing for symmetrical pre- and post-event periods of one week each surrounding the news of Trump's official memecoin on January 18, 2025.

Consistent with the extant literature, this study calculates cryptocurrency returns as $ln(P_t/P_{t-1})$ where P_t is the digital asset's price at time t. It divides the sample into pre- and post-event based on the first announcement highlighting the launch of the official memecoin of the newly elected President of the US, namely 2:44 AM UTC on January 18, 2025.[5] Similar to the market model in Perdichizzi and Reghezza (2023), we compute cumulative abnormal returns (CARs) to examine the information cascade effects. Consistent with De Blasis et al. (2023), we measure returns from January 1, 2025, to January 10, 2025, to compute a mean benchmark return for each cryptocurrency over a period of stability preceding the sample. We then subtract these benchmark returns (MRs) from the ones computed over the sample period to get the excess returns (ARs) over the market benchmark and cumulate them to obtain the CARs.

2.2. Methodology

Following Galati et al. (2024a), Galati and Capalbo (2024), and De Blasis et al. (2023), we analyze the Trump memecoin launch effect on cryptocurrency markets using a scalar BEKK multivariate GARCH model. We assume logarithmic returns follow a normal distribution with zero mean and conditional covariance matrix H_t, specified as:

$$H_t = (1 - a - b)\bar{H} + a(e_{t-1}e'_{t-1}) + bH_{t-1}, \tag{1}$$

where $\bar{H} = \sum_{t=1}^{T} e_{t-1}e'_{t-1}$ is the unconditional covariance matrix. Parameter matrices $a, b > 0$, and $a + b < 1$ guarantee stationarity and positive definiteness.

We then conduct a contagion test as per the literature above and adopt a stringent significance level ($\alpha = 0.001$), consistent with (Galati, 2024), minimizing Type I errors with high-frequency data.

3. Results

3.1. Volatility spillover effects

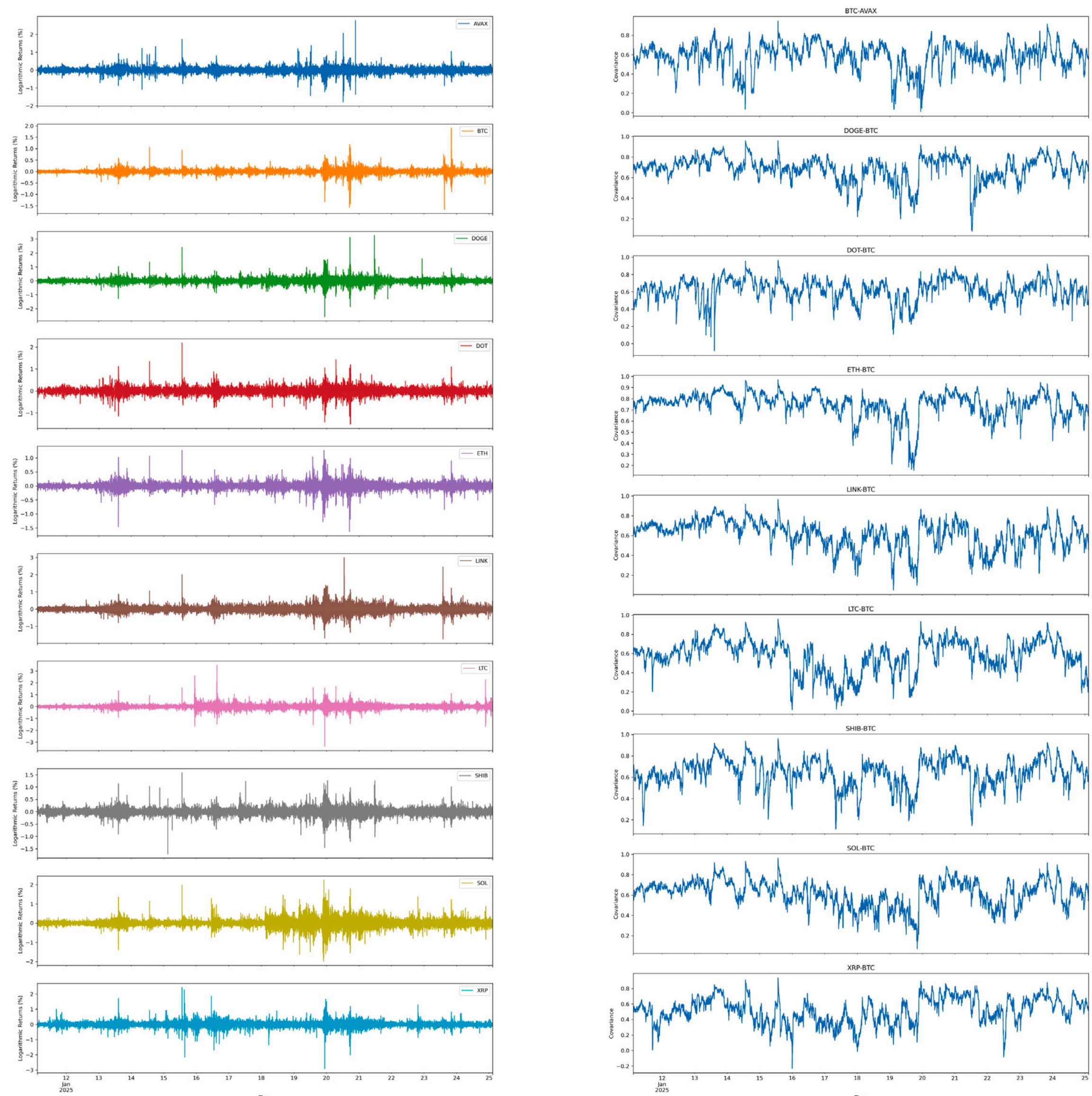
The figures presented in this section offer a preliminary analysis of the relationships among crypto-assets, estimated using the BEKK-MGARCH model. The covariance patterns in Fig. 1(b) reveal a marked increase in interconnectedness among assets, particularly in the post-event period. These results support the hypothesis of heightened volatility spillovers triggered by the event. Similarly, Fig. 1(a) highlights increased fluctuations in stationary logarithmic returns over the same period, reflecting greater market instability and rapid adjustments. The right-hand panels of all plots reveal substantial movements in returns across all analyzed crypto-assets, further underscoring the systemic impact of the event.

