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Examining the Influence of Bitcoin Market Cycles on Earnings Reporting Behavior in Firms with Cryptocurrency Exposure

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ABSTRACT

Purpose: This study examines whether stages of the Bitcoin market cycle are associated with discretionary accruals of U.S.-listed companies with measurable exposure to Bitcoin. We aim to address a gap in the crypto-accounting literature, as the prior literature has concentrated on disclosure quality, fair value measurement, and audit risk, but not on accrual-based earnings management behavior in different market conditions.
Method: Discretionary accruals are measured with Modified Jones Model and estimates are analyzed with Linear Mixed Models with an AR(1) repeated covariance structure to address severe serial autocorrelation. The data are an unbalanced panel of 10 firms and 162 firm-quarter observations from Q1 2020 to Q4 2025.
Findings: Within this sample, discretionary accruals yield no statistically significant association with Bitcoin market cycle phase, cryptocurrency exposure intensity, and the interaction between both of them. Only profitability has proved to be relevant. This could indicate that reporting incentives in this firm category are also driven by traditional profitability dynamics, rather than crypto market sentiment. These findings can be explained by rational expectations theory and the political cost hypothesis. Results may suggest that the combination of ASU 2023-08's fair value standard, audit oversight, and governance structures limits market-driven accrual manipulation among early-adopting firms.
Implications: For investors and analysts, the emphasis on profitability metrics over Bitcoin cycle conditions as a reporting signal has practical implications for how cryptocurrency-exposed companies are evaluated. For standard setters in jurisdictions where accounting standards for cryptocurrencies are still being developed, this research gives insight on whether fair value standards and market sentiment acts as behavioral constraint.
Novelty/Value: This study provides the first longitudinal, firm-level empirical test of Bitcoin market cycle effects on earnings management, contributing to emerging literature on institutional constraints in crypto-reporting environments.

Keywords: Bitcoin market cycles, Discretionary accruals, ASU 2023-08, Earnings management, Cryptocurrency exposure, Linear mixed models.

INTRODUCTION

Bitcoin has become a balance sheet asset for publicly listed firms, and its growing footprint in corporate financial statements prompts a question that remains unaddressed directly in the accounting literature: does the cycle of Bitcoin markets induce measurable pressure on how managers report earnings? Bitcoin being a part of the firm's asset base implies that the conditions under which financial statements are created tend to be fundamentally different from the traditional asset-holding corporations as the market value of Bitcoin can fluctuate over 50% in a quarter.

The accounting treatment around Bitcoin has been a cause of reporting complication itself. Prior to the adoption of ASU 2023-08, Bitcoin was an indefinite-lived intangible asset under the impairment only model, which did not allow for upward revaluation and resulted in asymmetrical reporting conditions (Luo & Yu, 2024). In response, the Financial Accounting Standards Board issued Accounting Standards Update – ASU 2023-08, requiring fair value measurement of crypto assets with all changes recognized directly in net income each reporting period (Financial Accounting Standards Board, 2023). The question of whether managers react to such volatility through accrual discretion, therefore, remains open.

The amount of research on fair value measurement and audit monitoring is mixed, but valuable as a starting point for the present subject. Thesing & Velte (2021) provide a structured review of 48 archival studies on fair value measurement and earnings quality, showing that fair value measurements are generally linked to mixed earnings quality, that lower-level, more judgement-dependent fair value measurements are associated with lower earnings quality, and that stronger corporate governance and audit oversight are consistently associated with higher earnings quality throughout this body of research. This last point is consistent with more recent evidence on audit-side monitoring. Firms subject to expanded audit disclosure requirements that increase the visibility of high-risk reporting areas to auditors, management, and audit committees have been found to experience a significant decrease in the likelihood of internal control weaknesses and accounting misstatements, consistent with heightened scrutiny disciplining reporting behavior once a risk area becomes more visible (Dee et al., 2026).

Across the literature, it appears that the earnings quality consequences of fair-value measured items are highly dependent on the degree of judgment employed and the intensity of oversight applied to them. This dynamic has not yet been tested in a setting in which the fair-valued item is a highly visible, sentiment-driven asset such as Bitcoin, and in which ASU 2023-08 has only just moved crypto holdings from an impairment-only model into this same fair value framework. While previous research has documented that firm-level financial characteristics such as profitability and leverage are associated with accrual-based earnings management (Bansal, 2024), this literature was developed largely outside the context of cryptocurrency-holding firms, where asset volatility and evolving standards lead to a distinct reporting environment. The gap this paper addresses is the fact that not only is the population of Bitcoin-exposed firms an unstudied population, but the existing determinants of discretionary accruals have not been tested under conditions where the underlying asset itself exhibits sentiment-driven volatility. To the best of our knowledge, no prior study has investigated the impact of Bitcoin market cycles as a proxy for market sentiment on discretionary accruals of listed companies with Bitcoin exposure.

In this study, we empirically examine each characteristic and provide the first longitudinal firm-level evaluation of whether accrual-based reporting decisions under the present U.S. regulatory environment reflect Bitcoin market conditions. The results offer information for standard-setters on the impact of the fair value system in ASU 2023-08 as a behavioral constraint. For investors and users of financial statements they inform how to judge profits quality in this rising group of firms. Rather than assuming that volatility in the cryptocurrency market naturally leads to reporting pressure, a test is conducted to see whether such an effect is observed in practice. Therefore, results are published as they appear since null findings can be considered a substantive finding. Specifically, we examine whether Bitcoin market cycles affect the level of discretionary accruals reported by crypto-exposed firms and if the degree of a firm's Bitcoin exposure moderates that link. A supporting test examines the statistical significance of firm profitability, a more conventional accrual predictor, after controlling for cycle and exposure-based factors.

