Analyzing the Cryptocurrency Market: Event Studies and Pricing Factors

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ABSTRACT

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This thesis investigates the application of event study methodologies and cross-sectional factors in cryptocurrency markets, with a focus on understanding market dynamics and the drivers of cryptocurrency returns. Through two distinct but complementary studies, this work addresses both the methodological challenges of event studies in highly volatile markets and the role of novel factors in pricing ERC-20 tokens.

The first study examines the suitability of traditional event study methodologies in the context of cryptocurrency markets. Given the unique characteristics of cryptocurrencies—such as non-normal return distributions and extreme volatility—the study explores the efficacy of various parametric and non-parametric statistical tests. It identifies non-parametric approaches as more robust, particularly for smaller and highly volatile cryptocurrencies, and highlights the importance of sample size in achieving reliable results.

The second study investigates cross-sectional return predictors in the cryptocurrency market, with a specific focus on ERC-20 tokens. By leveraging both traditional factors such as size and momentum, as well as novel on-chain variables—including transaction value, transfer counts, and active addresses—the study constructs crypto-specific factors that provide deeper insights into token valuation and market behavior. It further demonstrates the relevance of these factors in explaining the variation in token returns.

Collectively, these studies contribute to the growing body of research on cryptocurrency markets by refining event study methodologies and introducing novel factors to better understand market reactions and return dynamics. The findings have broad implications for financial analysis in emerging and volatile asset classes, offering tools for researchers and investors to navigate the complexities of cryptocurrency markets.

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Dedication

To my resilience, strength, and dedication to knowledge.

To my commitment and growth throughout this journey.

To the person I have become through perseverance and dedication.

Contribution of Authors

Chapter 2 (Essay 1) of this thesis is a working paper co-authored with Juliane Proelss and Denis Schweizer. The manuscript is under review.

Chapter 3 (Essay 2) of this thesis is a working paper co-authored with Denis Schweizer. The manuscript is under review.

All manuscripts have been reformatted and reorganized according to the requirements set out in the guidelines of the School of Graduate Studies.

Table of Contents

List of Figures

List of Tables

Chapter 1: Introduction

The exponential growth of cryptocurrency markets has introduced a new and complex asset class to the field of finance, challenging conventional market theories and analytical methodologies. Cryptocurrencies, known for their decentralized nature and rapid adoption, are distinct from traditional financial assets in terms of volatility, liquidity, and underlying technology. This unique behavior prompts an urgent need to examine both market efficiency and the determinants of returns in cryptocurrency markets. This thesis addresses two primary research questions: (1) How effective are existing event study methodologies in detecting market efficiency within cryptocurrency markets? (2) What are the key empirical factors driving cross-sectional returns of crypto-assets, particularly ERC-20 tokens? By integrating event study analysis with asset pricing models, this thesis provides a comprehensive exploration of the mechanisms underlying cryptocurrency markets, contributing significantly to the evolving literature on digital finance.

Can Event Study Methodology Keep Up with Cryptocurrencies?

Event studies are pivotal in finance, enabling the assessment of how swiftly and accurately market prices reflect new information. Historically, event studies have been applied extensively to traditional financial markets to test market efficiency, evaluate regulatory impacts, and analyze corporate events. Seminal works by Fama, Fisher, Jensen, and Roll (1969) introduced the basic framework, while subsequent research, such as Brown and Warner (1980, 1985), focused on refining statistical techniques to improve accuracy. In response to non-normal return distributions often observed in financial markets, Corrado (2011) proposed adjustments to parametric tests, enhancing robustness against misspecification.

However, the application of event study methodologies to cryptocurrency markets remains limited. Cryptocurrencies exhibit highly non-normal return distributions characterized by skewness, high kurtosis, and extreme volatility, as noted by Liu and Tsyvinski (2018) and Biais et al. (2023). These distributional characteristics can cause substantial bias in traditional parametric tests, leading to inaccurate detection of abnormal returns. Prior research, including studies by Shanaev et al. (2019) and Tomić (2020), has utilized event studies to explore market efficiency in response to security incidents and blockchain events, yet these studies often lack comprehensive evaluations of test effectiveness in cryptocurrency contexts.

This study builds on the framework proposed by Marks and Musumeci (2017), conducting an extensive evaluation of six parametric and four non-parametric statistical tests to assess their suitability for cryptocurrency markets. Non-parametric tests, such as the Wilcoxon signed-rank test (1945), Corrado's rank test (1989), and Cowan's generalized sign test (1992), have shown promise in handling extreme return characteristics, making them more appropriate for volatile markets. The results of this study highlight that non-parametric tests perform particularly well under conditions of high volatility and non-normal return distributions, supporting previous findings by Ante and Fiedler (2021) and Joo et al. (2020).

Event studies also confront the joint hypothesis problem, a fundamental issue in testing market efficiency. This problem arises from the dependence on an asset pricing model to estimate abnormal returns, making the interpretation of results contingent on the model's validity. For cryptocurrencies, existing pricing models may not fully capture their unique features, as observed by Liu et al. (2022) and Cong et al. (2018). Therefore, this study not only evaluates event study methodologies but also seeks to refine asset pricing models to better represent cryptocurrency markets, offering a more comprehensive analysis of market efficiency.

Deciphering Cryptocurrency Returns: Novel Factors and Insights

The emergence of cryptocurrencies has driven researchers to develop theoretical models that address their pricing mechanisms. Unlike traditional assets, which are typically valued based on expected future cash flows, cryptocurrencies lack such cash flows, prompting alternative valuation approaches. Initial theoretical models, such as those by Huberman et al. (2017) and Pagnotta and Buraschi (2018), focus on decentralized consensus mechanisms and their impact on intrinsic value, while empirical models often incorporate factors unique to cryptocurrency markets, including liquidity, momentum, and network effects.

