“Examining the return dynamics of Bitcoin and Ethereum around major international football tournaments”

AUTHORS	Wendy Wendy Hansen Tandra Mochammad Ridwan Ristyawan

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Wendy Wendy (Indonesia), **Hansen Tandra** (Indonesia),
Mochammad Ridwan Ristyawan (Indonesia)

EXAMINING THE RETURN DYNAMICS OF BITCOIN AND ETHEREUM AROUND MAJOR INTERNATIONAL FOOTBALL TOURNAMENTS

Abstract

Cryptocurrencies have become increasingly important alternative investment assets, yet their returns remain sensitive to market conditions and external developments. Major international football tournaments attract substantial global attention, but evidence on whether these periods coincide with systematic changes in cryptocurrency returns remains limited. This study examines the return dynamics of Bitcoin and Ethereum before, during, and after major international football tournaments using monthly data from May 2016 to December 2025. Tournament-specific OLS regressions with market controls, calendar and trend adjustments, Newey–West HAC inference, and Benjamini-Hochberg FDR correction were employed in this study. The results show substantial heterogeneity across tournaments, cryptocurrencies, and temporal phases. Although several tournament-window coefficients are nominally significant, broader FDR adjustment substantially narrows the supported findings. The strongest evidence is concentrated around the FIFA World Cup, with a negative association between the tournament period and Bitcoin returns, and a negative associations between the pre-tournament periods and Ethereum returns. International football tournament periods are not uniformly associated with cryptocurrency returns, and the observed patterns depend on the specific asset, tournament phase, and event context. These findings are consistent with a potential behavioral or investor-attention mechanism, although attention and sentiment are not directly measured.

Keywords cryptocurrency, Bitcoin, Ethereum, football, returns

JEL Classification G14, G41

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Wendy Wendy, Dr., Associate Professor, Department of Management, Faculty of Economics and Business, Universitas Tanjungpura [Tanjungpura University], Indonesia. (Corresponding author)

Hansen Tandra, Dr., Graduate School, Universitas Tanjungpura[Tanjungpura University], Indonesia.

Mochammad Ridwan Ristyawan, Dr., Department of Management, Faculty of Economics and Business, Universitas Tanjungpura [Tanjungpura University], Indonesia.

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INTRODUCTION

Football has become one of the world's most prominent sports, with growing influence on economic activity and financial markets. Empirical evidence on the relationship between football development, sporting performance, and economic outcomes indicates that football-related events are associated with changes in the returns of various financial instruments (Aygün et al., 2023; Batmunkh, 2021; Conejo et al., 2007; Eissa & Al Refai, 2018; Graziano & Vicentini, 2017). For example, the 2022 FIFA World Cup generated an estimated gross value added of USD 1.6-2.4 billion, equivalent to approximately 0.7-1.0% of Qatar's gross domestic product (GDP) in that year (Bibolov et al., 2024). These findings suggest that major football tournaments constitute important global economic events capable of generating extensive media coverage and public engagement while also attracting collective attention well beyond the sports sector itself.

The rapid expansion of cryptocurrencies has created a new setting in which the financial relevance of major social events can be examined.

Bitcoin and Ethereum have attracted substantial interest from both individual and institutional investors, yet their returns remain highly volatile and sensitive to speculative expectations and market sentiment (Hanol Lee & Wie, 2023; LoPiccolo & Parisi, 2023; Wilson, 2019). Compared with conventional financial assets, cryptocurrency markets may be particularly responsive to shifts in public attention and market sentiment, both of which have been associated with short- and medium-term fluctuations in cryptocurrency prices and returns (Li et al., 2025; Song, 2025). Major international football tournaments may influence financial markets through several potential channels, including increased tourism activity, extensive global media exposure, and broader economic activity in host countries. They may also generate substantial public attention that coincides with changes in investor behavior and market sentiment. Nevertheless, such attention-related mechanisms should be regarded as plausible interpretations rather than directly observed transmission channels.

The Efficient Market Hypothesis (EMH) posits that asset prices rapidly incorporate available information. However, behavioral responses and external shocks may lead to temporary deviations from price formation based purely on fundamentals, particularly in highly volatile cryptocurrency markets (Gill et al., 2023; Goyal et al., 2026). Existing studies have examined cryptocurrency responses to macroeconomic announcements, regulatory changes, political developments, and technological disruptions, yet evidence regarding return dynamics surrounding major non-economic global events remains relatively limited (Aydoğan et al., 2025; Jiang et al., 2023; Lawuobahsumo et al., 2024; Nakagawa & Sakemoto, 2023). This limitation raises the question of whether globally prominent football tournaments coincide with systematic changes in cryptocurrency returns across different event periods. Specifically, existing evidence remains insufficient to determine whether Bitcoin and Ethereum exhibit distinct return patterns before, during, and after major international football tournaments and whether such patterns differ across tournaments and cryptocurrencies. Addressing this gap is important for understanding whether large-scale non-economic events coincide with changes in return dynamics in highly speculative digital asset markets. Although shifts in investor attention and sentiment may provide plausible behavioral explanations for such patterns, these mechanisms should not be interpreted as directly identified unless they are explicitly measured.

1. LITERATURE REVIEW AND HYPOTHESES

The cryptocurrency market offers a unique setting for examining how financial assets respond to both economic and non-economic developments. High volatility, speculative trading, continuous market operation, and pronounced sensitivity to shifts in investor expectations make cryptocurrency returns potentially responsive to information, sentiment, and changes in public attention. In this context, major international football tournaments represent globally salient events that may coincide with changes in investor behavior across different time periods. There interconnected perspectives as a follows: the characteristics of cryptocurrency returns, behavioral responses to football-related events, and the role of investor attention in financial-market dynamics.

Cryptocurrencies are alternative financial assets characterized by high volatility, heavy-tailed return distributions, and substantial investment risk. Bitcoin and Ethereum exhibit pronounced return variability, with Ethereum generally displaying greater risk than other major cryptocurrencies (Bruhn & Ernst, 2022; Huang et al., 2024; Shalini et al., 2024). Despite these risks, cryptocurrencies offer substantial return potential and may provide hedging, safe-haven, and diversification benefits under certain market conditions (Amairi et al., 2019; Chowdhury & Abdullah, 2024; Dua, 2025). However, the strong correlation between Bitcoin and Ethereum may limit diversification benefits within cryptocurrency portfolios. Their returns are influenced by investor behavior, speculative trading, fear of missing out, macroeconomic conditions, interest rates, regulatory developments, and movements in traditional financial markets (Ilyin et al., 2024; Manohar, 2025). These characteristics make cryptocurrency markets particularly relevant for examining whether globally salient external events coincide with systematic changes in return dynamics.

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Behavioral finance provides an important framework for understanding the sensitivity of cryptocurrency returns to non-economic events. Investor decisions are not determined exclusively by fundamental information but may also reflect attention constraints, emotional responses, cognitive biases, and social interactions. These mechanisms are particularly relevant in cryptocurrency markets, where prices are highly responsive to speculative expectations, public attention, and rapidly changing sentiment.