LITERATURE REVIEW

Behavioral Finance Theory

Behavioral Finance Theory suggests that market sentiment influences decision-making, in ways that typically vary from rational models (Prasetiyo, 2023; Almansour et al., 2023). This variation increases in cryptocurrency markets where Bitcoin's price cycles are seen as distinct structures of public optimism and anxiety that may impose external reporting pressure on firms exposed to Bitcoin. This study includes Bitcoin market cycles as a proxy for that market-driven pressure and examine whether it is associated with earnings management behavior. As market sentiment changes, stakeholder expectations on reported performance may also change, and managers can respond by choosing from among the accounting choices available to them (Makarchuk et al., 2023).

However, this pressure might not affect all organizations equally in terms of discretionary accrual behavior. Firms with significant exposure to Bitcoin could potentially have high volatility earnings due to price fluctuations, which amplifies the behavioral pressure of market cycles on them compared to firms with negligible crypto holdings (Yuhanitha & Robiyanto, 2021; Anderson et al., 2026). Likewise, mining companies do not view Bitcoin market cycles as an investment but as a fundamental operating reality, since their revenue is inherently related to Bitcoin pricing and network circumstances. The behavioral pressure of a bear cycle on a mining firm is therefore categorically different from that on a non-mining firm holding Bitcoin as a treasury asset, a distinction justifying miner as a separate variable inside this behavioral framework.

Agency Theory

Agency Theory views the relationship between manager and shareholder as a principal-agent contract in which the management, as agent, acts on behalf of the shareholder, the principal, but keeps private knowledge about the true condition of the firm that the owner cannot fully verify. Information asymmetry together with different interests might lead managers to act in a way that is not consistent with the preference of shareholders (Siahaan, 2025). Usually, managers have a better understanding of the internal operation of a firm and this might lead to them acting in a way that is inconsistent with goals of shareholders (Amer et al., 2025; Jensen & Meckling, 1976). This conflict is the theoretical basis from which predictions of PAT's contractual origins are formed. Where Agency Theory describes the reasons the conflict of interest emerges, PAT highlights the accounting decisions managers make to resolve it in their advantage. In this research, discretionary accruals are considered as the observable form of an agency problem that is not immediately visible by outside stakeholders.

Positive Accounting Theory

Positive Accounting Theory (PAT) explains how the agency conflict stated and the external constraints identified by Behavioral Finance Theory, are converted to specific accounting decisions. According to PAT, managers choose accounting policies strategically to maximize utility and fulfill contractual obligations (Sya'ban & Yusnaini, 2026; Watts & Zimmerman, 1990). For firms holding Bitcoin, strategic behavior may manifest through discretionary accruals, which we try to quantify using the Modified Jones Model.

Profitability is said to be the most direct predictor for earnings management behavior, where the less earning performers have a greater motivation to manipulate reported outcomes through accrual discretion, meanwhile the most profitable firms have less motive to interfere (Bansal, 2024). Leverage provides a parallel incentive through debt-covenant pressure, but the evidence regarding its direction is mixed, with some studies showing upward accrual manipulation under high leverage (Ghose et al., 2025; Khanh & Anh Phung, 2019) and others suggesting creditor monitoring suppresses it (Wang et al., 2024), rendering its impact in cryptocurrency unpredictable.

This PAT framework now has a regulatory dimension due to the approval of ASU 2023-08. Before the standard, Bitcoin's impairment-only methodology led to asymmetric recognition, which increased the possibility of managers' accrual incentives in downward price cycles (Luo & Yu, 2024).

Financial Accounting Standards Board (2023) ASU 2023-08 requires fair value measurement with all changes to be recognized directly in net income but whether this structural change meaningfully reduces incentives for earnings management, especially among early adopters, is an open theoretical question that this study contributes to addressing.

Hypothesis Development

The research model in Figure 1 was designed to illustrate the theoretical relationships among the key variables under investigation. The research model serves as a visual representation that clarifies the study's logical flow.

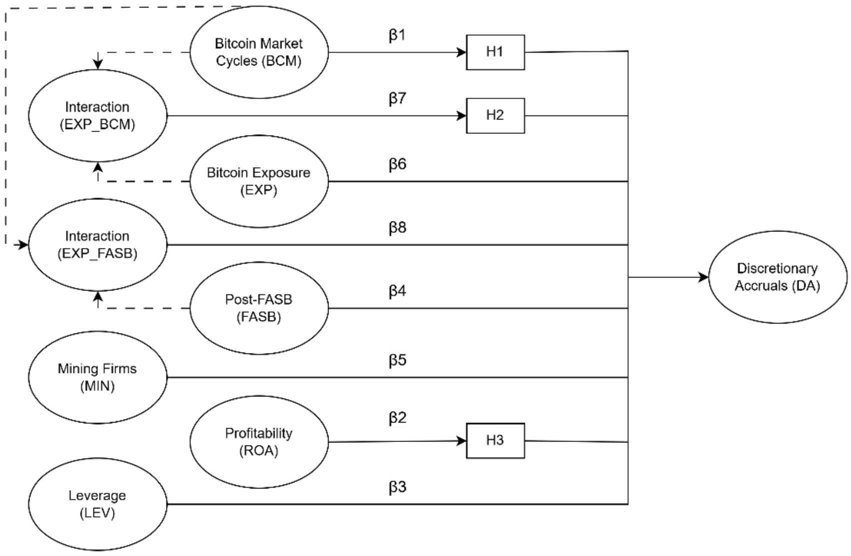

Figure 1. The Research Model
Source: Author's work

BCM is a dummy variable with a value of 1 for bull market and 0 for bear market, so that β1 in the regression can directly reflect the difference in the discretionary accruals between the bull and bear markets. A negative and large β1 would show that firms manipulate earnings to a greater extent in bull markets. This finding would be in line with the notion of Behavioral Finance Theory that the optimism of investors increases managerial incentives to report favorably (Barberis & Thaler, 2003; Collins et al., 2024). A positive and significant β1 would suggest that firms adopt a more conservative reporting stance in bear phases, similar with income smoothing behavior under PAT (Sya'ban & Yusnaini, 2026; Watts & Zimmerman, 1990).

H_1: Bitcoin market cycles influence the level of discretionary accruals reported by firms with cryptocurrency exposure.