Liu et al. (2022) introduced a three-factor model for cryptocurrencies, incorporating factors such as momentum, size, and investor attention, which are tailored to the unique characteristics of crypto-assets. Bhambhwani et al. (2019) and Howell et al. (2018) further explored factors like investor sentiment and on-chain activities, suggesting that these variables play a crucial role in shaping cryptocurrency returns. This study extends this body of work by concentrating specifically on ERC-20 tokens—tokens that operate within the Ethereum blockchain and account for a significant share of the crypto market.

The choice of ERC-20 tokens is driven by their standardized characteristics and the wealth of on-chain data available, which provides insights into blockchain activities such as transaction volume, active addresses, and transfer counts. Empirical research, such as Ante (2023), has highlighted the importance of these on-chain variables in explaining cross-sectional returns of cryptocurrencies. This study utilizes a sample of over 1,000 ERC-20 tokens, examining 19 characteristics, including market-related predictors (e.g., size and volume), on-chain factors (e.g., transaction counts), and quasi-value metrics (e.g., transaction value-to-market cap ratios). The results indicate that significant risk premiums are associated with these factors, aligning with previous findings by Ramos et al. (2021) and Chokor and Alfieri (2021).

By constructing long-short zero-investment portfolios based on these predictors, this study reveals statistically significant risk premiums related to size, liquidity, and transaction volume, further supporting the role of on-chain activity as a proxy for intrinsic value. Additionally, the introduction of quasi-value predictors, inspired by concepts from the stock market such as book-to-market ratios (Fama and French, 1992), offers a novel perspective on evaluating the valuation of tokens.

Contributions of this Thesis

This thesis contributes to the literature by integrating event study methodologies with empirical asset pricing models, providing a holistic understanding of cryptocurrency markets. Key contributions include:

1. **Refined Event Study Tests for Cryptocurrencies**: The comprehensive evaluation of event study tests in this thesis offers a more accurate framework for detecting abnormal returns in cryptocurrency markets. The findings suggest that non-parametric tests are better suited to handle the extreme return distributions of digital assets, providing insights that build on the work of Corrado (2011) and Cowan (1992).
2. **Crypto-Specific Asset Pricing Factors**: By focusing on ERC-20 tokens and incorporating on-chain variables as predictors, this study extends the empirical asset pricing literature. The identification of significant risk premiums linked to market-related, on-chain, and quasi-value predictors contributes to a better understanding of cross-sectional return variations in cryptocurrencies. This aligns with the research of Liu et al. (2022) and Bhambhwani et al. (2019), who have emphasized the importance of crypto-specific factors.
3. **Implications for Investors, Policymakers, and Researchers**: This thesis provides

practical implications for market participants and regulators. The refined event study methodologies can aid in regulatory assessments of market efficiency, while the empirical pricing factors can inform investment strategies and risk management in the crypto space. Furthermore, the insights from this research can serve as a foundation for future studies exploring market behavior and pricing dynamics in digital finance.

Chapter 2: Can Event Study Methodology Keep Up with Cryptocurrencies?

Abstract

This study evaluates the suitability of various event study methodologies for cryptocurrency markets, focusing on identifying the most effective statistical tests for event-induced returns and volatility across different cryptocurrency sub-samples. Through extensive analysis, we find that non-parametric tests provide more robust and reliable results, particularly in environments characterized by high volatility and non-normal return distributions. Our findings demonstrate that value-weighted indices serve as effective benchmarks for large-cap cryptocurrencies due to their ability to capture market-wide trends. However, these indices demonstrate limitations when applied to smaller or highly volatile cryptocurrencies. This research enhances the adaptability of event study methodologies to the dynamic nature of cryptocurrency markets, offering broader implications for these emerging and volatile financial markets.

2.1. Introduction

Event study methodology is a fundamental tool in finance and corporate finance, offering a robust framework for analyzing the effects of specific events on asset prices. Its wide-ranging applications include assessing market efficiency, evaluating the impact of corporate actions, regulatory changes, and technological innovations, among other phenomena. By quantifying how markets react to events, event studies generate critical insights into the functioning of financial markets, thereby guiding investment strategies, corporate governance, and policy decisions. As financial markets evolve, particularly with the emergence of new asset classes like cryptocurrencies, the importance of adapting event study methodologies to these changes becomes increasingly evident.

Cryptocurrencies, underpinned by blockchain technology, represent one of the most disruptive innovations in modern finance. Their unique characteristics, including rapid growth and sharp declines, distinguish them from traditional investments like stocks and bonds. Unlike these traditional assets, cryptocurrency returns are often characterized by non-normal distributions, exhibiting skewness, high positive excess kurtosis, and unstable distribution parameters over time. These properties, coupled with phases of extreme market fluctuations like "bull runs" and "crypto winters," pose significant challenges to standard event study methodologies, which typically assume normality in return distributions. While previous research has attempted to address such distributional issues for traditional financial assets (e.g., Corrado, 2011), the distinct behavior of cryptocurrencies necessitates tailored approaches to better capture their abnormal returns.

Several studies have explored the application of event study methodologies within cryptocurrency markets, focusing on different types of events and their implications for market efficiency. For example, Ante and Fiedler (2021) analyzed price reactions to large Bitcoin transactions, contributing to the understanding of weak-form efficiency. Other studies have assessed semi-strong form efficiency by examining how cryptocurrencies respond to publicly available information, including general news (Joo et al., 2020; Yue et al., 2021), blockchain-related events like forks (Tomić, 2020), and security breaches (Shanaev et al., 2019; Ramos et al., 2021; Almaqableh et al., 2022). In addition, researchers have examined the effects of regulatory changes (Öget, 2022; Chokor and Alfieri, 2021) and social media influences (Ante, 2023), providing insights into how effectively cryptocurrency markets process external information.

Moreover, the impact of "black swan" events, such as the COVID-19 pandemic (Abraham, 2021) and cryptocurrency exchange failures (Yousaf et al., 2023), has also been examined in the context of cryptocurrency price behavior. In the corporate domain, Jumah and Karri (2020) investigated how public disclosures related to corporate involvement with cryptocurrencies affect stock prices. Collectively, these studies offer a broad understanding of how various events shape the dynamics and efficiency of cryptocurrency markets.