Major international football tournaments constitute highly visible social events capable of generating collective attention and emotional responses across countries. Football-related developments, including match outcomes, injuries, player transfers, and tournament eliminations, have been shown to influence fan engagement, financial-market behavior, and the valuation of football-related digital assets (Gómez-Martínez et al., 2020; Sóti et al., 2020). Seminal evidence from conventional financial markets was provided by Edmans et al. (2007), who demonstrated that international football results can affect stock market returns through changes in investor mood. Their study documented significant negative market reactions following national-team defeats, with particularly pronounced effects after elimination-stage losses in the FIFA World Cup.

This evidence provides an important behavioral-finance foundation for considering international football events as externally generated sources of collective sentiment that may extend beyond equity markets to speculative digital assets. Social sentiment and public attention, commonly proxied by Google search trends, social media activity, and the Crypto Fear & Greed Index, also play an important role in football-related market responses (Luo et al., 2026; Ozcelebi et al., 2026). Fan sentiment is further reflected in betting markets and social media platforms, where national loyalty, team popularity, goals, penalties, victories, and defeats generate real-time emotional reactions. Sentiment analysis of Twitter messages has proven useful for identifying changes in fan engagement and collective mood during football matches (Aloufi & El Saddik, 2018; Wunderlich & Memmert, 2020). These findings suggest that football-related emotions may extend beyond sports consumption and be associated with broader economic and investment behavior (Albrecht et al., 2025).

The relationship between football events and asset returns may also vary across tournament phases. Before a tournament, optimism, anticipation, media exposure, and fear of missing out may increase speculative participation. During the tournament, heightened public attention may divert investors from financial-market monitoring, while realized match outcomes may alter collective mood and risk preferences. After the tournament, declining attention, disappointment, or profit-taking may be associated with further return adjustments. This temporal pattern is consistent with the "buy the rumor, sell the news" heuristic observed in fan token markets, where prices tend to rise before sporting events but weaken during or after them (Saggu et al., 2024). Similar return patterns have been documented in equity markets, particularly during high-stakes football competitions (Galloppo & Boido, 2020; Truong et al., 2021).

Football tournaments may also be associated with financial behavior through changes in collective mood. Victories can generate optimism and a greater willingness to assume risk, whereas defeats and eliminations may produce pessimism, risk aversion, and selling pressure. Major sporting events, including UEFA Champions League eliminations, may therefore amplify spillover effects in fan token markets and other football-related digital assets. An investor-attention perspective provides a complementary mechanism. Investors have limited cognitive capacity and cannot process all available information simultaneously. During major international football tournaments, extensive media coverage and public engagement may divert attention away from monitoring and trading financial assets. Such a reallocation of attention may coincide with changes in trading intensity, liquidity, and short-term market momentum in Bitcoin and Ethereum. Attention diversion may occur not only during the tournament but also before and after it, as media intensity and investor engagement vary across tournament phases. Empirical evidence supports the broader role of attention, sentiment, and behavioral trading in transmitting football-related developments to financial and cryptocurrency markets (Lee & Byun, 2013; Shao & Cheng, 2025; Wanat & Leksowski, 2022).

Overall, the literature suggests that cryptocurrency returns are sensitive to behavioral and market conditions and that football-related events may be associated with financial behavior and the valuation of football-related digital assets. However, systematic evidence remains limited regarding whether Bitcoin and Ethereum exhibit distinct return patterns before, during, and after major international football tournaments, particularly when multiple tournaments and leading cryptocurrencies are examined within a common empirical framework. This research gap limits the current understanding of how globally salient non-economic events are associated with the temporal return dynamics of speculative digital asset markets.

Therefore, this study aims to examine the return dynamics of Bitcoin and Ethereum before, during, and after major international football tournaments. Based on the preceding literature, the following hypotheses are proposed as a follows:

H1: Pre-tournament periods of major international football tournaments are significantly associated with Bitcoin returns.

H2: Tournament periods of major international football tournaments are significantly associated with Bitcoin returns.

H3: Post-tournament periods of major international football tournaments are significantly associated with Bitcoin returns.

H4: Pre-tournament periods of major international football tournaments are significantly associated with Ethereum returns.

H5: Tournament periods of major international football tournaments are significantly associated with Ethereum returns.

H6: Post-tournament periods of major international football tournaments are significantly associated with Ethereum returns.

2. METHODS

This study employs monthly secondary data covering the period from May 2016 to December 2025. The observation period begins in May 2016 to ensure sufficient data availability for both Bitcoin and Ethereum while covering multiple editions of major international football tournaments. Monthly closing prices and trading volumes for Bitcoin, Ethereum, and the S&P 500 Index were obtained from Investing.com. Data on the Effective Federal Funds Rate were collected from the Federal Reserve Economic Data database maintained by the Federal Reserve Bank of St. Louis.

The analysis includes six major international football tournaments: the FIFA World Cup, Africa Cup of Nations, AFC Asian Cup, Copa America, UEFA European Championship, and CONCACAF Gold Cup. The tournament editions included in the observation period are presented in Table 1. Based on the official tournament schedules, three tournament-period dummy variables were constructed for each competition. PRE identifies the two months preceding the tournament, EVE represents the official tournament period, and POST identifies the two months following the tournament. Each variable equals 1 when a monthly observation falls within the corresponding period and 0 otherwise. These indicators classify broader tournament-related periods and do not represent individual match outcomes, victories, defeats, or elimination events. Following previous studies examining the relationship between major events and financial-market returns (Azar, 2014; Benhamed et al., 2023; Dubey, 2022), this study estimates separate regression models for Bitcoin and Ethereum. Monthly cryptocurrency returns are modeled as a function of trading activity, stock-market performance, monetary-policy conditions, and tournament-period indicators.

Table 1. Major international football tournaments included in the analysis

Source: Compiled from official records of FIFA, CAF, AFC, CONMEBOL, UEFA, and CONCACAF.

International Football Tournament	Editions Covered, 2016–2025
FIFA World Cup	2018 and 2022
Africa Cup of Nations	2017, 2019, 2021, 2023, and 2025
AFC Asian Cup	2019 and 2023
Copa America	2016, 2019, 2021, and 2024
UEFA European Championship	2016, 2021, and 2024
CONCACAF Gold Cup	2017, 2019, 2021, 2023, and 2025

Technically, cryptocurrency returns are calculated using monthly simple returns as follows:

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$$RET_t = \frac{(P_t - P_{t-1})}{P_{t-1}}, \quad (1)$$

where RET_t represents the monthly cryptocurrency return, P_t is the closing price in month t, and P_{t-1} is the closing price in the preceding month.

The empirical models are specified as follows:

$$BTCR_t = a_0 + a_1 LogBTCV_t + a_2 SP500_t + a_3 FED_t + a_4 PRE_t + a_5 EVE_t + a_6 POST_t + e_t, \quad (2)$$

$$ETHR_t = a_0 + a_1 LogETHV_t + a_2 SP500_t + a_3 FED_t + a_4 PRE_t + a_5 EVE_t + a_6 POST_t + e_t, \quad (3)$$

where $BTCR_t$ and $ETHR_t$ denote the monthly returns of Bitcoin and Ethereum, respectively. $LogBTCV_t$ and $LogETHV_t$ represent the natural logarithms of Bitcoin and Ethereum trading volume. SP500t is the monthly return of the S&P 500 Index, while FED_t denotes the Effective Federal Funds Rate. PRE_t, EVE_t, and $POST_t$ are binary variables identifying the pre-tournament, tournament, and post-tournament periods of tournament t, and e_t is the error term. The coefficients associated with these variables measure conditional differences in cryptocurrency returns between tournament and non-tournament periods after controlling for market activity and macro-financial conditions.