The interaction term EXP_BCM tests whether the firm's Bitcoin balance sheet exposure is a source of amplification or suppression of the earnings management behavior caused by the cycle as discussed in H1. A positive and significant β7 would imply that enterprises with higher exposure to Bitcoin are more likely to engage in earnings management in bull markets, implying that higher economic stake in Bitcoin increases the reporting incentives dictated by investor mood (Modani et al., 2023). A negative and substantial β7 would suggest a lowering impact, where firms with more exposure are more conservative in their reporting – perhaps because material Bitcoin holdings are subject to more scrutiny from auditors and regulators, which limits managerial discretion, in line with the agency theory's premise that external monitoring reduces the information gap between managers and shareholders when the stakes under management are more visible (Ali & Helal, 2023; Jensen & Meckling, 1976).

H_2: Bitcoin exposure moderates the relationship between Bitcoin market cycles and discretionary accruals among firms with cryptocurrency exposure.

In addition to the cycle-driven hypothesis documented in H1 and H2, this analysis also considers ROA to be a firm-specific driver of discretionary accruals consistent with the primary premise of agency theory that reporting incentives are highest where the difference between actual and intended performance is largest. A negative and significant β2 would suggest that lower performance firms are more likely to manage earnings upwards, consistent with managers using their informational advantage to narrow the gap between reported and expected performance and to protect compensation, reputation, or continued access to capital (Bansal, 2024; Jensen & Meckling, 1976). A positive and significant β2 would instead indicate that firms with higher profits are associated with higher accrual management, more consistent with opportunistic income smoothing among enterprises with sufficient earnings buffers to manage (Abogun et al., 2021; DeFond & Park, 1997).
H_3: Firm profitability significantly affects discretionary accruals among firms with cryptocurrency exposure.

RESEARCH METHOD

Research Design

This study applied a quantitative, longitudinal research approach. The data consisted of unbalanced panel data from Q1 2020 to Q4 2025. The design is observational and ex post facto, that is, no experimental modification takes place. The dependent variable is discretionary accruals and the main independent variable is Bitcoin market cycle phase. The unit of study is the firm-quarter. A quarterly report period is chosen to match prescribed reporting periods under U.S. GAAP and to allow for within-year cyclical fluctuation in Bitcoin prices that would be obscured by annual statistics.

Data Collection and Samples

The population target group is publicly listed U.S. firms that report Bitcoin holdings and are reported under U.S. GAAP during the period of the study. Inclusion criteria were as such:

1. Listed on a U.S. exchange with publicly available quarterly financial statements
2. Disclosed quantifiable Bitcoin holdings sufficient to construct the exposure variable (EXP) for at least four consecutive quarters
3. Non-zero Bitcoin exposure for a meaningful portion of the research window
4. Not a foreign private issuer, which would make filings subject to differing reporting criteria.

Applying these criteria, the final sample includes 10 firms (see Table 1), among which 6 are Bitcoin mining firms and 4 are non-mining corporations with strategic Bitcoin holdings. The final dataset contains 162 firm-quarters observations over an unbalanced panel due to differences in Bitcoin exposure date and holdings availability.

The sample size is small by design, reflecting the limited population of U.S. listed corporations that both hold meaningful, quantifiable Bitcoin and meet all inclusion criteria. Firms outside this sample were removed due to unavailable BTC holdings data, near-zero Bitcoin exposure, or foreign issuer status; these are structural elements of the current cryptocurrency disclosure landscape rather than arbitrary sampling decisions. The 10-firm sample is thus a near-census of the identifiable qualifying population, which eliminates sampling error within this population while acknowledging limited external generalization. This is a sensible trade-off given the growing nature of this firm category (Anderson et al., 2026; Luo & Yu, 2024).

Quarterly financial statement data for all 10 sample enterprises in the study period were obtained from LSEG Refinitiv. Bitcoin holdings numbers were obtained via Bitcointreasuries.net, cross-checked and verified for accuracy through regulatory filings, audited financial statements, company disclosures, and official news, as this data are not consistently captured in standardized databases. Bitcoin price data were obtained from Investing.com daily closing prices, with quarter-end dates defined as March 31, June 30, September 30, and December 31 for the EXP variable, and daily averages calculated within each quarter for BCM classification.

Table 1. Sample Classification and ASU 2023-08 Adoption

No.	Company Name	Classification	ASU 2023-08 Adoption
1	Block Inc. (XYZ)	Non-mining	01 Jan 2023
2	Tesla (TSLA)	Non-mining	01 Jan 2024
3	Coinbase Global (COIN)	Non-mining	01 Jan 2024
4	Semler Scientific (SMLR)	Non-mining	01 Jan 2024
5	Riot Platforms (RIOT)	Mining	01 Jan 2023
6	Core Scientific (CORZ)	Mining	01 Jan 2024
7	Cipher Mining (CIFR)	Mining	01 Jan 2023
8	Hut 8 Mining (HUT)	Mining	01 Jul 2023
9	Marathon Digital (MARA)	Mining	01 Jan 2023
10	CleanSpark (CLSK)	Mining	01 Oct 2023

Source: Author's work

Operationalization of Variables

Discretionary Accruals

We estimate discretionary accruals at the quarterly level using the Modified Jones Model (Dechow et al., 1995). The approach breaks down total accruals into non-discretionary (economically driven) and discretionary (managerially influenced) parts. The equation (1) for the estimation of discretionary accruals is:

$$DA_{i,t} = \left(\frac{TA_{i,t}}{A_{i,t-1}}\right) - NDA_{i,t} \tag{1}$$

Calculation of total accruals divided by total assets is formulated by equation (2):

$$\frac{TA_{i,t}}{A_{i,t-1}} = \alpha_1\left(\frac{1}{A_{i,t-1}}\right) + a_2\left(\frac{\Delta REV_{i,t}}{A_{i,t-1}}\right) + a_3\left(\frac{PPE_{i,t}}{A_{i,t-1}}\right) \tag{2}$$

Calculation of non discretionary accruals is formulated by equation (3):

$$NDA_{i,t} = a_1\left(\frac{1}{A_{i,t-1}}\right) + a_2\left(\frac{\Delta REV_{i,t} - \Delta REC_{i,t}}{A_{i,t-1}}\right) + a_3\left(\frac{PPE_{i,t}}{A_{i,t-1}}\right) \tag{3}$$

Where:
TA_t = total accruals obtained from net income - operating cash flow
A_{t-1} = total assets t-1
ΔREV = changes in revenue between t and t-1
PPE = net property, plant, and equipment
ΔREC = changes in receivables between t and t-1

PPE is presented on a net basis, and the unavailability of quarterly gross PPE across all companies is acknowledged as a limitation. However, this method also has a precedent where previous studies such as from Kothari et al. (2005) and Gonçalves et al. (2021). Lagged total assets (A_{t-1}) for Q1 2020 observations is based on Q4 2019 data.