The latest event study research in cryptocurrency markets has attempted to adjust key aspects of traditional event study methodologies to better adapt to the unique features of the crypto ecosystem. For instance, these studies often employ diverse estimation windows — ranging from minutes to months — and models such as the mean return model and the market model to calculate expected returns more precisely. Improved expected return estimation facilitates the detection of abnormal returns. Statistical methods used in these analyses include standard t-tests and various nonparametric tests, which are better suited to accommodate the unique distributional characteristics of cryptocurrency returns. More details of these previous studies, including their sample selection, sample period, statistical tests applied, estimation periods, and key findings, are summarized in Table A1 to provide a comprehensive overview of existing event study methodologies in cryptocurrency markets.

– Table A1 about here –

However, significant limitations remain in the existing body of research. The choice of estimation windows, return models, and test statistics in previous studies has often been ad hoc, lacking systematic criteria for application. Moreover, these studies predominantly focus on highly traded or large-cap cryptocurrencies, primarily issued during the boom periods of 2016 and 2017, when market activity and trading volumes surged. While convenient, this focus introduces selection bias and limits the generalizability of findings, as highly traded or large-cap cryptocurrencies exhibit distinct return behaviors and efficiency levels compared to smaller-cap ones.

Another critical challenge lies in the distributional peculiarities of cryptocurrency returns, particularly for small-cap tokens. The foundation of event studies—reliance on the Central Limit Theorem (CLT)—becomes problematic when applied to the highly skewed and fat-tailed distributions of cryptocurrency returns. As noted by Brown and Warner (1985), the convergence rate to normality slows in such cases, potentially leading to misspecifications. This limitation underscores the urgent need for refined event study methodologies that can handle the statistical complexities of the entire cryptocurrency market, including its smaller and more volatile segments.

To address these challenges, it is essential to evaluate the effectiveness of both parametric and nonparametric tests under the unique conditions of cryptocurrency markets. The widely used cross-sectional t-test, for example, often struggles with increased variance in returns around event dates, particularly when returns are equal-weighted (Corrado, 2011). Patell (1976) introduced standardized abnormal returns to mitigate this issue, and Boehmer, Musumeci, and Poulsen (BMP, 1991) further refined this approach by accounting for event-day volatility. However, both methods are prone to cross-sectional correlation, which can lead to an over-rejection of the null hypothesis. To address this, Kolari and Pynnönen (2010) proposed adjusted versions of the Patell and BMP tests.

In addition to parametric tests, researchers have employed nonparametric tests that impose fewer distributional assumptions. Pioneering work by Wilcoxon (1945) introduced the signed-rank test, while Corrado (1989) developed a nonparametric test based on ranking daily returns. Corrado and Zivney (1992) extended this approach to account for volatility changes due to events. Given the high skewness of cryptocurrency returns, the generalized sign test by Cowan (1992) appears particularly suitable for this context.

In traditional stock markets, studies such as Marks and Musumeci (2017) have systematically evaluated event study methodologies to determine their suitability under varying distributional conditions. However, similar analyses in cryptocurrency markets remain limited. The distinct feature of cryptocurrency returns — such as non-normality, skewness, and extreme volatility — pose significant challenges for existing test statistics, potentially leading to biased estimates, wider confidence intervals, and unreliable inferences. To overcome these challenges, this study employs the method proposed by Marks and Musumeci (2017), tailoring it to the unique statistical properties of cryptocurrency returns. By identifying the most effective event study methodologies for this asset class, the study aims to improve the reliability and validity of empirical findings.

This paper contributes to the literature by establishing systematic criteria for selecting appropriate event study techniques under different cryptocurrency market conditions. These criteria improve the robustness of empirical results, facilitating a deeper understanding of market reactions in this rapidly evolving sector. The remainder of the paper is organized as follows: Section 2.2 introduces the datasets, Section 2.3 establishes the research design and details the parametric and non-parametric tests applied, Section 2.4 presents the empirical results, and Section 2.5 provides concluding remarks and directions for future research.

2.2 Data

To construct a comprehensive and survivorship bias free data set of cryptocurrencies, we follow the approach of Buchwalter et al. (2024) collecting cryptocurrencies prices from CoinMarketCap starting August 2015 when Ethereum started to trade until July 2023. Market data from cryptocurrency data providers, such as CoinMarketCap or CoinGecko, come with several challenges, most prominently stemming from the lack of regulation that some coins or tokens are created without a related venture and are “scams”. Scam tokens often have artificially inflated prices due to wash trading, fake volume, pump and dump schemes, and other deceptive practices. This makes the data unreliable and can mislead the token’s true market value and liquidity. Furthermore, coins and tokens can be removed from the cryptocurrency data providers at some point in time when e.g. the trading volume is too low and are deemed “dead,” which can lead to a survivorship bias.

To minimize the impact of the challenges on the results, we applied the data cleaning procedures as described in Buchwalter et al. (2024)[1] to the comprehensive dataset of “active” and “dead” cryptocurrencies. This resulted in a dataset of 6,448,883 daily cryptocurrency price observations for 17,792 unique cryptocurrencies. The dataset is thereby among the most

[1] The cleaning process involves several steps: removing stable coins, excluding economically insignificant cryptocurrencies based on minimum market capitalization or volume, truncating data for "inactive" or "dead" cryptocurrencies, eliminating those with significant data gaps, removing cryptocurrencies subject to market manipulation, and imputing small data gaps with the average trading return evenly distributed over the missing periods.

comprehensive datasets used in the context of cryptocurrency research.

In the second step, we ensure that the event study methodology can be meaningfully applied. We require cryptocurrencies to have a minimum return history of 190 days to allow for sufficiently long estimation and event window combinations, this reduces the dataset to 5,685,595 observations and 8,794 cryptocurrencies. Next, we account for obvious market manipulations including but not limited to pump-and-dump schemes. Therefore, we remove cryptocurrencies from the sample when a daily return is lower than minus 90%, or when daily returns are greater than 10,000% for more than four times resulting in removing 810 cryptocurrencies. This approach helps mitigate potential biases and ensures that our findings are not unduly influenced by extreme price movements or anomalies typically associated with smaller, less liquid cryptocurrencies. Based on the final sample, we calculate a market capitalization-weighted cryptocurrency index with daily rebalancing, referred to as the value-weighted index (*VW*).