The model was estimated using Ordinary Least Squares (OLS), with separate estimations performed for each cryptocurrency and each international football tournament. To test the robustness of the baseline estimation results, the model specification is subsequently expanded by including cryptocurrency volatility based on the standard deviation from six months before ($CVOL6_t$) and tournament period overlap ($OVER_t$) as additional control variables:

$$RET_t = a_0 + a_1 LogVOL_t + a_2 SP500_t + a_3 FED_t + a_4 CVOL6_t + a_5 OVER_t + a_6 PRE_t + a_7 EVE_t + a_8 POST_t + e_t. \quad (4)$$

Because the construction of $CVOL6_t$ requires six monthly observations, the effective robustness-estimation sample begins in October 2016, resulting in 111 monthly observations after adjustment. To account for potential heteroskedasticity and serial correlation in the monthly time-series data, the robustness models were estimated using OLS with Newey-West heteroskedasticity and autocorrelation consistent (HAC) standard errors, employing the Bartlett kernel and automatic bandwidth selection.

To further account for recurring calendar patterns and gradual changes in cryptocurrency-market conditions, month-of-year fixed effects and a linear time trend were included in the robustness specifications, with January serving as the reference month. As an additional robustness check, contemporaneous trading volume was replaced by its one-month lagged value to reduce concerns that current trading volume may itself respond to contemporaneous market developments or tournament-related attention. A leave-one-edition-out analysis was also conducted for the FIFA World Cup and UEFA European Championship to assess whether the estimated tournament-window associations were disproportionately driven by a particular tournament edition. Individual editions were sequentially excluded while maintaining the same control variables, month-of-year fixed effects, linear trend, and Newey–West HAC inference. Finally, the potential problem of multiple hypothesis testing was addressed using the Benjamini-Hochberg False Discovery Rate (BH-FDR) procedure. Rather than restricting the correction to the three PRE, EVE, and POST coefficients within each tournament–cryptocurrency pair, the revised analysis applies a broader, hypothesis-aligned correction.

For each cryptocurrency and tournament phase, the six tournament-specific p-values are treated as a single family of hypotheses. This results in six hypothesis families: Bitcoin–PRE, Bitcoin-EVE, Bitcoin-POST, Ethereum-PRE, Ethereum-EVE, and Ethereum-POST. As an additional conservative assessment, a global BH-FDR correction was applied jointly to all 36 tournament-window coefficients, comprising six tournaments, three temporal phases, and two cryptocurrencies. Nominal p-values obtained from the Newey-West HAC es-

timations were ranked and adjusted using the BH-FDR procedure. The resulting adjusted p-values, or q-values, were used to determine which nominally significant associations remained robust after accounting for multiple testing. Accordingly, the regression analysis is used to estimate the direction and magnitude of the conditional associations between tournament periods and cryptocurrency returns, while the robustness procedures evaluate the stability of these associations under alternative specifications and more conservative statistical inference.

3. RESULTS AND DISCUSSION

This section begins with the descriptive statistics of the study variables, followed by diagnostic tests to assess model adequacy. The results of the multiple linear regression analysis are then presented and discussed. Figure 1 depicts the performance of the returns for the two cryptocurrencies under investigation in this study: Bitcoin and Ethereum. Over the past decade, both assets have shown considerable variability in returns, indicating the inherent volatility of the cryptocurrency market. Both Bitcoin and Ethereum exhibit substantial return fluctuations over time, with Ethereum displaying greater return variability than Bitcoin. The significant volatility in the returns of both cryptocurrencies underscores the necessity of careful investment decision-making in crypto assets. In 2017, both Bitcoin and Ethereum reached their peak returns, followed by their lowest returns in 2018. This trend indicates that, despite differences in return magnitude, the two cryptocurrencies generally exhibit similar return patterns.

Table 2 outlines the descriptive statistics for the study variables, detailing the mean, median, maximum, minimum, and standard deviation (Std.