Bitcoin Market Cycles

Bitcoin Market Cycle is a dummy variable equal to 1 (bull phase) as equation (4) when the average daily closing price of Bitcoin in quarter t is higher than or equal to the average daily closing price of Bitcoin in quarter t-4 (year-over-year comparison). Meanwhile it is classified as 0 (bear phase) in equation (5) when the average daily closing price of Bitcoin in quarter t is lower than the average daily closing price of Bitcoin in quarter t-4. The year-over-year definition is used because it considers the year-long seasonal noise and it captures the quarterly fluctuations typical of Bitcoin markets.

$$Bull\ (1) = Average\ Daily\ BTC\ Price\ Q_t \geq Average\ Daily\ BTC\ Price\ Q_{t-4} \tag{4}$$

$$Bear\ (0) = Average\ Daily\ BTC\ Price\ Q_t < Average\ Daily\ BTC\ Price\ Q_{t-4} \tag{5}$$

The price-cycle method is consistent with recent findings that Bitcoin's return and volatility behavior changes systematically around structural cycle markers such as halving events, enabling the usage of cycle anchored price comparisons over shorter noisy periods (Veloso et al., 2025). Additionally, robustness evaluations using different kinds of thresholds of 10% and 20% led to a worse model fit (higher AIC/BIC) than the baseline, indicating the YoY definition as the ideal one. A visual of Bitcoin market cycle (bull/bear) against this study's timeline can be seen in Figure 2.

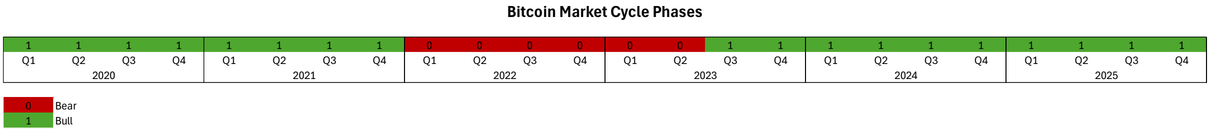

Figure 2. Bitcoin Market Cycle Phases
Source: Author's work

Bitcoin Exposure Interaction with Bitcoin Market Cycles

We operationalize H2 by using the interaction term EXP_BCM = EXP × BCM to assess whether the amount of a firm's Bitcoin exposure amplifies or dampens the effect of BCM on discretionary accruals. EXP is defined by the following equation (6):

$$EXP_{i,t} = \frac{BTC\ holdings_{i,t} \times Quarter\ end\ closing\ price_t}{Total\ assets_{i,t}} \tag{6}$$

This ratio shows the economic weight of Bitcoin on the balance sheet of the firm at the reporting date and is therefore comparable for firms of varying magnitude. Given the sample size, it is likely that the EXP_BCM and EXP_FASB interaction terms will have high collinearity with their component terms. Implications regarding each variable's statistical power are further developed in the Results and Discussions sections.

Control Variables

It is important to note that this research implements many control variables to capture the core analysis accurately and address the biases resulting from the characteristics of the firm. Table 2 shows the control variables derived from a mixing of the relevant theory, and allow each variable to have a clear definition of measurement and an explanation.

Regression Model

The research model is depicted in detail through Figure 1, meanwhile the discretionary accruals are estimated as the following equation (7):

$$\begin{aligned} DA_{i,t} = \beta_0 + \beta_1 BCM_t + \beta_2 ROA_{i,t} + \beta_3 LEV_{i,t} + \beta_4 FASB_{i,t} + \beta_5 MIN_i + \beta_6 EXP_{i,t} \\ + \beta_7 EXP\_BCM_{i,t} + \beta_8 EXP\_FASB_{i,t} + \varepsilon_{i,t} \end{aligned} \tag{7}$$

The estimation method used is linear mixed models. There are two reasons that this dataset is not optimal for ordinary least squares. First, observations are nested inside firms, leading to dependence within clusters, violating the independent assumptions of OLS. Second, the time autocorrelation pattern of quarterly accruals, supported by an AR(1) rho of .941 in the final model, requires explicit modelling of residual serial dependence. Linear Mixed Models (LMM) with a first-order autoregressive AR(1) repeating covariance structure were used and calculated in IBM SPSS Statistics.

Table 2. Operationalization of Control Variables

Variable	Operationalization	Theoretical Basis
Profitability (ROA)	Net income ÷ Total assets	PAT income-smoothing hypothesis (Bansal, 2024)
Leverage (LEV)	Total liabilities ÷ Total assets	PAT debt covenant hypothesis (Ghose et al., 2025; Wang et al., 2024)
Post-FASB (FASB)	Firm specific dummy, 1 for ASU 2023-08 adoption date onwards. FASB is coded firm-specifically, with each firm's dummy activating from its own ASU 2023-08 adoption date (see Table 1).	Regulatory constraint on fair value discretion (Anderson et al., 2026; Thesing & Velte, 2021)
Mining company (MIN)	1 = mining firms 0 = non-mining firms	Mining, payment-acceptance, and investment are distinct reasons firms hold Bitcoin, with mining firms facing an operationally embedded exposure rather than a discretionary treasury decision, motivating MIN as a separate control (Anderson et al., 2026)
Bitcoin exposure (EXP)	(BTC holdings × Quarter-end closing price) ÷ Total assets	Controlling for EXP isolates BCM's effect from the firm's underlying Bitcoin concentration; fair-value exposure ratios of this form are consistent with recent firm-level treatment of crypto holdings (Anderson et al., 2026) and with exposure-based risk pricing in Bitcoin-holding firms (Gao et al., 2025)
Interaction EXP & FASB (EXP_FASB)	EXP × FASB	Firms with higher Bitcoin exposure may face larger reporting changes under ASU 2023-08 (Anderson et al., 2026)