Our final sample is comprised of 7,984 cryptocurrencies and 5,097,332 daily observations with a mean (median) daily return of 0.44% (-0.28%) a standard deviation of 17.51%. Returns are not normally distributed with a 5% (95%) quintile of -14.47% (15.90%) and a skewness of 22.77 and a kurtosis of 1319. Based on the final sample we calculate a value-weighed market index.

Cryptocurrencies exhibit varied levels of price volatility and market behavior depending on factors such as market capitalization and trading volume. Larger market cap cryptocurrencies generally demonstrate greater liquidity and stability, potentially reducing the impact of market-wide events. In contrast, smaller cryptocurrencies exhibit stronger price fluctuations compared to larger cryptocurrencies, which may impact the statistical significance of event study tests. Furthermore, cryptocurrencies with high trading volumes may respond more sensitively to market news, reflecting greater investor engagement and sentiment-driven movements. Consequently, segmenting the market into distinct sub-categories is crucial for nuanced analysis. To account for this, we distinguish four different segments. Specifically, we identify the top 100 cryptocurrencies by volume (Top100 Volume) or market capitalization (Top100 MC) at any point in time, representing the largest and most liquid cryptocurrencies (see e.g., Kosc et al., 2019). Furthermore, we categorize cryptocurrencies as larger (≥ 25M MC) or smaller (< 25M MC) than 25 million MC at any point in time, which is a typical minimum requirement in cryptocurrency research (see e.g., Liu et al., 2022). By distinguishing cryptocurrencies by size and liquidity, we can better isolate the effects of specific events and provide a more nuanced analysis of market reactions.

Table 1 Panel A provides an overview of the number of different cryptocurrencies included in our respective size sub-samples as of January 1 each year, while Panel B shows the descriptive statistics by sub-sample and for the value-weighted index. The table reveals several key differences between smaller cryptocurrencies (with less than 25 million MC or non-reported MC) and larger cryptocurrencies (with more than 25 million MC).

– Table 1 about here –

On average, smaller cryptocurrencies have lower daily mean (median) returns of 0.4% (-0.3%) compared to 0.6% (-0.1%) for larger cryptocurrencies. They also exhibit higher standard deviations (18.1% compared to 13.6%), indicating greater volatility. Additionally, smaller cryptocurrencies display higher positive skewness (40.2 compared to 21.3) and larger kurtosis, indicating more pronounced fat tails.

The top 100 cryptocurrencies by market capitalization and volume show higher average daily returns, with mean (median) returns of 0.8% (0%) and 1.3% (0%), respectively. Their standard deviations are only slightly higher, at 14.4% and 14.6%, respectively, with skewness (32.7 and

18.9, respectively) somewhat lower but still positive, indicating the presence of fat tails.

2.3 Methodology

2.3.1 Research Design

The primary objective of this research is to evaluate which event study techniques can consistently and reliably detect abnormal returns by properly rejecting or failing to reject the null hypothesis ($H_0: AR = 0$). To achieve this, we adopt the simulation framework proposed by Marks and Musumeci (2017), generating event-induced effects ($\Delta_{i,E}$) that incorporate both event-induced returns ($\bar{r}_{i,E}$) and event-induced volatility ($\hat{\theta}_{i,E}$). The original dataset, consisting of 5,097,332 daily realized returns, serves as the base data for testing the impact of simulated events.

The simulation procedure begins by randomly selecting an event date from the original dataset, which typically contains daily returns for multiple cryptocurrencies. From the set of cryptocurrencies available on that date, we randomly select one daily return to represent the benchmark for that event. Since event studies focus on detecting abnormal returns induced by specific events, we estimate the expected return for the selected cryptocurrency as the benchmark. Expected returns are calculated using the value-weighted crypto-market index ($R_{VW,E}$) as a proxy for the market factor. Specifically, the following equation is used to estimate the market beta ($\hat{\beta}_i$) over a 100-day period ending 11 days prior to the event date:

$$E\left(R_{i,E}\right) = \hat{\alpha}_i + \hat{\beta}_i \cdot R_{VW,E} \tag{1}$$

Here, $\hat{\beta}_i$ captures the relationship between the cryptocurrency and the market index.

The simulated event effect ($\Delta_{i,E}(\bar{r}_{i,E}, \hat{\theta}_{i,E})$) is generated by introducing an average event-induced return ($\bar{r}_{i,E}$) set between 0% and 5%, and event-induced volatility ($\hat{\theta}_{i,E}$) proxied by the standard error of the regression from Equation (1). Using the randomly selected daily return as the benchmark and its corresponding expected return, we calculate the abnormal return for the cryptocurrency on the event date as follows:

$$AR_{i,E} = \left(R_{i,E} + \Delta_{i,E}\right) - E\left(R_{i,E}\right) \quad (2)$$

This abnormal return ($AR_{i,E}$) represents one element of the testing sample. The procedure is repeated iteratively, selecting new event dates and calculating abnormal returns until the desired sample size (N) is reached.

Once the sample is formed, the average abnormal return (AAR_n) is calculated as:

$$AAR_n = \frac{1}{N}\sum_{i=1}^{N} AR_{i,E} \quad (3)$$

The sample-based average abnormal return (AAR_n) is then tested using various event study statistical techniques to evaluate their ability to detect the simulated event-induced returns under different conditions, including scenarios with or without event-induced volatility.

This research design provides a systematic framework for assessing the performance of event study techniques in cryptocurrency markets. By simulating event-induced returns and volatility, the study ensures that the evaluation of statistical tests is robust and tailored to the unique characteristics of cryptocurrencies. The findings contribute to identifying the most effective methodologies for analyzing abnormal returns in this highly dynamic and volatile market.