Table 1 presents the dynamic conditional covariance estimates obtained from the BEKK-MGARCH model, alongside the corresponding t-test statistics assessing the presence of contagion. The results provide strong evidence of financial contagion and volatility spillover

[3] We did not select the cryptocurrencies but collected the largest available from the Gemini exchange. We only exclude the USD Coin as per its inherent design, not supposed to be a speculative asset for making profits unless a de-pegging process happens.

[4] Unlike other memecoins that are only traded on blockchains, $TRUMP can be traded through proper centralized exchanges in the secondary market. This implies that spillover effects are plausible to show in centralized exchanges like Gemini.

[5] Refer to the news at https://x.com/realDonaldTrump/status/1880446012168249386.



(a) Crypto-assets stationary logarithmic returns

(b) Crypto-assets covariances

Fig. 1. Crypto-assets stationary logarithmic returns and covariances.

effects in the cryptocurrency market following the introduction of Trump's memecoin. Specifically, the BEKK dynamic conditional covariance coefficients reveal statistically significant differences in the mean logarithmic returns (used as a proxy for volatility) between the pre- and post-event periods. These findings reject the null hypothesis of equal means, indicating that the event induced shifts in volatility dynamics across assets.

Most post-event coefficients are significant at the 0.001 level, with substantial increases in covariances observed for pairs such as ETH, SOL, and LINK, indicating stronger co-movement and enhanced market integration following the event. Exceptions include SHIB and DOT, which exhibit significance at the 0.01 level. In contrast, LTC and XRP show notable declines in mean covariance post-event, suggesting that spillover effects are not uniformly distributed across assets. Overall, the findings highlight the systemic impact of the memecoin introduction on the broader cryptocurrency market.

3.2. Information cascade effects

Building on the documented evidence of heterogeneous impacts across crypto-assets, the cumulative abnormal returns (CARs) analysis provides compelling evidence of information cascade effects in cryptocurrency markets triggered by the launch of Trump's memecoin. These results underscore the event's transformative impact on market dynamics, marked by asset-specific responses and heightened volatility.