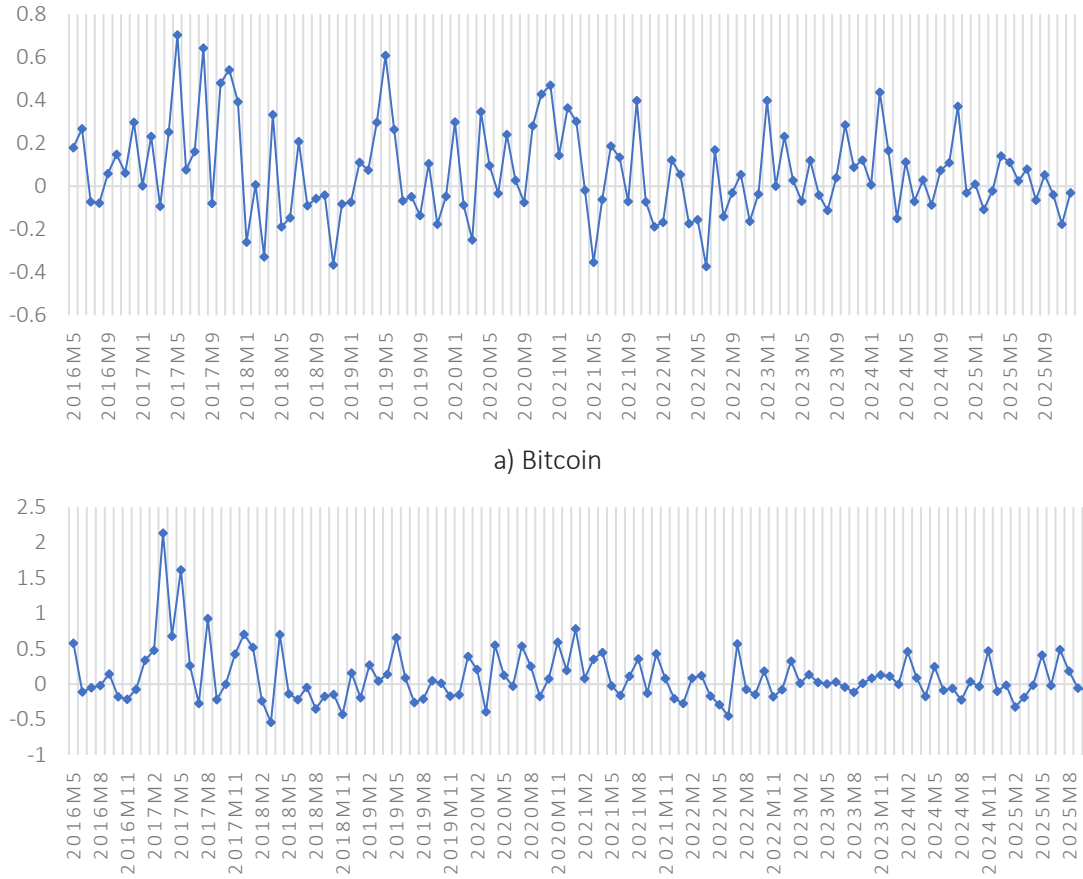


Figure 1. The return for both Bitcoin and Ethereum from 2016M5 to 2025M12

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Dev.). The analysis reveals that certain variables, such as Bitcoin ($BTCR_t$) and Ethereum ($ETHR_t$) returns, display considerable variability, as indicated by standard deviations that exceed their means. This suggests significant fluctuations in these return series. Conversely, other variables demonstrated a more consistent distribution, with mean values exceeding their standard deviations. In terms of central tendency, the Ethereum trading volume exhibits the highest mean and median values, recorded at 17.46 and 16.92, respectively. Furthermore, the maximum and minimum values for Ethereum trading volumes are the most extreme, reaching 23.64 and 14.48, respectively. The Federal Funds rate (FED_t) demonstrates the greatest standard deviation, at 1.92, signifying substantial variability throughout the sample period. In contrast, the dummy variables corresponding to the pre-, event, and post-event periods exhibited the lowest values relative to the other variables in the dataset. Notably, the S&P 500 return variable presents the smallest standard deviation among all variables at 0.04, indicating its relatively stable behavior during the observation period. This study conducted a couple of classical assumption tests to fit the data for further regression analysis. These tests included assessments of normality, multicollinearity, heteroscedasticity, and linearity.

Table 3 presents the results of the classical assumption tests applied to the regression models for the six international football events. Overall, the results indicate that the regression models for all international football events are free of multicollinearity, heteroscedasticity, and linearity issues. This indicates that the explanatory variables do not exhibit excessive correlation with each other, the variance of the error terms remains relatively stable, and the functional relationship between the dependent and independent variables is well-defined. However, the normality test results indicated that the distribution of the regression residuals deviated from normality, as indicated by a significance value below the 0.05 threshold. Although these results indicate a violation of the normality assumption, they do not necessarily in-

Table 2. Descriptive statistics

Variable	Mean	Median	Maximum	Minimum	Std. Dev.
$BTCR_t$	0.07	0.03	0.70	–0.37	0.21
$ETHR_t$	0.10	0.01	2.14	–0.54	0.38
$Log(BTCV_t)$	15.55	15.11	24.50	10.92	1.77
$Log(ETHV_t)$	17.46	16.92	23.64	14.48	1.54
$SP500_t$	0.01	0.02	0.13	–0.13	0.04
FED_t	2.25	1.76	5.33	0.05	1.92
$PREWC_t$	0.03	0.00	1.00	0.00	0.18
$EVEWC_t$	0.03	0.00	1.00	0.00	0.18
$POSTWC_t$	0.03	0.00	1.00	0.00	0.18
$PREAF_t$	0.09	0.00	1.00	0.00	0.28
$EVEAF_t$	0.08	0.00	1.00	0.00	0.27
$POSTAF_t$	0.07	0.00	1.00	0.00	0.26
$PREAFC_t$	0.03	0.00	1.00	0.00	0.18
$EVEAFC_t$	0.03	0.00	1.00	0.00	0.18
$POSTAFC_t$	0.03	0.00	1.00	0.00	0.18
$PRECA_t$	0.06	0.00	1.00	0.00	0.24
$EVECA_t$	0.06	0.00	1.00	0.00	0.24
$POSTCA_t$	0.07	0.00	1.00	0.00	0.26
$PREEURO_t$	0.04	0.00	1.00	0.00	0.20
$EVEEURO_t$	0.05	0.00	1.00	0.00	0.22
$POSTEURO_t$	0.05	0.00	1.00	0.00	0.22
$PREGC_t$	0.09	0.00	1.00	0.00	0.28
$EVEGC_t$	0.08	0.00	1.00	0.00	0.27
$POSTGC_t$	0.09	0.00	1.00	0.00	0.28

Table 3. Classical assumption test

Test	FIFA World Cup	African Cup	Asian Cup	Copa America	Euro	Gold Cup
Bitcoin						
Normality	14.63	12.50	18.31	12.52	13.63	6.71
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.04)
Multicollinearity	1.17-2.86	1.24-1.89	1.23-1.81	1.22-2.28	1.14-2.50	1.36-1.87
Heteroskedasticity	3.85	6.38	3.99	12.74	5.02	18.24
	(0.70)	(0.38)	(0.68)	(0.05)	(0.54)	(0.01)
Linearity	0.83	0.99	0.10	0.85	0.50	0.81
Ethereum						
Normality	512.59	265.22	517.65	573.81	517.43	500.81
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Multicollinearity	1.31-4.56	1.20-2.92	1.16-5.50	1.17-5.97	1.08-7.69	1.09-3.77
Heteroskedasticity	3.95	10.87	3.68	4.77	5.54	5.02
	(0.68)	(0.09)	(0.72)	(0.57)	(0.48)	(0.54)
Linearity	0.56	0.10	0.19	0.90	0.35	0.64

validate the use of Ordinary Least Squares (OLS) estimation in this study. In large-sample settings, the OLS estimator remains unbiased and consistent even when the normality assumption is not met, provided that other key assumptions, particularly multicollinearity, are satisfied.

Table 4 shows that the impact of football tournaments on cryptocurrency returns varies across events and assets, provided as a baseline estimate. In general, Bitcoin and Ethereum returns exhibit a negative response during the World Cup, Copa America, and Euro periods, whereas the Asian Cup primarily affects Bitcoin during the pre- and post-tournament phases. The African Cup and Gold Cup do not show consistently significant return patterns. Conversely, S&P 500 returns have a positive and significant effect across almost all specifications, indicating that global financial market conditions remain a crucial determinant of cryptocurrency returns. Overall, the baseline results suggest that the dynamics of cryptocurrency returns surrounding tournaments differ based on the type of tournament, the asset, and the time phase.