2.3.2 Parametric and Non-Parametric Tests

Next, we calculate a variety of parametric tests, which typically require that abnormal returns are normally distributed, as well as nonparametric tests which do not require such an assumption to study which of the tests is most suitable in the context of cryptocurrencies.[2] Including following

[2] We use Stata eventsudy2 module to do all event study calculations.

tests for absolute abnormal returns: 1) **The standard t-test for AAR (t-test)** provides a standard significance test assuming cross-sectional independence. It is sensitive to non-normal distributions and event-induced volatility and may not be suitable for non-normal returns. 2) **The t-test for AAR (CDA T)** by Brown and Warner (1980/1985) adjusts for cross-sectional dependence using crude dependence adjustment (CDA) but still assumes normality, making it biased for non-normal returns. 3) **The z-test on abnormal standardized returns (Patell Z)** by Patell (1976) adjusts for heteroscedasticity but also assumes normality. It is robust against the distribution of Ars across the cumulative event window but sensitive to cross-sectional correlation and event-induced volatility. 4) **The z-test on abnormal standardized returns (Adj. Patell Z)** with Kolari and Pynnönen (2010) adjustments corrects for cross-sectional correlation and is suitable for non-normal returns, albeit with a complex calculation. 5) **The z-test on average abnormal cross-sectional standardized returns (StdCSect Z)** suggested by Boehmer et al. (1991) adjusts for event-induced variance but is not suitable for non-normal returns due to its normality assumption. It is robust against the distribution of Ars across the cumulative event window and accounts for event-induced volatility and serial correlation. 6) **The z-test on average abnormal cross-sectional standardized returns (Adj. StdCSect Z)** with Kolari and Pynnönen (2010) adjustments accounts for cross-sectional correlation and is suitable for non-normal returns.

In addition, we include following sign/rank tests: 7) **The rank test (Rank)** by Corrado (1989) examines these returns using non-standardized ranks, providing an assessment without normal distribution assumptions. 8) **The Corrado and Zivney (1992) Rank Test (Rank Z)** modifies the original Rank Test by Corrado (1989) to include a consideration for event-induced volatility of rankings. It achieves this through the application of re-standardized abnormal returns, thereby enhancing the test's sensitivity to fluctuations caused by the event. However, it may exhibit inferior performance for longer event windows but is robust against skewness in the return distribution. 9) **The generalized sign test (Gen. Sign Z)** by Cowan (1992) extends the traditional sign test to address non-independence among observations, such as in clustered events, by considering both the sign and the magnitude of returns. Lastly, 10) **the Wilcoxon (1945) rank test (Wilcoxon) is applied across various fields beyond finance, assessing differences in median values by analyzing signs and magnitudes of abnormal returns, though it is less powerful in small sample sizes.** These tests are chosen for their robustness against non-normal distributions and their ability to thoroughly analyze both the sign and magnitude of abnormal returns, enhancing our comprehensive event study analysis. For further details and formulas of the significance tests used, please also refer to Event Study Tools[3].

2.4 Empirical Results

The primary goal of this research is to establish systematic criteria for selecting appropriate event study test statistics under specific conditions. To achieve this, we analyze the performance of various event study methodologies across four distinct subsamples: Top 100 by MCAP, MCAP ≥ 25M, Top 100 by Volume, and MCAP < 25M. These subsamples reflect key cryptocurrency characteristics such as token capitalization, trading volume, and market dynamics, which may influence the performance and specification of statistical tests.

In addition to token characteristics, market conditions are incorporated into the analysis by introducing event-induced returns and volatility ($\Delta_{i,E}(\bar{r}_{i,E}, \hat{\theta}_{i,E})$). These factors allow us to assess how test performance varies under different levels of induced market effects, ranging from no impact ($\Delta_{i,E}= 0$) to significant abnormal returns ($\bar{r}_{i,E} > 0$) and heightened volatility ($\hat{\theta}_{i,E} > 0$). By

[3] See also https://www.eventstudytools.com/significance-tests

varying sample sizes, we further examine how the robustness and sensitivity of event study techniques are influenced by dataset size and distributional characteristics. This comprehensive approach provides insights into the conditions under which specific tests are most effective, particularly in the context of the volatile and highly heterogeneous cryptocurrency market.

2.4.1 SAR Distribution

In this section, we compare the empirical distributions of standardized abnormal returns (SAR) with the theoretical normal distribution (N (0,1)) across four cryptocurrency sub-samples.

Figure 1 – Panel A shows the distribution of SAR for the **Top 100 cryptocurrencies by market capitalization** and **Panel C** for cryptocurrencies with a **market capitalization greater than USD 25 million**. Both empirical distribution deviate from the theoretical N (0,1) distribution, exhibiting heavier tails and a slight right skew. This indicates the presence of extreme abnormal returns, suggesting that events in large-cap cryptocurrencies, while generally more stable, still experience significant deviations from normality.

– Figure 1 – Panel A about here –

– Figure 1 – Panel C about here –

In contrast, **Figure 1 – Panel B** presents the SAR distribution for the **Top 100 cryptocurrencies by trading volume**. The empirical distribution here also shows heavier tails, but the right skew is more pronounced compared to the market capitalization sub-sample. This suggests that high-volume cryptocurrencies are more sensitive to market events, often leading to large, sentiment-driven price swings. The deviations from normality are more significant in this sub-sample, implying that tests relying on normality assumptions may be less reliable.

– Figure 1 – Panel B about here –

Finally, **Figure 1 – Panel D** shows the SAR distribution for cryptocurrencies with a **market capitalization less than USD 25 million (excluding outliers)**. Despite excluding outliers, the distribution still exhibits significant deviations from the normal distribution, with pronounced right skew and heavy tails. This suggests that smaller-cap cryptocurrencies are still highly volatile, even after removing extreme cases. The persistence of large price fluctuations in this sub-sample indicates that smaller cryptocurrencies are more susceptible to market shocks, and parametric tests relying on normality assumptions, like the Patell test, may be inadequate for capturing these effects.