Fig. 2 illustrates the CARs of the crypto-assets analyzed over the sample period. In the pre-event phase, most cryptocurrencies experienced gains, likely driven by speculative anticipation or market optimism surrounding Trump's potential inauguration as the 47th President of the United States. This suggests that investors, even in the absence of concrete information, engaged in speculative buying, an outcome consistent with the "fear of missing out" (FOMO) phenomenon, which is a well-documented feature of cryptocurrency markets in prior research (Baur and Dimpfl, 2018).

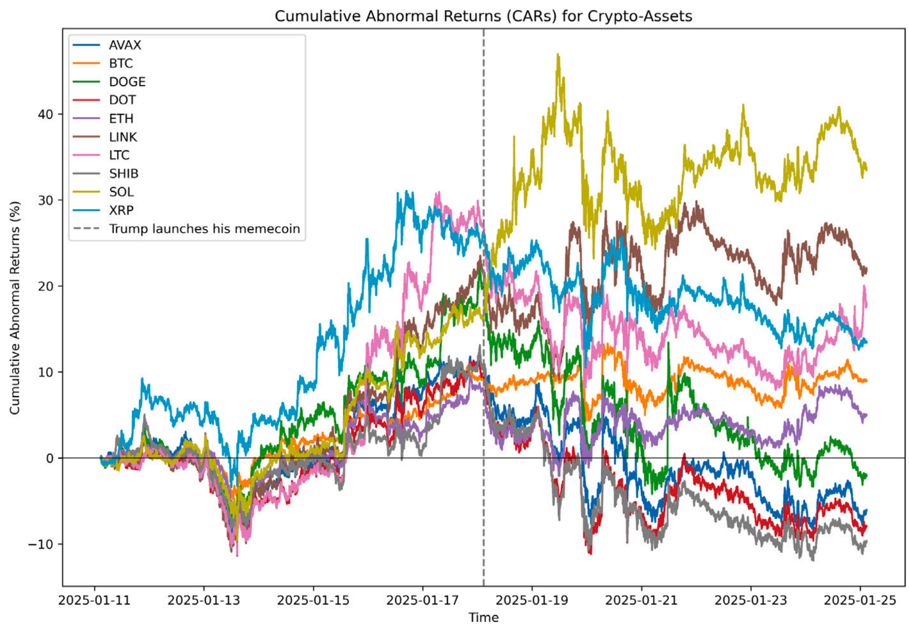


Fig. 2. Crypto-assets cumulative abnormal returns (CARs) over the entire sample period.

Table 1
BEKK dynamic conditional covariance coefficients and contagion effect tests. Pre-event period is from 11.01.2025 to 18.01.2025. Post-event period is from 18.01.2025 to 25.01.2025.

	Mean	Variance	T-statistic
Post-event BEKK-covariances BTC_AVAX	0.6000	0.0164	16.25***
Pre-event BEKK-covariances BTC_AVAX	0.5694	0.0193	
Post-event BEKK-covariances BTC_DOGE	0.7028	0.0093	17.95***
Pre-event BEKK-covariances BTC_DOGE	0.6735	0.0177	
Post-event BEKK-covariances BTC_DOT	0.6263	0.0163	2.94**
Pre-event BEKK-covariances BTC_DOT	0.6210	0.0161	
Post-event BEKK-covariances BTC_ETH	0.7809	0.0061	43.06***
Pre-event BEKK-covariances BTC_ETH	0.7150	0.0175	
Post-event BEKK-covariances BTC_LINK	0.6535	0.0140	49.64***
Pre-event BEKK-covariances BTC_LINK	0.5619	0.0203	
Post-event BEKK-covariances BTC_LTC	0.5577	0.0335	−15.31***
Pre-event BEKK-covariances BTC_LTC	0.5936	0.0220	
Post-event BEKK-covariances BTC_SHIB	0.6417	0.0168	−2.72**
Pre-event BEKK-covariances BTC_SHIB	0.6468	0.0178	
Post-event BEKK-covariances BTC_SOL	0.6448	0.0111	32.44***
Pre-event BEKK-covariances BTC_SOL	0.5887	0.0191	
Post-event BEKK-covariances BTC_XRP	0.4684	0.0258	−40.92***
Pre-event BEKK-covariances BTC_XRP	0.5604	0.0252	