Source: Author's work

All variables are fixed effects in the model. BCM, FASB and MIN are categorical factors whereas ROA, LEV, EXP, EXP_BCM and EXP_FASB are continuous covariates. The final specification does not include random effects, as the random intercept was considered redundant since it was not providing relevant information above and beyond the fixed effects structure and the AR(1) repeated covariance, hence was omitted. The recurring effect was defined as a numeric sequential integer from 1 (Q1 2020) to 24 (Q4 2025) contained within company name as subject identification. In the repeated covariance structure, AR(1) is chosen to explicitly depict the first order serial dependence in quarterly accrual data. Model fit is assessed through Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC), with lower values indicating superior fit.

RESULTS AND DISCUSSION

Results

Assumptions Check

First is the residual normality test. Unlike OLS regression, Linear Mixed Models do not require the outcome variable to be normally distributed, the model is valid as long as the residuals are normally distributed and at the sample size of n = 162, the central limit theorem provides reasonable asymmetric protection against moderate deviations. Normality of residuals is visually checked with a Normal Q-Q plot as illustrated in Figure 3. The plot reveals that residuals closely track the conceptual diagonal in the central part of the distribution, with slight deviations in the upper and lower tails, a sign of mild platykurtosis rather than systematic distributional error. The tail deviations are not serious enough to invalidate the inferences of the model but they are noted as a minor concern. Future replications with larger samples would naturally mitigate this concern.

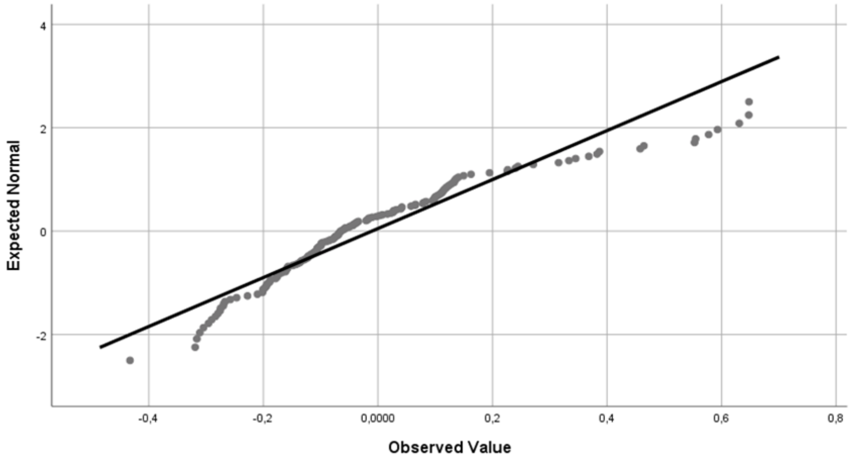

Figure 3. Normal Q-Q Plot of Residuals
Source: Data Processed – IBM SPSS Statistics 25

Second is the multicollinearity test. For diagnostic purposes, variance inflation factor (VIF) diagnostics were run on a supporting OLS specification to assess multicollinearity, as VIF output is not directly produced by LMM.

Table 3. Collinearity Statistics

Variable	Tolerance	VIF
BCM	.474	2.110
ROA	.712	1.404
LEV	.666	1.502
FASB	.452	2.213
MIN	.762	1.312
EXP	.027	37.702
EXP_BCM	.025	39.434
EXP_FASB	.054	18.657

Source: Data Processed – IBM SPSS Statistics 25

The main predictors do not pose a concern, as seen in Table 3 are all well below the conventional threshold of 10. However, the interaction terms are highly multicollinear as EXP (VIF = 37.702), EXP_BCM (VIF = 39.434), and EXP_FASB (VIF = 18.657) are far above this threshold. Mean-centering of EXP was attempted as a corrective procedure, but was not implemented since it did not result in any substantial reduction of VIF values. This validates that the collinearity is structural. However, this result is mathematically expected because EXP is a ratio variable that includes the Bitcoin price, and EXP_BCM and EXP_FASB are direct products of EXP and the binary indicators. The practical implication is that the standard errors for these three terms will be inflated and thus increase the likelihood of Type II error that is, a failure to detect a true effect when one exists. This could directly impact the interpretation of H2 where null findings on these variables are not as reliably interpreted as the null finding on H1 where collinearity is not an issue.

Third is regarding autocorrelation. The estimated AR(1) covariance structure resulted in a rho of .941, suggesting severe positive autocorrelation across firm-quarters. Ignoring this autocorrelation would systematically deflate OLS standard errors and make significance tests unreliable. Thus, the selection of an LMM with an AR(1) error structure is not a methodological preference but a statistical necessity, and the significance of both covariance parameters provides a direct retrospective validation of the selection.

Descriptive Statistics

For continuous variables, descriptive statistics can be seen from Table 4. The mean of the dependent variable, discretionary accruals (DA), is -.045, with a standard deviation of .263 and a range from -1.052 to .812. The negative average suggests a slight preference towards income decreasing accruals in the sample. However, the large dispersion suggests substantial heterogeneity in reporting practices across firms and time periods. The average ROA is -.024, implying that some of the cryptocurrency-exposed firms recorded losses in the observation window, consistent with the general volatility of the sector. The average LEV is .479, indicating that the sampled firms have a moderate leverage on average. However, the minimum and maximum values of .004 and 2.423 respectively suggest that there are large differences in the capital structure across firms. The average of the Bitcoin exposure variable (EXP) is 165.555 with a standard deviation of 224.283. The large standard deviation relative to the mean suggests a heavily right-skewed distribution, driven by a small number of firms with disproportionately large holdings, a pattern that partly explains the linearity concern noted in the limitations.