– Figure 1 – Panel D about here –

Overall, across all sub-samples, we observe systematic deviations from the normal distribution, particularly in terms of skewness and kurtosis. These findings imply that traditional parametric tests based on normality assumptions may not be suitable for the cryptocurrency market. This is particularly true for smaller or high-volume cryptocurrencies, where extreme price movements are more common. As a result, more robust non-parametric tests may be necessary to capture the full impact of events in these markets.

2.4.2 Simulated Average Abnormal Returns (AARs) Tests

As a first step, we evaluate whether Average Abnormal Returns (AARs) accurately reflect simulated event-induced returns across different scenarios. These scenarios include event-induced returns ranging from 0% to 5%, both with and without event-induced volatilities. The results presented in Table 2 detail the average abnormal returns for four sub-samples, with varying sample sizes from $N = 100$ to $N = 8{,}000$. In the baseline scenario ($\Delta_{i,E}(0, 0)$), where no event-induced returns or volatility are present, the AARs should theoretically converge to 0% if the value-weighted market index effectively captures systematic influences on cryptocurrency market prices.

– Table 2 about here –

For the sub-sample of the Top 100 cryptocurrencies by market capitalization (Panel A), significant bias in AAR estimates is observed, especially for smaller sample sizes. For instance, when $N = 100$, AAR values of -1.16% and -2.09% are recorded in scenarios without event-induced returns ($\Delta_{i,E}(0,0)$) or with event-induced volatility ($\Delta_{i,E}\left(0,\hat{\theta}_{i,E}\right)$). Even when event-induced returns range from 1% to 5%, the AAR estimates deviate from the true simulated returns. These biases are exacerbated by higher event-induced volatility $\hat{\theta}_{i,E}$, which further distorts AAR estimates. However, as sample sizes increase, the AAR estimates improve and converge closer to the true simulated returns, demonstrating that larger samples mitigate bias effectively.

A similar pattern emerges for smaller cryptocurrencies (Panel D), where lower market capitalization amplifies noise and volatility in AAR estimation. Smaller sample sizes produce significant biases in AARs, although increasing sample size reduces the deviation. However, the improvement is less pronounced compared to large-cap cryptocurrencies, suggesting that small-cap tokens face additional challenges due to heightened volatility and idiosyncratic factors. Similarly, the sub-sample of high-volume cryptocurrencies (Panel B) exhibits stronger deviations in AAR estimates, likely driven by susceptibility to extreme price movements and event-related shocks. These findings indicate that parametric tests relying on normality assumptions may be less reliable for sub-samples characterized by high volatility or extreme events.

The results indicate that AAR estimation improves with larger sample sizes. Larger datasets help smooth out noise and idiosyncratic factors, enabling the market index to better approximate expected returns. For large-cap cryptocurrencies, the value-weighted market index effectively captures market trends, enhancing the reliability of AAR estimation. However, for smaller-cap cryptocurrencies, higher levels of noise and volatility reduce the effectiveness of the market index as a predictor, particularly in smaller samples.

In summary, the results underscore the importance of market capitalization as a critical factor influencing the precision of AAR estimation. Large-cap cryptocurrencies exhibit more reliable AAR convergence compared to small-cap tokens, highlighting the role of market capitalization in reducing noise and enhancing estimation accuracy. Increasing the sample size significantly improves AAR precision by mitigating biases and enabling convergence to true simulated returns. Furthermore, the improvement in AAR estimation highlights the effectiveness of the market index as a predictor, as larger samples allow the index to filter out noise and better approximate expected returns. These findings provide valuable insights into the factors that influence the reliability of event study methodologies in cryptocurrency markets.

2.4.4 Performance Tests for Event Study Tests

This section evaluates the performance of both parametric and non-parametric statistical tests in correctly rejecting or failing to reject the null hypothesis (H_0: AAR = 0) across four cryptocurrency subsamples. The analysis uses the p-values reported in Tables 3, 4, and 5, focusing on the ability of these tests to detect abnormal returns under various scenarios.

In scenarios where no event-induced abnormal returns are present ($\Delta_{i,E}(0,0)$), a correctly performing test should fail to reject the null hypothesis, indicating no real abnormal return exists. Table 5 shows that for the two larger cryptocurrency subsamples—Top 100 by Market Capitalization and MCAP ≥ 25M—most tests perform adequately, with a significant number of p-values exceeding the 10% threshold. Interestingly, for these larger cryptocurrencies, the improved parametric tests (e.g., CDA T, Std-CSect Z, and Adj.Std-CSect Z) do not outperform the standard t-test, suggesting that symmetric return distributions dominate within this group.

When event-induced volatility ($\hat{\theta}_{i,E}$) is introduced, the performance of parametric tests declines significantly. Most fail to maintain robustness, incorrectly rejecting the null hypothesis even with larger sample sizes (N). In contrast, nonparametric tests, particularly Rank, Rank Z, and Gen.Sign Z, demonstrate greater resilience under these conditions. This dominance is especially evident in the small-cap subsample (MCAP<25M), where severe asymmetry and the presence of outliers pose challenges for parametric methods. Among parametric tests, only Std-CSect Z and Adj.Std-CSect Z show slight improvement due to their adjustments for event-induced variance.

For the Top 100 by Trading Volume subsample, parametric tests perform better under conditions with event-induced volatility than without it. This improved performance may be attributed to the higher susceptibility of high-volume cryptocurrencies to shifts in investor sentiment and speculative behavior, which lead to non-standard return distributions better managed by variance-adjusted methodologies.

The Wilcoxon test displays inconsistent behavior. It inappropriately rejects the null hypothesis for the Top 100 by Market Capitalization and MCAP ≥ 25M under both scenarios, while aligning correctly for the Top 100 by Volume and MCAP < 25M. This suggests that the Wilcoxon test may be less effective for detecting abnormalities in larger, more stable cryptocurrencies but better suited for subsamples characterized by higher trading volumes or smaller market caps.