Table 4. Regression results in specific mega sport-football event

Variable	World Cup		African Cup		Asian Cup		Copa America		Euro		Gold Cup	
	BTC	ETH	BTC	ETH	BTC	ETH	BTC	ETH	BTC	ETH	BTC	ETH
Constant	0.23	0.52	0.26*	0.49	0.30*	0.49	0.32*	0.58	0.37**	0.68	0.26*	0.53
	(0.17)	(0.54)	(0.15)	(0.50)	(0.15)	(0.53)	(0.16)	(0.51)	(0.18)	(0.60)	(0.15)	(0.50)
$Log(VOL_t)$	−0.01	−0.02	−0.01	−0.02	−0.01	−0.02	−0.01	−0.02	−0.02*	−0.03	−0.01	−0.02
	(0.01)	(0.03)	(0.01)	(0.03)	(0.01)	(0.03)	(0.01)	(0.03)	(0.01)	(0.03)	(0.01)	(0.02)
$SP500_t$	1.46***	2.20***	1.46***	2.24***	1.38***	2.31***	1.52***	2.48***	1.52***	2.42***	1.55***	2.50***
	(0.36)	(0.65)	(0.35)	(0.68)	(0.40)	(0.67)	(0.34)	(0.61)	(0.35)	(0.66)	(0.35)	(0.61)
FED_t	−0.01	−0.04*	−0.01	−0.04*	−0.01	−0.04*	−0.02	−0.04*	−0.02	−0.04*	−0.01	−0.04*
	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)
PRE_t	−0.07	−0.09	0.11	−0.01	−0.18***	−0.12	0.03	0.17	−0.15	0.07	0.10	0.23
	(0.08)	(0.19)	(0.11)	(0.13)	(0.06)	(0.08)	(0.16)	(0.11)	(0.10)	(0.09)	(0.13)	(0.16)
EVE_t	−0.12**	−0.18*	0.08	0.10	0.04	−0.01	−0.02	−0.21***	−0.07*	−0.23***	0.00	−0.07
	(0.06)	(0.11)	(0.05)	(0.09)	(0.09)	(0.10)	(0.05)	(0.06)	(0.04)	(0.08)	(0.03)	(0.09)
$POST_t$	−0.09*	−0.22*	−0.01	0.36	0.10***	0.01	−0.12***	−0.15**	−0.09**	−0.12	0.02	0.03
	(0.05)	(0.13)	(0.10)	(0.26)	(0.03)	(0.04)	(0.04)	(0.07)	(0.04)	(0.09)	(0.06)	(0.07)
R^2	0.14	0.13	0.15	0.17	0.15	0.11	0.14	0.15	0.15	0.13	0.14	0.14
Adjusted R^2	0.09	0.08	0.10	0.12	0.10	0.06	0.10	0.10	0.11	0.08	0.09	0.09
F-Statistic (Prob)	2.95***	2.62**	3.21***	3.68***	3.24***	2.26**	3.03***	3.16***	3.25***	2.76**	2.92**	2.96**
	(0.01)	(0.02)	(0.01)	(0.00)	(0.01)	(0.04)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)
Durbin-Watson Stat	1.80	1.73	1.81	1.80	1.79	1.69	1.74	1.70	1.76	1.71	1.78	1.70

Notes: ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

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Table 5. Robust OLS estimates with HAC Newey–West standard errors and additional controls, Bitcoin

Variable	World Cup	African Cup	Asian Cup	Copa America	Euro	Gold Cup
Constant	0.24	0.23	0.33*	0.32*	0.38**	0.28
	(0.22)	(0.21)	(0.19)	(0.18)	(0.18)	(0.19)
$Log(VOL_t)$	–0.01	–0.01	–0.02	–0.02*	–0.02*	–0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
$SP500_t$	1.49***	1.51***	1.41***	1.55***	1.53***	1.57***
	(0.35)	(0.38)	(0.42)	(0.39)	(0.39)	(0.38)
FED_t	–0.01	–0.01	–0.02	–0.02	–0.02	–0.02
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
$CVOL6_t$	0.06	0.16	–0.03	0.07	–0.02	–0.06
	(0.39)	(0.43)	(0.39)	(0.39)	(0.37)	(0.40)
$OVER_t$	–0.01	–0.03	0.00	0.16*	0.08	0.01
	(0.06)	(0.06)	(0.05)	(0.09)	(0.07)	(0.07)
PRE_t	–0.07	0.12	–0.17**	0.03	–0.19*	0.10
	(0.09)	(0.11)	(0.07)	(0.16)	(0.10)	(0.12)
EVE_t	–0.13**	0.09	0.03	–0.21**	–0.16**	0.00
	(0.06)	(0.06)	(0.10)	(0.10)	(0.08)	(0.04)
$POST_t$	–0.09	0.00	0.10***	–0.08**	–0.07*	0.01
	(0.06)	(0.05)	(0.04)	(0.04)	(0.04)	(0.07)
R^2	0.15	0.16	0.16	0.15	0.17	0.15
Adjusted R^2	0.08	0.09	0.09	0.08	0.10	0.08
Wald F-Statistic	5.37***	4.33***	5.29***	3.98***	3.37***	3.90***
(Prob)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Durbin-Watson Stat.	1.80	1.82	1.79	1.76	1.81	1.77

Notes: ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 5 shows that the robust results for Bitcoin vary across tournaments. S&P 500 returns have a positive and significant impact across all specifications, whereas trading volume, the Fed rate, and Bitcoin volatility generally do not show consistent effects. Regarding the tournament variables, the World Cup, Copa America, and the Euro exhibit negative and significant effects during the tournament period; conversely, the Asian Cup shows a negative effect during the pre-tournament period and a positive effect during the post-tournament period. Copa America also shows a negative effect during the post-tournament period, while the Euro displays a negative pattern spanning from the pre-tournament to the post-tournament period. Overall, the robust results confirm that the dynamics of Bitcoin returns surrounding football tournaments differ based on the type of tournament and the specific time phase.

Table 6 shows that the robust results for Ethereum also vary across tournaments. S&P 500 returns have a positive and significant impact across all specifications, whereas Ethereum volatility shows a positive influence during the World Cup and African Cup (AF). The overlap variable is also significant, showing a negative effect for the World Cup and AF, and a positive effect for the Copa America. During the tournament period, AF exhibits a positive and significant effect on Ethereum returns, while the Copa America shows a highly significant negative effect. Furthermore, the World Cup shows a negative effect during the post-tournament period, whereas the Asian Cup, Euro, and Gold Cup do not display significant temporal effects. Overall, Ethereum's response to football tournaments is heterogeneous, depending on the type of tournament and the observation period.

Table 7 presents the robustness results for Bitcoin returns after incorporating month-of-year fixed effects and a linear time trend. The inclusion of these additional controls does not eliminate several tournament-window associations observed in the baseline estimations. During the FIFA World Cup, the EVE coefficient remains negative and sta-

Table 6. Robust OLS estimates with HAC Newey–West standard errors and additional controls, Ethereum

Variable	World Cup	African Cup	Asian Cup	Copa America	Euro	Gold Cup
Constant	0.44	0.31	0.41	0.45	0.49	0.47
	(0.42)	(0.44)	(0.53)	(0.51)	(0.57)	(0.49)
$Log(VOL_t)$	−0.02	−0.02	−0.02	−0.02	−0.02	−0.02
	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)	(0.02)
$SP500_t$	2.13***	2.23***	2.27***	2.39***	2.35***	2.45***
	(0.73)	(0.72)	(0.70)	(0.64)	(0.66)	(0.66)
FED_t	−0.03	−0.02	−0.03	−0.03	−0.03	−0.03
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
$CVOL6_t$	0.38**	0.34*	0.34	0.34	0.33	0.29
	(0.18)	(0.18)	(0.23)	(0.24)	(0.24)	(0.19)
$OVER_t$	−0.14*	−0.19***	−0.14**	0.11***	−0.06	−0.11
	(0.08)	(0.06)	(0.07)	(0.04)	(0.12)	(0.10)
PRE_t	−0.12	−0.01	−0.12	0.16	0.02	0.20
	(0.15)	(0.13)	(0.09)	(0.12)	(0.05)	(0.13)
EVE_t	−0.21	0.19**	0.06	−0.30***	−0.13	−0.06
	(0.14)	(0.08)	(0.13)	(0.04)	(0.13)	(0.11)
$POST_t$	−0.27*	0.33	0.01	−0.09	−0.08	−0.01
	(0.14)	(0.25)	(0.04)	(0.06)	(0.08)	(0.06)
R^2	0.17	0.21	0.15	0.16	0.15	0.17
Adjusted R^2	0.11	0.14	0.08	0.10	0.08	0.10
Wald F-Statistic	5.27***	4.62***	3.20***	14.87***	5.47***	3.62***
(Prob)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Durbin-Watson Stat.	1.86	1.93	1.79	1.80	1.79	1.78

Notes: ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

tistically significant at the 1% level, indicating lower Bitcoin returns during the tournament period relative to non-tournament months after controlling for calendar seasonality, market conditions, volatility, tournament overlap, and the underlying time trend. For the African Cup of Nations, the EVE coefficient is positive and marginally significant at the 10% level. In the Asian Cup specification, the PRE coefficient is negative and significant at the 5% level, whereas the EVE and POST coefficients are not statistically significant.