Table 4. Descriptive Statistics of Continuous Variables

Variables	n	Min	Max	Mean	SD
DA	162	-1.052	.812	-.045	.263
ROA	162	-1.057	.357	-.024	.145
LEV	162	.004	2.423	.479	.423
EXP	162	.000	959.726	165.555	224.283
EXP_BCM	162	.000	959.726	151.255	228.896
EXP_FASB	162	.000	959.726	139.719	229.172

Source: Data Processed – IBM SPSS Statistics 25

For continuous variables, descriptive statistics can be seen from Table 5. The post-ASU 2023-08 indicator (FASB) shows 95 firm-quarter observations (58.6%) in the post-adoption period and the remaining 67 (41.4%) in the pre-adoption period, providing a reasonably balanced split. The Bitcoin market cycle indicator (BCM) consists of 120 observations (74.1%) as bull-phase quarters and 42 (25.9%) as bear-phase quarters. This distributional imbalance reflects the mainly upward trend of Bitcoin prices over the sample period, and is worth bearing in mind when interpreting the BCM result. Finally, the indicator of the mining firm (MIN) indicates there are 95 observations (58.6%) for mining firms that corresponds to the fact that the sample consists unbalanced panel of six mining firms and four non-mining firms during the observation window.

Table 5. Descriptive Statistics of Categorical Variables

Variables	Frequency of 0s		Frequency of 1s	
	Frequency	Percentage	Frequency	Percentage
FASB	67	41.4	95	58.6
BCM	42	25.9	120	74.1
MIN	67	41.4	95	58.6

Source: Data Processed – IBM SPSS Statistics 25

Additionally, Figure 4 shows the distribution of discretionary accruals during Bitcoin market cycles, with periods of bull markets shaded in green and of bear markets shaded in red. To summarize, discretionary accruals are spread around zero across the observation period, implying that both income-increasing and income-decreasing accruals are present under both market circumstances.

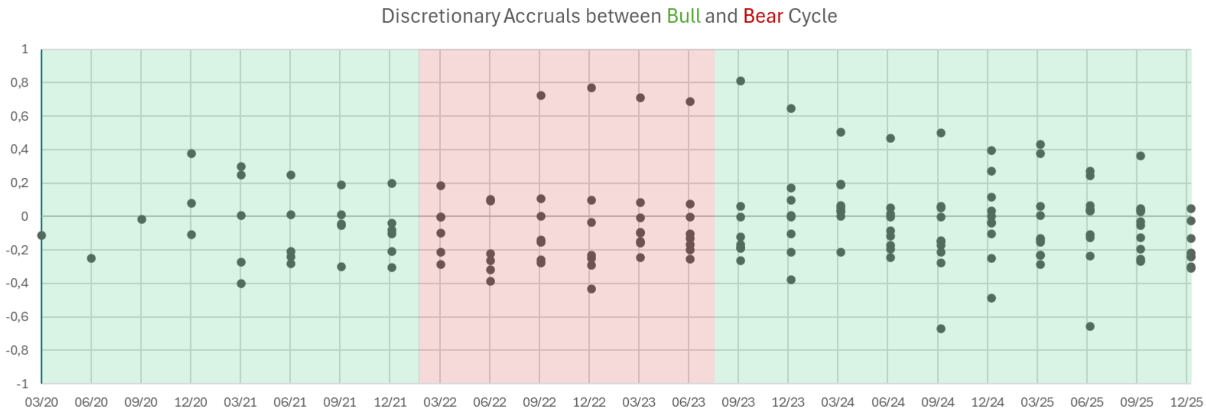

Figure 4. Discretionary Accruals Trend in Bitcoin Market Cycle
Source: Data Processed – Excel Chart

Linear Mixed Models: Fixed Effects

Before analyzing individual predictors, the overall model fit was assessed to determine the adequacy of the final specification. The Linear Mixed Model had Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) of −261,253 and −255,192, respectively. The values obtained were consistently lower than those yielded by alternative model specifications tested during the selection process, indicating that the baseline year-over-year BCM operationalization is a better fit to the observed data. The AR(1) autocorrelation parameter was estimated at AR1 rho = .941, which suggests severe and statistically significant serial dependence over repeated quarterly observations within firms. The magnitude of this autocorrelation implies that the within-firm quarterly residuals are highly persistent and that it was necessary to explicitly model this structure via the AR(1) covariance specification to produce unbiased standard errors. Table 6 reports the fixed effects estimates together with the corresponding Type III F-statistics and the associated p-values for all predictors.

The estimated value of the BCM variable, which shows the phase of the Bitcoin market cycle, was .021 ($F = .576$, $p = .449$). The positive sign of this estimate indicates that bear-phase quarters are associated with marginally higher discretionary accruals relative to bull-phase quarters, however the significance is negligible as reflected by the low F-statistic and the p-value is well above the $\alpha = .05$ level. No statistically significant pattern between Bitcoin market cycle phase and discretionary accruals is found in this sample.

The EXP_BCM interaction term is a test of whether the firm's level of Bitcoin balance sheet exposure conditions the relationship between market cycle phase and discretionary accruals. The estimate for this term was near zero ($F= .003$, $p = .958$). The size of this coefficient is close to zero indicating that the variation in Bitcoin exposure does not seem to magnify or mitigate any cycle-related difference in discretionary accruals. However, it is worth noting that EXP_BCM has a variance inflation factor of 39.434, which persisted after mean-centering of EXP confirming that this multicollinearity is structural, not a scaling artifact. This considerably inflates the standard error on the interaction term and raises the risk of Type II error, implying that the result should be taken as speculative rather than as definitive evidence of no moderation effect.