***, **, and * indicate the significance level at 0.1%, 1%, and 5%, respectively.

In the post-event period, three key dynamics emerged. First, Solana outperformed all other assets, likely due to its direct technological linkage as the blockchain hosting Trump's memecoin. Chainlink also exhibited strong performance, possibly due to its association with Oracle, a prominent US company. Second, established cryptocurrencies such as Bitcoin, Ethereum, Ripple, and Litecoin stabilized following modest pre-event gains, reflecting their resilience and relative insulation from cascading speculative effects. Third, other memecoins, including Dogecoin and Shiba Inu, were notably vulnerable to an "asset substitution" effect where speculative capital migrated toward the newly introduced Trump token. Similarly, Avalanche and Polkadot, despite their robust technological foundations, lost value as investor confidence gravitated toward Solana and Chainlink.

Fig. 3 also clearly illustrates how the exogenous shock of the launch of Trump's memecoin disrupted previously uniform market movements. While assets displayed strong co-movements in the pre-event period, post-event CARs diverged sharply, ranging from Solana's +20% to Dogecoin's and Shiba Inu's −20%. This event underscores how asset-specific narratives, technological linkages, and investor perceptions can markedly amplify differences in returns following significant informational shocks.

4. Conclusion

The study examines the impact of launching a cryptocurrency associated with a political figure, such as the US President, on cryptocurrency markets, focusing on volatility spillovers and information cascade effects. The analysis revealed significant heterogeneity in market responses, with assets like Solana benefiting due to direct associations. The event not only bolstered assets leveraging the same blockchain infrastructure but also stabilized established cryptocurrencies like Bitcoin and Ethereum, which serve as anchors for the broader market. This indicates that investor sentiment extends beyond technological fundamentals to incorporate geopolitical and policy narratives tied to influential leaders. These dynamics highlighted the cryptocurrency market's heightened sensitivity to external events and its susceptibility to speculative shifts. As digital assets increasingly intersect with political and economic developments, monitoring these interactions is essential for understanding their implications for market stability.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix. Additional descriptive tables

See Tables A.1 and A.2.

Data availability

The data that has been used is confidential.