A similar negative pre-tournament association is observed for the UEFA European Championship, where the PRE coefficient is significant at the 5% level. For the Gold Cup, the EVE coefficient is positive and significant at the 5% level, while no statistically significant PRE or POST association is identified. In contrast, none of the Copa America tournament-window coefficients is statistically significant. Across the specifications, the S&P 500 return exhibits a consistently positive and statistically significant association with Bitcoin returns, suggesting that broader financial-market movements remain an important correlate of cryptocurrency performance. The explanatory power of the models is relatively stable, with R-squared values ranging from approximately 0.25 to 0.30. Overall, the results indicate that the identified Bitcoin return patterns are not fully explained by recurring monthly seasonality or a deterministic linear trend. Nevertheless, the statistical significance of the tournament-window coefficients should be interpreted as conditional associations rather than causal effects, particularly given the limited number of observations within each tournament phase.

Table 8 shows that the Ethereum results remain broadly stable after controlling for month-of-year fixed effects and a linear trend. A negative PRE association is observed for the World Cup at the 5% level, while the World Cup POST and African Cup POST coefficients are marginally significant at the 10% level. Most other tournament-window coefficients are statistically insignificant. The S&P 500 return and cryptocurrency volatility remain consistently positive and significant across speci-

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Table 7. Robustness with month-of-year fixed effects and linear trend, Bitcoin

Variable	World Cup	African Cup	Asian Cup	Copa America	Euro	Gold Cup
Constant	0.16	0.19	0.24*	0.28*	0.36**	0.19
	(0.16)	(0.18)	(0.14)	(0.15)	(0.17)	(0.14)
$Log(VOL_t)$	–0.01	–0.02*	–0.01	–0.02*	–0.02**	–0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
$SP500_t$	1.59***	1.67***	1.52***	1.72***	1.71***	1.74***
	(0.42)	(0.36)	(0.45)	(0.34)	(0.38)	(0.40)
FED_t	0.00	0.01	0.01	0.00	–0.00	0.00
	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)
$CVOL6_t$	0.29	0.45	0.21	0.22	0.24	0.21
	(0.35)	(0.49)	(0.41)	(0.41)	(0.47)	(0.43)
$OVER_t$	–0.04	–0.06	0.00	0.03	0.06	–0.02
	(0.06)	(0.06)	(0.07)	(0.05)	(0.08)	(0.05)
PRE_t	–0.14	0.16	–0.22**	–0.05	–0.34**	0.14
	(0.12)	(0.13)	(0.10)	(0.18)	(0.15)	(0.09)
EVE_t	–0.10***	0.12*	–0.00	–0.02	–0.08	0.08**
	(0.04)	(0.07)	(0.13)	(0.06)	(0.08)	(0.04)
$POST_t$	–0.07	–0.02	0.06	–0.08	–0.06	0.06
	(0.09)	(0.06)	(0.06)	(0.08)	(0.09)	(0.06)
R^2	0.26	0.29	0.27	0.25	0.30	0.27
Adjusted R^2	0.09	0.13	0.11	0.08	0.14	0.11
Wald F-Statistic	18.41***	10.80***	12.64***	11.49***	4.69***	6.16***
(Prob.)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Durbin-Watson Stat.	1.74	1.78	1.71	1.67	1.71	1.74

Notes: ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. Month-of-year fixed effects and a linear trend are included; January is the reference month. Trading volume: Contemporaneous log volume.

Table 8. Robustness with month-of-year fixed effects and linear trend, Ethereum

Variable	World Cup	African Cup	Asian Cup	Copa America	Euro	Gold Cup
Constant	0.12	–0.10	–0.03	0.05	–0.01	0.02
	(0.29)	(0.36)	(0.35)	(0.35)	(0.35)	(0.34)
$Log(VOL_t)$	–0.01	–0.00	–0.00	–0.01	–0.01	–0.01
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
$SP500_t$	2.07***	2.09***	2.37***	2.37***	2.34***	2.36***
	(0.70)	(0.64)	(0.62)	(0.66)	(0.65)	(0.67)
FED_t	–0.01	–0.00	0.00	–0.00	–0.00	–0.01
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
$CVOL6_t$	0.93***	0.91***	0.96***	0.99**	0.98**	0.94**
	(0.31)	(0.31)	(0.35)	(0.39)	(0.38)	(0.38)
$OVER_t$	–0.05	–0.09	0.04	–0.09	–0.01	–0.02
	(0.05)	(0.08)	(0.06)	(0.08)	(0.08)	(0.05)
PRE_t	–0.28**	0.04	–0.14	0.17	–0.07	0.16
	(0.11)	(0.12)	(0.12)	(0.15)	(0.13)	(0.11)
EVE_t	–0.09	0.13	–0.13	0.06	0.01	0.08
	(0.16)	(0.10)	(0.12)	(0.17)	(0.11)	(0.15)
$POST_t$	–0.25*	0.31*	–0.11	0.15	0.13	0.13
	(0.14)	(0.17)	(0.12)	(0.14)	(0.12)	(0.09)
R^2	0.36	0.37	0.34	0.34	0.34	0.35
Adjusted R^2	0.22	0.23	0.20	0.20	0.19	0.21
Wald F-Statistic	10.16***	4.81***	7.33***	6.36***	5.14***	4.30***
(Prob.)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Durbin-Watson Stat.	1.96	1.94	1.86	1.87	1.88	1.88

Notes: ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. Month-of-year fixed effects and a linear trend are included; January is the reference month. Trading volume: Contemporaneous log volume.

fications. Tables 9 and 10 report robustness results using lagged trading volume. For Bitcoin, the World Cup EVE coefficient remains negative and significant, while negative PRE associations persist for the Asian Cup and Euro. Positive EVE associations are also observed for the African Cup and Gold Cup at the 10% level. For Ethereum, the World Cup PRE association remains negative and significant, while the World Cup POST and African Cup POST coefficients retain marginal significance. Hence, replacing contemporaneous trading volume with its lagged value produces results that are broadly consistent with the main robustness specifications, indicating that the principal tournament-window associations are not driven solely by contemporaneous trading-volume movements

Tables 11 and 12 present the leave-one-edition-out robustness analysis for the FIFA World Cup and Euro Cup. For Bitcoin, the negative World Cup EVE association remains significant when the 2018 edition is excluded and remains marginally significant when the 2022 edition is omitted, although the POST coefficient becomes significant in the latter specification. For Ethereum, the estimated World Cup associations are more sensitive to the excluded edition: the PRE coefficient is significant when 2018 is excluded, whereas the EVE and POST coefficients become significant when the 2022 edition is omitted. For the Euro Cup, the negative Bitcoin PRE association remains evident across both exclusion exercises, while Ethereum results are generally weaker and more edition-sensitive. The leave-one-edition-out results indicate that some tournament-window associations are relatively stable, whereas others depend more strongly on particular tournament editions.