In summary, subsamples of larger-cap cryptocurrencies demonstrate greater resilience in identifying the absence of events, reducing the likelihood of false positives. Conversely, for small-cap cryptocurrencies, the reliability of the tests diminishes in the presence of volatility. Nonparametric tests—Rank, Rank Z, and Gen.Sign Z—consistently outperform parametric tests, demonstrating superior accuracy in environments with pronounced data anomalies.

– Table 3 about here –

To further evaluate the effectiveness of these tests, we analyzed scenarios with simulated event-induced returns ranging from 1% to 5%, as detailed in Table 6. Ideally, effective tests should produce p-values below the 10% significance level when detecting abnormal returns.

For large-cap cryptocurrencies, the effectiveness of tests improves with larger sample sizes when detecting smaller abnormal returns (e.g., 1% or 2%). For instance, when the induced return is 1%, all tests become effective at N=1,000. For the Top 100 by Trading Volume subsample, the sample size threshold decreases to N=250. As induced returns increase to 3% or more, all tests demonstrate strong detection power, becoming sample-size invariant. Therefore, results for returns exceeding 3% are omitted to focus on the more challenging cases of low-induced returns.

In contrast, for the small-cap subsample (MCAP<25M), the detection power of parametric tests declines sharply for smaller induced abnormal returns (e.g., 1% or 2%). For example, in Panel D, parametric tests such as the t-test, CDA T, Std-CSect Z, and Adj.Std-CSect Z fail to detect these returns, yielding high p-values and a loss of test power. Nonparametric tests—Rank, Rank Z, and Gen.Sign Z—continue to outperform parametric tests, demonstrating robustness across various scenarios.

– Table 4 about here –

Upon introducing event-induced volatility, $\hat{\theta}_{i,E}$, alongside varying levels of event-induced returns, we observed consistent patterns in Table 5 that mirror those reported in Table 4. Across all four subsamples, lower induced returns, such as 1% or 2%, significantly reduce the power of all tests, necessitating larger sample sizes (N), particularly for the small-cap subsample. However, once the induced returns reach 3% or higher, most statistical tests are able to properly reject the null hypothesis. This indicates that both parametric and nonparametric tests are effectively sensitive to the presence of genuine event-induced abnormal returns, thereby improving their reliability in detecting significant market impacts.

– Table 5 about here –

Notably, in scenarios where no induced returns or volatility are present ($\Delta_{i,E}(0,0)$), most parametric tests fail by incorrectly rejecting the null hypothesis (H_0: AAR = 0). This issue becomes more pronounced when event-induced volatility is introduced, as increasing the sample size (N) does not significantly improve precision for parametric methods.

Under scenarios featuring event-induced returns, both with and without added volatility, nonparametric tests consistently outperform parametric tests. Nevertheless, the reliability of parametric tests improves markedly with larger sample sizes. This finding underscores the critical role of sample size in the statistical detection of abnormalities. It suggests that while both test types can be effective, their performance depends heavily on the sample size, distribution characteristics, and expected event magnitude.

Once the induced abnormal returns reach a certain threshold, such as 3% or higher, most tests perform equally well, regardless of sample size or cryptocurrency subsamples. However, small-cap cryptocurrencies pose greater challenges for parametric tests due to increased volatility and noise. When the induced return is relatively low (e.g., 1% or 2%), small-cap cryptocurrencies require significantly larger sample sizes for reliable detection. In general, nonparametric tests, especially Rank, Rank Z, and Gen.Sign Z, exhibit relatively consistent performance across various scenarios and subsamples, reinforcing their robustness in handling the complexities of cryptocurrency returns.

2.4.5 Robustness Performance Tests

For the N=100 sample size, the results are particularly unstable, heavily dependent on the specific cryptocurrencies randomly drawn. This instability suggests that drawing small samples introduces more noise and variability into the test results. To address this, we performed a bootstrap analysis by iteratively drawing N=100 samples 80 times, resulting in a total of 8,000 randomly drawn events.

During each iteration, we applied each of the 10 statistical tests to determine the appropriateness of rejecting or retaining the null hypothesis ($H_0: AAR = 0$). The decision to reject or fail to reject H_0 was classified as correct if it aligned with the expected outcome for the given scenario—whether abnormal returns or event-induced volatility were present. Conversely, incorrect decisions occurred when the test outcome contradicted the expected result.

After completing the 80 draws, the number of correct decisions for each test was aggregated, and the percentage correct was calculated by dividing the total number of correct decisions by 80 and expressing the result as a percentage. This metric captures the reliability of each test across varying conditions. By replicating this procedure for multiple scenarios and significance levels (10%, 5%, and 1%), we assessed the robustness and reliability of the statistical tests.

Results for the "percentage correct" at the 10% significance level are presented in Table 6. Notably, nonparametric tests generally outperform parametric tests, achieving correct decision rates above 90% across various scenarios and subsamples. Interestingly, simpler parametric tests such as the t-test and Crude Dependence Adjustment Test (CDA T) performed comparably to more complex parametric tests, especially in subsamples of large cryptocurrencies and those with high trading volumes. This pattern confirms that all tests exhibit enhanced detection capabilities under scenarios with clear event-induced returns or volatility, as evidenced by increased correct decision rates corresponding to heightened event-induced activity.

– Table 6 about here –

When the significance level decreases from 10% to 5% or 1%, as shown in Tables 7 and 8, correct decision rates decline across all tests, as expected. For large-cap and high trading volume subsamples, the performance differences between parametric and non-parametric tests are minimal. However, in scenarios featuring induced volatility, non-parametric tests, particularly Rank, Rank Z, and Generalized Sign Z, demonstrate a slight performance advantage over parametric tests. This advantage is evident in the higher average detection ratios reported in the first rows of Tables 7 and 8.

For the small-cap subsample, the performance gap between parametric and non-parametric tests becomes more pronounced. Non-parametric tests—especially Rank, Rank Z, and Generalized Sign Z—consistently outperform parametric tests, demonstrating higher reliability in detecting abnormal returns. Parametric tests struggle with the increased noise and prevalence of outliers inherent in small-cap cryptocurrencies, which violate the normality assumptions underlying these methods.