ROA was the only predictor to reach statistical significance in the model, yielding an estimate of .956 ($F = 424.800$, $p < .001$). The nearly proportional positive relationship suggests that the growth in discretionary accruals is almost the same as the growth in firm profitability within a quarter. The magnitude and importance of this relationship is quite impressive relative to the insignificant results for the cryptocurrency-specific variables, and suggests the primary driver of accrual behavior within this sample is profitability. The substantially larger F-statistic relative to the other predictors further indicates that ROA contributed the strongest explanatory evidence among the fixed effects included in the model.

The estimate for LEV, one of the control variables, was −.059 (F = 1.238, p = .268), showing a weak negative relationship between leverage and discretionary accruals, but the relationship was not statistically significant. The FASB dummy that captures the transition to ASU 2023-08 fair value reporting within each firm produced an estimate of .023 (F = .452, p = .503), providing no statistically detectable shift in discretionary accruals around the adoption date within this sample. The MIN dummy, separating mining firms from non-mining firms, produced an estimate of −.090 (F = .478, p = .508), suggesting that mining firms tend to report somewhat lower discretionary accruals on average, but this difference is again not statistically significant. The EXP variable that measures the raw Bitcoin balance sheet exposure as a percentage of total assets yielded an estimate of .000 (F = 1.193, p=.277), with no significant relation with discretionary accruals beyond the interaction terms. Finally, the EXP_FASB interaction term yielded a small negative estimate of −.000 (F = 2.980, p = .086). While this is close to the conventional significance level of α = .05, the negative direction suggests a tentative pattern in which firms with a higher Bitcoin exposure may report marginally lower discretionary accruals after the adoption of ASU 2023-08. Since this is below the standard significance threshold, this is reported as an observational pattern only, and not interpreted as a substantive finding, within the scope of this study.

Table 6. Tests of Fixed Effects & Estimates of Fixed Effects

	Estimate	F	p-value
Intercept	.038		
BCM = 0	.021	.576	.449
ROA	.956	424.800	.000
LEV	-.059	1.238	.268
FASB = 0	.023	.452	.503
MIN = 0	-.090	.478	.508
EXP	.000	1.193	.277
EXP_BCM	.000	.003	.958
EXP_FASB	-.000	2.980	.086

Source: Data Processed – IBM SPSS Statistics 25

Robustness Test

The robustness test results (see Table 7) repeatedly supports the baseline model specification and the null findings on the main hypotheses. Alternative operationalizations of BCM based on 20% price-change QoQ thresholds resulted in worse model fit than the baseline specification, as reflected by higher AIC and BIC values. This indicates that the baseline BCM coding scheme defined by directional quarterly price movement, captures the relevant market cycle variation most efficiently. It also means the null on H1 is not a threshold artifact, no matter how aggressively bull and bear phases are defined, BCM does not predict DA within this sample. The YoY measure smooths out short-term volatility, and may be better able to capture the sustained cycle conditions that would theoretically build enough managerial pressure to affect reporting behavior. ROA persists to be the only consistently significant predictor across alternative BCM specifications whereas the coefficients for BCM and the interaction terms remained statistically insignificant, supporting the main findings.

Additionally, robustness test using only non-mining sample (n=4 firms, 67 observations) yielded insignificant p-value on all variables except ROA. This was conducted to examine whether the primary results were influenced by the presence of Bitcoin mining firms in the sample, with operations that are inherently tied to Bitcoin price movements. Results are directionally consistent with the full-sample findings, but is not interpretable as confirmatory evidence. The statistical power of a subsample of four firms is very low and no meaningful inference independent of the main model can be made. Thus, these findings should be viewed merely as supportive evidence that the overall pattern of results does not change and not as a distinct basis for statistical judgment.

As a further robustness test we estimated only the main independent variables, eliminating the controls (Table 7). The major results were not affected with ROA being statistically significant and BCM staying insignificant. This suggests that the non-significant findings of the main hypotheses do not depend on control variables. The reduced model also shows lower AIC and BIC values than the baseline specification. This is expected since information criteria balance model fit with model complexity, and a simpler model may achieve lower AIC and BIC when the removed control variables provide little more explanatory information. However, baseline specification was kept as the main model since control variables were added on theoretical basis with supporting past research, not just to improve model fit.

Table 7. Robustness Test Results

	20% BCM Threshold		Non-Mining Only		Main Variables Only	
	Estimate	**p-value**	**Estimate**	**p-value**	**Estimate**	**p-value**
Intercept	.051		-.135		-.039	
BCM = 0	-.006	.581	.027	.510	.028	.245
ROA	.947	.000	1.339	.000	.980	.000
LEV	-.067	.209	.101	.293		
FASB = 0	.026	.452	-.021	.637		
MIN = 0	-.092	.503				
EXP	.000	.107	-.001	.676		
EXP_BCM	-.000	.610	-.001	.772	.000	.473
EXP_FASB	-.000	.086	.002	.271		
		Values		**Values**		**Values**
AIC		-259.035		-102.119		-295.917
BIC		-252.974		-97.964		-289.791
AR1 rho		.942		.956		.936

Source: Data Processed – IBM SPSS Statistics 25

Discussion

The first hypothesis (H1) that Bitcoin market cycles would have a significant impact on discretionary accruals was not supported ($p = .449$). The BCM=0 (bear phase) estimate of .021 suggests that bear-phase quarters are associated with slightly higher discretionary accruals compared to bull phase quarters, but this difference is neither statistically significant nor large enough to carry interpretive weight. Within this sample, we find no evidence that bull or bear phase of the Bitcoin market cycle systematically affects accrual-based reporting behavior. These results could imply that institutional reporting structures are more robust to market-based behavioral influences than behavioral finance. The rational expectations theory of Muth (1961) suggests that auditors, analysts and regulators expect the information content of asset price cycles, which can reduce the marginal incentive for managers to change discretionary reporting in response to asset price cycles. This interpretation indicates consistency with the political cost hypothesis in PAT (Pappas et al., 2024; Watts & Zimmerman, 1990) that reporting discretion is limited in high visibility environments. Visibility-constrained analysis is also consistent with recent evidence that disclosure of firms' crypto holdings is highly associated with the involvement of an audit firm and market liquidity conditions, suggesting that reporting choices around crypto assets continue to be subject to meaningful external oversight even as the behavior of the underlying asset's price fluctuates (Anderson et al., 2026). However, caution is warranted when strong conclusions are drawn from a null finding in a sample of 10 firms. BCM does not predict DA in this sample, but this should not be generalized to the population it represents.