Table 13 reports the hypothesis-aligned Benjamini–Hochberg FDR correction. After adjustment, *H2* (Bitcoin–EVE) remains supported with an adjusted p-value of 0.05, while *H4* (Ethereum–PRE) retains evidence at the 10% level with an adjusted p-value of 0.08. In contrast, *H1, H3, H5*, and *H6* are not supported after multiple-testing correction. These results suggest that the most robust evidence is concentrated in the Bitcoin tour-

Table 9. Robustness with lagged trading volume, month-of-year fixed effects and linear trend, Bitcoin

Variable	World Cup	African Cup	Asian Cup	Copa America	Euro	Gold Cup
Constant	0.18	0.20	0.30	0.34	0.48**	0.22
	(0.20)	(0.23)	(0.20)	(0.20)	(0.21)	(0.20)
$Log(VOL_{t-1})$	–0.01	–0.02	–0.02	–0.02	–0.03**	–0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
$SP500_t$	1.53***	1.54***	1.38**	1.58***	1.48***	1.65***
	(0.47)	(0.41)	(0.53)	(0.40)	(0.41)	(0.43)
FED_t	0.00	0.01	0.00	0.00	–0.01	0.00
	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)
$CVOL6_t$	0.27	0.42	0.17	0.17	0.17	0.18
	(0.38)	(0.48)	(0.41)	(0.42)	(0.45)	(0.43)
$OVER_t$	–0.04	–0.06	0.00	0.04	0.08	–0.02
	(0.06)	(0.07)	(0.07)	(0.06)	(0.08)	(0.06)
PRE_t	–0.13	0.16	–0.21**	–0.07	–0.38**	0.13
	(0.11)	(0.13)	(0.10)	(0.19)	(0.16)	(0.09)
EVE_t	–0.09**	0.12*	0.01	–0.04	–0.10	0.08*
	(0.04)	(0.07)	(0.14)	(0.06)	(0.08)	(0.04)
$POST_t$	–0.08	0.00	0.08	–0.08	–0.07	0.07
	(0.09)	(0.06)	(0.07)	(0.08)	(0.10)	(0.06)
R^2	0.26	0.29	0.27	0.25	0.31	0.27
Adjusted R^2	0.09	0.13	0.11	0.08	0.16	0.11
Wald F-Statistic (Prob.)	14.53***	8.20***	11.66***	11.19***	5.16***	4.74***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Durbin-Watson Stat.	1.74	1.78	1.72	1.67	1.73	1.74

Notes: ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. Month-of-year fixed effects and a linear trend are included; January is the reference month. Trading volume: Lagged log volume.

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Table 10. Robustness with lagged trading volume, month-of-year fixed effects and linear trend, Ethereum

Variable	World Cup	African Cup	Asian Cup	Copa America	Euro	Gold Cup
Constant	0.08	–0.03	–0.03	0.05	0.04	0.03
	(0.38)	(0.38)	(0.40)	(0.43)	(0.42)	(0.40)
$Log(VOL_{t-1})$	–0.01	–0.01	–0.00	–0.01	–0.01	–0.01
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
$SP500_t$	2.02***	2.06***	2.35***	2.32***	2.30***	2.31***
	(0.70)	(0.64)	(0.60)	(0.67)	(0.66)	(0.67)
FED_t	–0.01	–0.01	0.00	–0.00	–0.01	–0.01
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
$CVOL6_t$	0.94***	0.90***	0.96***	0.99**	0.97**	0.94**
	(0.31)	(0.31)	(0.35)	(0.39)	(0.38)	(0.37)
$OVER_t$	–0.05	–0.09	0.04	–0.08	–0.01	–0.02
	(0.05)	(0.07)	(0.06)	(0.08)	(0.08)	(0.05)
PRE_t	–0.27**	0.04	–0.14	0.16	–0.08	0.15
	(0.11)	(0.12)	(0.12)	(0.15)	(0.13)	(0.11)
EVE_t	–0.09	0.13	–0.13	0.06	0.01	0.08
	(0.17)	(0.10)	(0.12)	(0.18)	(0.11)	(0.15)
$POST_t$	–0.25*	0.31*	–0.11	0.15	0.12	0.13
	(0.14)	(0.17)	(0.12)	(0.14)	(0.12)	(0.09)
R^2	0.36	0.37	0.34	0.34	0.34	0.35
Adjusted R^2	0.22	0.23	0.20	0.20	0.19	0.21
Wald F–Statistic (Prob.)	8.52***	4.60***	7.57***	6.30***	5.06***	4.73***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Durbin–Watson Stat.	1.96	1.95	1.86	1.87	1.88	1.88

Notes: ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. Month-of-year fixed effects and a linear trend are included; January is the reference month. Trading volume: Lagged log volume.

Table 11. Leave-one-edition-out robustness analysis: FIFA World Cup

Variable	BTC Excl. 2018	BTC Excl. 2022	ETH Excl. 2018	ETH Excl. 2022
Constant	0.19	0.17	0.12	0.11
	(0.16)	(0.15)	(0.25)	(0.27)
$Log(VOL_t)$	–0.01	–0.01	–0.01	–0.01
	(0.01)	(0.01)	(0.01)	(0.01)
$SP500_t$	1.72***	1.67***	2.31***	2.17***
	(0.41)	(0.46)	(0.66)	(0.78)
FED_t	0.01	0.01	–0.00	–0.00
	(0.01)	(0.01)	(0.02)	(0.02)
$CVOL6_t$	0.24	0.30	0.92***	0.90***
	(0.41)	(0.38)	(0.32)	(0.33)
$OVER_t$	–0.03	–0.04	–0.04	–0.05
	(0.06)	(0.06)	(0.05)	(0.05)
PRE_t	–0.10	–0.17	–0.30**	–0.24
	(0.12)	(0.14)	(0.12)	(0.16)
EVE_t	–0.11***	–0.09*	0.10	–0.28**
	(0.04)	(0.05)	(0.11)	(0.11)
$POST_t$	0.02	–0.16**	–0.05	–0.44***
	(0.06)	(0.08)	(0.07)	(0.09)
Observations	105	105	105	105
R^2	0.26	0.22	0.38	0.35
Adjusted R^2	0.09	0.03	0.23	0.20
Wald F-Statistic (Prob.)	24.10***	20.24***	18.06***	32.53***
	(0.00)	(0.00)	(0.00)	(0.00)
Durbin–Watson Stat.	1.60	1.72	1.81	2.02

Notes: ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. Month-of-year fixed effects and a linear trend are included; January is the reference month. Trading volume: lagged log volume. Excl. is excluded a period of tournament (2018 and 2022).