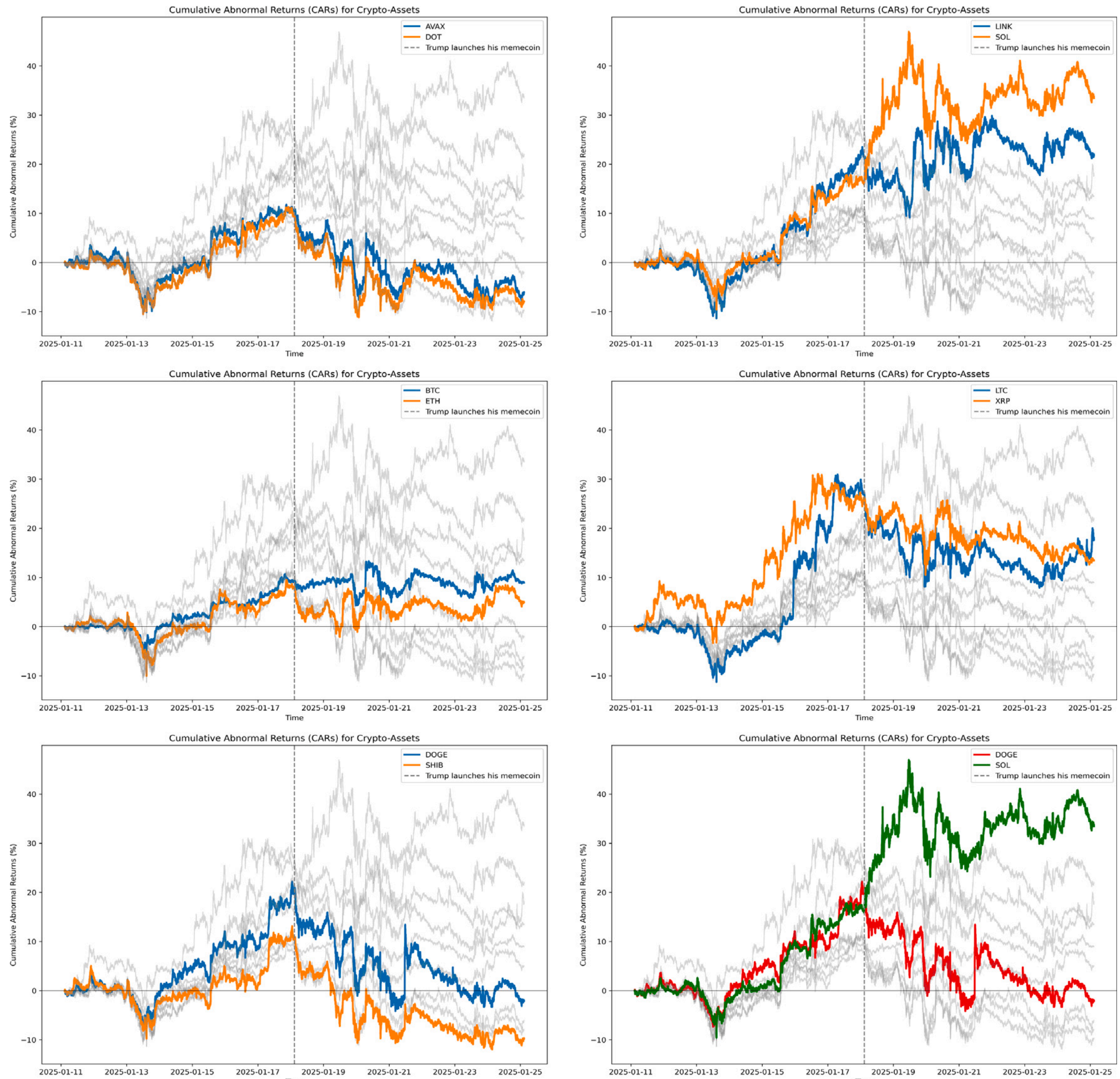


Fig. 3. Crypto-assets cumulative abnormal returns (CARs) over the sample period divided by token type.

Table A.1
Descriptive statistics of crypto-assets returns. The table shows the descriptive statistics for pre-event, post-event and the entire period. *Jarque–Bera* represents the test statistics from the normality test (expressed in $\times 10^6$). *ADF* represents the augmented Dickey–Fuller test. $ARCH(6)$ and $ARCH(12)$ correspond to the test statistics from the ARCH test with 6 and 12 lags, respectively. $Q(6)$, $Q(12)$, $Q^2(6)$, and $Q^2(12)$ represent the test statistics from the Ljung–Box test for serial correlation in returns and squared returns with 6 and 12 lags, respectively.

	AVAX	BTC	DOGE	DOT	ETH	LINK	LTC	SHIB	SOL	XRP
Panel A: pre-event period (11 January 2025 – 18 January 2025, 10,080 min observations)										
Mean	0.0012	0.001	0.0024	0.0011	0.0006	0.0022	0.0027	0.0012	0.0016	0.0033
Median	0.0	0.0	0.0	0.0	0.0002	0.0004	0.0	0.0	0.0006	0.003
Max	1.7183	1.0623	2.4108	2.1947	1.2727	2.0006	3.4942	1.5844	1.9706	2.4334
Min	−1.0753	−0.5492	−1.2732	−1.1455	−1.4618	−0.8671	−1.64	−1.713	−1.3993	−2.1508
Std. Dev.	0.1141	0.0676	0.1266	0.1214	0.0896	0.1284	0.1554	0.1138	0.1107	0.1691
Skewness	0.7667	0.866	0.9303	0.746	0.0077	0.5711	2.2678	0.3318	1.0581	0.4452
Excess Kurtosis	14.4065	14.91	18.9967	17.7691	24.3005	9.7941	48.147	15.4098	23.1657	18.5879
Jarque–Bera	88158.0*	94630.0*	153022.0*	133547.0*	248017.0*	40836.0*	982255.0*	99919.0*	227274.0*	145448.0*
ADF	−27.4*	−17.2*	−99.0*	−19.8*	−16.7*	−18.8*	−14.4*	−16.6*	−16.3*	−21.6*
ARCH(1)	252.6*	167.8*	45.8*	122.4*	1719.3*	94.0*	202.5*	138.5*	469.2*	378.3*
ARCH(6)	492.9*	665.8*	415.3*	428.9*	2191.3*	779.4*	1472.5*	369.8*	999.1*	680.8*
ARCH(12)	542.2*	753.2*	444.3*	472.7*	2256.6*	849.9*	1701.2*	412.9*	1026.5*	707.4*
Q(6)	23.6*	17.6*	8.1	25.0*	36.8*	34.9*	26.6*	14.3*	73.4*	13.7*
Q(12)	37.9*	24.8*	18.1	37.8*	43.6*	55.7*	71.5*	16.5	85.2*	25.1*
$Q^2(6)$	717.7*	1038.0*	565.8*	619.5*	4379.7*	1160.3*	2041.4*	540.8*	1592.9*	1088.0*