The second hypothesis (H2) that firms with higher Bitcoin exposure would have a stronger BCM - DA relationship was not supported ($p = .958$). The coefficient on EXP_BCM is positive but essentially small, and does not provide any evidence that a higher balance sheet exposure to Bitcoin enhances or reduces any cycle-related reporting effect. The null on H1, together with this result, suggests that the phase of the Bitcoin market cycle or the intensity of a firm's exposure to it are not related to observable accrual responses in this sample. An interpretation consistent with theory is that firms with the largest Bitcoin holdings are subject to greater audit scrutiny, stricter valuation procedures, and greater investor or regulatory attention which may constrain the behavioral latitude implied by exposure-amplification theories (Chen et al., 2025; Hirshleifer, 2001). However, this null finding should be interpreted with explicit caution given the severe multicollinearity of EXP_BCM (VIF = 39.434).

High multicollinearity increases the standard errors, which increases the probability of Type II error, that is, the failure to detect a significant EXP_BCM effect may partly reflect statistical limitation rather than a true absence of any moderating relationship. Thus, the null on H2 is presented as an inconclusive finding, not as confirming evidence that there is no moderation effect.

ROA seems to be the sole statistically significant predictor in the model, supporting the third hypothesis (H3) with very low p-value < .001 . The positive near-proportional relationship suggests that profitable firms have larger discretionary accruals, which is consistent with the PAT income-smoothing hypothesis. This hypothesis states that managers try to smooth income upwards by using accrual discretion when actual performance improves, in an effort to lower the perceived variance of reported performance (Bansal, 2024; Watts & Zimmerman, 1990). The strength and dominance of this finding suggests that traditional profit driven reporting incentives are the main determinant of accrual behavior in this sample, regardless of the cryptocurrency specific market conditions.

It is worth explicitly benchmarking the direction of this relationship as the accrual literature reports both signs for the profitability-earnings management relationship depending on the underlying motive being captured. Table 8 compares the ROA coefficient from our investigation with two recent studies representing each direction.

Table 8. Comparison between Similar Literature

Study	Setting	Relationship examined	Direction	Comparison to this study
This study	U.S. crypto-exposed firms, 2020-2025	Profitability → Discretionary Accruals	Positive	
(Liu et al., 2026)	International, multi-study synthesis	Firm profitability/ performance → income smoothing via accruals	Positive, reported consistently across the studies reviewed	Same direction. Supports this study's result as income-smoothing rather than distress-driven behavior
(Luu Thu, 2023)	Vietnamese listed firms, 2010–2021	Financial distress risk → discretionary accruals	Negative, weaker financial health associated with higher DA	Opposite direction. Shows the earnings management style driven by distress did not supported by this study's outcome

Source: Author’s work

CONCLUSION

This study examines whether the phases of the Bitcoin market cycle are associated with accrual-based earnings management. A longitudinal panel of 10 U.S. listed firms was sampled with cryptocurrency exposure over 162 firm-quarters from Q1 2020 to Q4 2025. Overall, the results indicate that discretionary accrual behavior of crypto-holding firms is largely determined by the financial performance at the firm level, rather than the changes in Bitcoin market conditions. This implies that the presence of Bitcoin exposure alone does not necessarily influence the accrual-based reporting practices of firms within this sample. Theoretically, the findings expand the applicability of Positive Accounting Theory to firms with cryptocurrency exposure, indicating that earnings management incentives may be more important than Bitcoin market sentiment. From a practical perspective, the results suggest that investors, analysts and auditors should continue to focus on the traditional financial performance metrics when examining the reporting behavior of the firms exposed to cryptocurrencies. From a policy perspective, this study provides evidence that may help inform future accounting standard development by evaluating whether market sentiment is associated with accrual-based reporting behavior in firms with cryptocurrency exposure, providing empirical evidence for jurisdictions where cryptocurrency accounting standards are still developing.

These findings are subject to several limitations. First, the sample of 10 firms limited to early voluntary ASU 2023-08 adopters reduces the generalizability of the findings and does not allow for a highly accurate pre-post regulatory comparison. Second, structural multicollinearity in EXP-based interaction terms may have reduced the precision of the estimated interaction effects. Finally, the net

PPE may introduce some noise into the DA variable and the accrual only scope leaves genuine earnings management activities such as strategic Bitcoin liquidation timing untested.

Future research should consider expanding the sample as mandatory ASU 2023-08 adoption becomes effective and more firms enter the qualifying population to allow for more comprehensive analyses, and valid pre-post regulatory comparisons. The use of real earnings management proxies, especially those sensitive to the timing of asset disposals and revenue recognition in mining operations, could fill the most important scope gap identified by this study.

List of Abbreviations

AIC – Akaike Information Criterion
ASU – Accounting Standards Update
BCM – Bitcoin Market Cycles
BIC – Bayesian Information Criterion
BTC – Bitcoin
DA – Discretionary Accruals
EXP – Bitcoin Exposure
GAAP – Generally Accepted Accounting Principles
LEV – Leverage
LMM – Linear Mixed Model
MIN – Mining Companies
NDA – Non-Discretionary Accruals
OLS – Ordinary Least Squares
PAT – Positive Accounting Theory
PPE – Property, Plant, and Equipment
ROA – Return on Assets / Profitability
U.S. – United States
VIF – Variance Inflation Factor

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Authors' Contribution

JT contributed to the concept idea, basic theoretical framework, data collection including sample selection and requirements, and statistical analysis.

KD contributed to the supervision of the research, gave critical recommendations on research design and methodology, and gave insights on interpretation of test results.

Conflict of Interest

The authors declare no competing interests.

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Availability of Data and Materials

Dataset is available in Mendeley Data with the following DOI: 10.17632/9fcnt43jds.1

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