Table 12. Leave-one-edition-out robustness analysis: Euro Cup

Variable	BTC Excl. 2021	BTC Excl. 2024	ETH Excl. 2021	ETH Excl. 2024
Constant	0.38**	0.39**	–0.08	–0.07
	(0.18)	(0.18)	(0.34)	(0.35)
$Log(VOL_t)$	–0.02**	–0.02**	–0.00	–0.00
	(0.01)	(0.01)	(0.02)	(0.02)
$SP500_t$	1.70***	1.71***	2.26***	2.28***
	(0.40)	(0.41)	(0.66)	(0.63)
FED_t	–0.01	–0.01	0.00	0.00
	(0.02)	(0.02)	(0.03)	(0.03)
$CVOL6_t$	0.27	0.23	1.01***	0.99**
	(0.48)	(0.46)	(0.38)	(0.39)
$OVER_t$	0.07	0.07	–0.02	–0.02
	(0.08)	(0.08)	(0.08)	(0.08)
PRE_t	–0.21*	–0.50***	–0.11	–0.01
	(0.11)	(0.14)	(0.12)	(0.16)
EVE_t	–0.09	–0.08	0.00	0.05
	(0.07)	(0.11)	(0.11)	(0.14)
$POST_t$	–0.06	–0.07	0.02	0.27**
	(0.09)	(0.12)	(0.11)	(0.12)
Observations	105	105	105	105
R^2	0.29	0.31	0.34	0.34
Adjusted R^2	0.12	0.14	0.18	0.18
Wald F-Statistic	5.67***	5.10***	9.85***	3.52***
(Prob.)	0.00	0.00	0.00	0.00
Durbin-Watson Stat.	1.73	1.72	1.88	1.90

Notes: ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. Month-of-year fixed effects and a linear trend are included; January is the reference month. Trading volume: lagged log volume. Excl. is excluded a period of tournament (2021 and 2024).

nament-period association and the Ethereum pre-tournament association.

The findings indicate that major international football tournaments are not uniformly associated with cryptocurrency returns. After controlling for cryptocurrency volatility, tournament-window overlap, month-of-year fixed effects, a linear time trend, and Newey–West HAC inference, several tournament-window coefficients remain statistically significant at conventional levels. For Bitcoin, the most notable result is the negative association during the FIFA World Cup period, while additional nominal associations appear before the Asian Cup and UEFA European Championship and during African Cup and the Gold Cup. For Ethereum, the strongest nominal pattern is the negative pre-tournament association with the FIFA World Cup. However, the broader hypothesis-aligned Benjamini–Hochberg FDR correction substantially reduces the number of supported findings, leaving only *H2* for Bitcoin during the tournament period and *H4* for Ethereum in the pre-tournament period with limited support. This suggests that the evidence is concentrated in specific cryptocurrency–phase combinations rather than reflecting a general football-tournament effect.

The robustness analyses reinforce this interpretation. Replacing contemporaneous trading volume with its lagged value produces broadly similar coefficient patterns, while the inclusion of month-of-year fixed effects and a linear trend suggests that the main associations are not solely explained by calendar seasonality or gradual changes in cryptocurrency-market conditions. The leave-one-edition-out analysis also shows that some findings are more stable than others. In particular, the negative Bitcoin World Cup EVE association remains significant

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Table 13. Benjamini–Hochberg FDR-adjusted p-values

Hypothesis	Cryptocurrency	Lowest Raw P-Value	BH-FDR Adjusted P-Value	Result
H1	Bitcoin-PRE	0.02	0.11	Not supported
H2	Bitcoin-EVE	0.01	0.05	Supported
H3	Bitcoin-POST	0.30	0.58	Not supported
H4	Ethereum-PRE	0.01	0.08	Supported
H5	Ethereum-EVE	0.21	0.87	Not supported
H6	Ethereum-POST	0.07	0.26	Not supported

when the 2018 edition is excluded and remains marginally significant when the 2022 edition is omitted, whereas several Ethereum coefficients are more sensitive to the excluded edition. These results highlight the heterogeneity of tournament-related return patterns and support interpreting them as conditional associations rather than stable causal effects. The results are broadly consistent with behavioral-finance literature showing that salient sporting events can coincide with changes in financial-market behavior (Edmans et al., 2007; Palomino et al., 2009; Truong et al., 2021).

Differences across tournaments may reflect variation in global audience reach, media intensity, event timing, geographic relevance, investor composition, and market conditions, consistent with evidence that sports-related market responses vary across events and levels of prominence (Akhigbe et al., 2017; Floros, 2014). The stronger and more persistent evidence surrounding the FIFA World Cup suggests that highly salient tournaments may be more closely associated with cryptocurrency return dynamics than less prominent competitions. Nevertheless, because investor attention and sentiment are not directly measured, these mechanisms should be regarded as plausible behavioral interpretations rather than empirically identified channels. From an investment perspective, tournament-related signals should therefore be interpreted cautiously and not treated as a universal or systematic predictor of cryptocurrency returns.

CONCLUSION

This study examines Bitcoin and Ethereum return dynamics before, during, and after major international football tournaments. The findings reveal substantial heterogeneity across tournaments, cryptocurrencies, and temporal phases. After incorporating cryptocurrency volatility, tournament-window overlap, month-of-year fixed effects, a linear time trend, Newey–West HAC inference, lagged trading volume, leave-one-edition-out analysis, and broader BH-FDR correction, the strongest evidence is concentrated around the FIFA World Cup. In particular, Bitcoin shows a negative association during the tournament period, while Ethereum exhibits a negative association during the pre-tournament period. These findings indicate that major football tournaments are not uniformly associated with cryptocurrency returns and that the observed patterns depend on the specific asset, tournament phase, and event context. From a practical perspective, tournament-related periods should not be treated as a universal or systematic predictor of cryptocurrency performance. Investors and market analysts should interpret such signals cautiously and consider broader financial-market conditions alongside event-specific information. The study is subject to several limitations, including the use of monthly data, the relatively small number of observations within individual tournament windows, the focus on Bitcoin and Ethereum, and the absence of direct measures of investor attention, sentiment, and media intensity. Future research could employ higher-frequency data, a broader range of digital assets, larger event samples, and direct behavioral indicators.

DECLARATION OF GENERATIVE AI IN THE WRITING PROCESS

During the preparation of this manuscript, the authors used ChatGPT (OpenAI) to improve the grammar and readability of the manuscript. Furthermore, the authors also utilized SCOPUS AI to support the identification of relevant scholarly references. These tools were used solely as supporting aids for lan-

guage refinement and literature searching. All scientific content, data analysis, interpretation of results, conclusions, and final editorial decisions were independently developed, verified, and approved by the authors, who take full responsibility for the content of this publication.

AUTHOR CONTRIBUTIONS

Conceptualization: Wendy Wendy, Hansen Tandra.
Data curation: Hansen Tandra.
Formal analysis: Hansen Tandra, Mochammad Ridwan Ristyawan.
Investigation: Wendy Wendy, Hansen Tandra, Mochammad Ridwan Ristyawan.
Methodology: Hansen Tandra, Mochammad Ridwan Ristyawan.
Project administration: Wendy Wendy.
Supervision: Wendy Wendy.
Validation: Wendy Wendy, Mochammad Ridwan Ristyawan.
Visualization: Hansen Tandra.
Writing - original draft: Hansen Tandra.
Writing - review & editing: Wendy Wendy, Mochammad Ridwan Ristyawan.

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