(*continued on next page*)

Table A.1 (*continued*).

	AVAX	BTC	DOGE	DOT	ETH	LINK	LTC	SHIB	SOL	XRP
$Q^2(12)$	934.9*	1538.4*	716.1*	800.7*	5019.5*	1625.0*	2648.6*	703.6*	1815.2*	1305.9*
Panel B: post-event period (18 January 2025 – 25 January 2025, 10,080 min observations)										
Mean	−0.0019	−0.0003	−0.0025	−0.0023	−0.001	−0.0002	−0.0024	−0.0027	0.0018	−0.0006
Median	0.0	0.0009	0.0	0.0	−0.0008	−0.0004	0.0	0.0	0.0039	−0.0001
Max	2.7666	1.1848	3.2674	1.4307	1.2704	2.9887	1.7091	1.2633	2.2403	1.669
Min	−1.7814	−1.5654	−2.5859	−1.5239	−1.6364	−1.6874	−3.3624	−1.4563	−1.9948	−2.9212
Std. Dev.	0.1581	0.1185	0.2333	0.1643	0.1472	0.2271	0.1949	0.1673	0.284	0.1902
Skewness	0.4879	−0.8788	0.8766	−0.1824	−0.1386	0.5235	−0.4916	−0.0339	−0.1456	−0.6333
Excess Kurtosis	27.6531	20.433	21.488	7.8147	10.7696	9.0871	18.1799	6.1691	5.0515	15.5777
Jarque–Bera	229694.0*	126179.0*	139442.0*	18361.0*	34819.0*	25102.0*	99443.0*	11419.0*	7681.0*	73281.0*
ADF	−57.5*	−14.7*	−16.3*	−28.4*	−15.8*	−14.5*	−25.2*	−18.6*	−32.1*	−15.7*
ARCH(1)	60.4*	924.0*	1168.8*	369.5*	586.5*	510.8*	521.4*	463.9*	575.6*	255.0*
ARCH(6)	329.9*	1600.6*	1270.4*	1236.4*	1250.3*	907.1*	668.0*	1237.7*	1515.0*	871.4*
ARCH(12)	383.6*	1710.5*	1316.5*	1356.8*	1302.0*	1279.0*	718.1*	1392.3*	1641.5*	1010.6*
Q(6)	17.4*	39.6*	57.8*	59.2*	71.7*	113.8*	78.6*	50.5*	27.4*	99.5*
Q(12)	20.6*	52.2*	75.4*	80.3*	80.2*	137.7*	97.1*	71.2*	39.3*	110.7*
$Q^2(6)$	404.4*	3333.9*	2029.2*	2670.2*	2827.6*	1686.8*	1017.5*	2785.2*	3616.3*	1630.8*
$Q^2(12)$	512.0*	4717.4*	2354.0*	4242.2*	4076.9*	3431.1*	1292.8*	4576.1*	6349.3*	2306.4*
Panel C: entire period (11 January 2025 – 25 January 2025, 20,160 min observations)										
Mean	−0.0001	0.0005	0.0002	−0.0003	0.0001	0.0011	0.0008	−0.0004	0.0014	0.0014
Median	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.001	0.0014
Max	2.7666	1.9039	3.2674	2.1947	1.2727	2.9887	3.4942	1.5844	2.2403	2.4334
Min	−1.7814	−1.6573	−2.5859	−1.5239	−1.6364	−1.7465	−3.3624	−1.713	−1.9948	−2.9212
Std. Dev.	0.1319	0.0951	0.1721	0.1371	0.1149	0.1751	0.1714	0.1356	0.197	0.1701
Skewness	0.5546	−0.3394	0.9383	0.145	−0.1194	0.6196	0.6461	0.0801	−0.0321	−0.0984
Excess Kurtosis	25.2308	34.7849	29.9935	11.9406	16.0582	14.1437	29.8617	9.6904	11.2259	18.1457
Jarque–Bera	535774.0*	1016777.0*	758631.0*	119836.0*	216656.0*	169328.0*	750447.0*	78901.0*	105861.0*	276616.0*
ADF	−64.3*	−22.4*	−26.8*	−41.8*	−22.5*	−30.7*	−22.8*	−30.6*	−21.9*	−33.3*
ARCH(1)	233.8*	1206.0*	2852.0*	636.4*	2109.7*	1605.5*	713.4*	871.9*	1916.8*	755.5*
ARCH(6)	925.9*	2470.5*	3214.4*	2112.6*	3598.3*	2419.6*	1921.6*	2370.2*	4555.0*	1857.9*
ARCH(12)	1035.5*	2800.2*	3346.6*	2340.0*	3697.7*	3087.8*	2126.5*	2671.4*	4916.4*	2022.7*
Q(6)	33.4*	48.8*	88.9*	75.9*	101.3*	162.3*	84.0*	67.1*	68.6*	74.9*
Q(12)	46.0*	81.2*	121.8*	111.3*	122.5*	201.9*	144.5*	98.5*	95.4*	89.4*
$Q^2(6)$	1221.5*	4410.6*	5386.5*	4030.4*	8228.9*	4359.9*	3215.6*	4759.9*	11413.1*	3305.6*
$Q^2(12)$	1578.1*	6762.9*	6464.4*	6178.5*	11301.5*	8053.4*	4270.6*	7627.1*	20089.6*	4384.3*

***, **, and * indicate the rejection of the null hypothesis at the 1%, 5%, and 10% significance level, respectively.

Table A.2
BEKK dynamic conditional correlation matrices. Pre-event period is from 11.01.2025 to 18.01.2025. Post-event period is from 18.01.2025 to 25.01.2025.

	AVAX	BTC	DOGE	DOT	ETH	LINK	LTC	SHIB	SOL	XRP
Panel A: pre-event period (11 January 2025 – 18 January 2025)										
AVAX	1									
BTC	0.625235	1								
DOGE	0.641961	0.714916	1							
DOT	0.649388	0.633885	0.666449	1						
ETH	0.674204	0.818227	0.740232	0.665304	1					
LINK	0.669224	0.679879	0.691353	0.716093	0.755127	1				
LTC	0.468308	0.472619	0.486273	0.491991	0.512995	0.515811	1			
SHIB	0.614023	0.658468	0.777281	0.6262	0.705673	0.661741	0.462205	1		
SOL	0.634409	0.67867	0.675473	0.604173	0.749957	0.660899	0.439326	0.652516	1	
XRP	0.498732	0.459975	0.528532	0.586131	0.506983	0.548666	0.47149	0.497143	0.46524	1
Panel B: post-event period (18 January 2025 – 25 January 2025)										
AVAX	1									
BTC	0.525833	1								
DOGE	0.550241	0.660967	1							
DOT	0.617627	0.65822	0.701213	1						
ETH	0.57698	0.731263	0.725516	0.728898	1					
LINK	0.538265	0.583533	0.636563	0.687018	0.715996	1				
LTC	0.532939	0.629717	0.685332	0.69964	0.704787	0.645028	1			
SHIB	0.6122	0.670154	0.831349	0.754408	0.772117	0.694725	0.719906	1		
SOL	0.49315	0.601526	0.592234	0.58289	0.624682	0.537556	0.546287	0.646707	1	
XRP	0.514259	0.634491	0.677135	0.693988	0.667917	0.629218	0.690414	0.695646	0.527041	1

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