– Table 7 about here –

– Table 8 about here –

This bootstrap analysis confirms the robustness of the methodology and underscores the value of iterating sample formation to provide a more reliable comparison of test performance. Iteration reduces the influence of sample-specific biases and outliers, enhancing the generalizability of results. Across detection ratios for each scenario and average detection ratios, non-parametric tests, particularly Rank, Rank Z, and Generalized Sign Z, consistently outperform parametric tests across all subsamples at the commonly used significance levels of 5% and 1%.

When the induced abnormal returns reach 3% or higher, most tests exhibit reliable performance. However, non-parametric tests maintain a slight advantage in scenarios with event-induced volatility. This further highlights their robustness in addressing the unique challenges posed by high volatility and non-normal return distributions in cryptocurrency markets.

2.5 Conclusion

This study marks the first exploration into the applicability of event study methodologies using crypto-asset returns, a significant advancement given the unique volatility and trading dynamics of this asset class. Utilizing the simulation approach pioneered by Marks and Musumeci (2017), we analyzed the performance of six parametric and four non-parametric test statistics across four distinct subsamples. These subsamples were scrutinized under various scenarios, encompassing conditions both with and without event-induced returns or volatilities.

Our findings highlight the context-dependent nature of event study methodologies in cryptocurrency markets, emphasizing that the choice of statistical tests depends on factors such as sample size, token characteristics, market conditions, and coin capitalization. The dynamic and volatile nature of cryptocurrencies necessitates careful consideration of these variables to ensure the reliability of empirical findings.

Traditional t-tests, while widely used in event studies, prove to be largely unsuitable for cryptocurrency markets. Their sensitivity to non-normal distributions and event-induced volatility often leads to biased results and unreliable conclusions. This limitation underscores the importance of employing alternative methodologies that are better suited to the unique statistical properties of cryptocurrency returns.

For events without induced volatility and an event impact of at least 3%, parametric tests—excluding t-tests—are generally appropriate. This suitability extends to scenarios involving Top 100 tokens by market capitalization or other large-cap cryptocurrencies. Without event-induced volatility and for events with an impact of 3% or higher, parametric tests can reliably detect abnormal returns. When event-induced volatility is introduced, parametric tests remain effective provided the event impact is at least 4%, demonstrating their adaptability in such conditions.

In contrast, non-parametric tests consistently outperform parametric counterparts in scenarios characterized by high volatility and smaller market capitalizations. Among these, the Rank, Rank Z, and Generalized Sign Z tests emerge as the best overall performers for cryptocurrency event studies. Their robustness against non-normal distributions and heightened volatility makes them particularly well-suited for small-cap tokens and other subsamples prone to outliers and extreme price movements.

In summary, the results of this research not only underscore the importance of meticulous test selection and calibration but also provide a practical framework for applying event study methodologies to cryptocurrency markets. By tailoring test selection to specific scenarios and adjusting for factors such as significance levels, sample size, and market conditions, researchers can significantly enhance the accuracy and reliability of their findings. These insights have implications beyond cryptocurrencies, offering a foundation for the application of refined event study methods in other emerging or volatile markets. This study serves as a stepping stone for further advancements in financial analysis techniques, paving the way for a deeper understanding of dynamic and complex asset classes.

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Figure 2. 1: Empirical versus Theoretical distribution of standardized abnormal returns (SAR) for Top 100 Cryptocurrencies by Market Capitalization (MCAP)

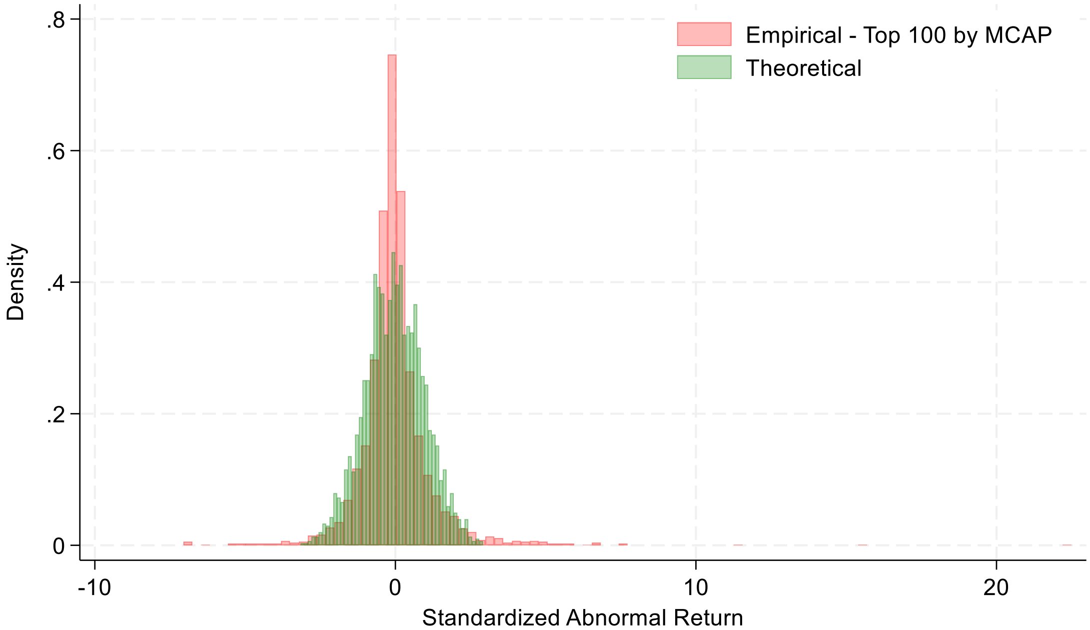

Figure 2. 2: Empirical versus Theoretical distribution of standardized abnormal returns (SAR) for Top 100 Cryptocurrencies by Trading Volume (Volume)

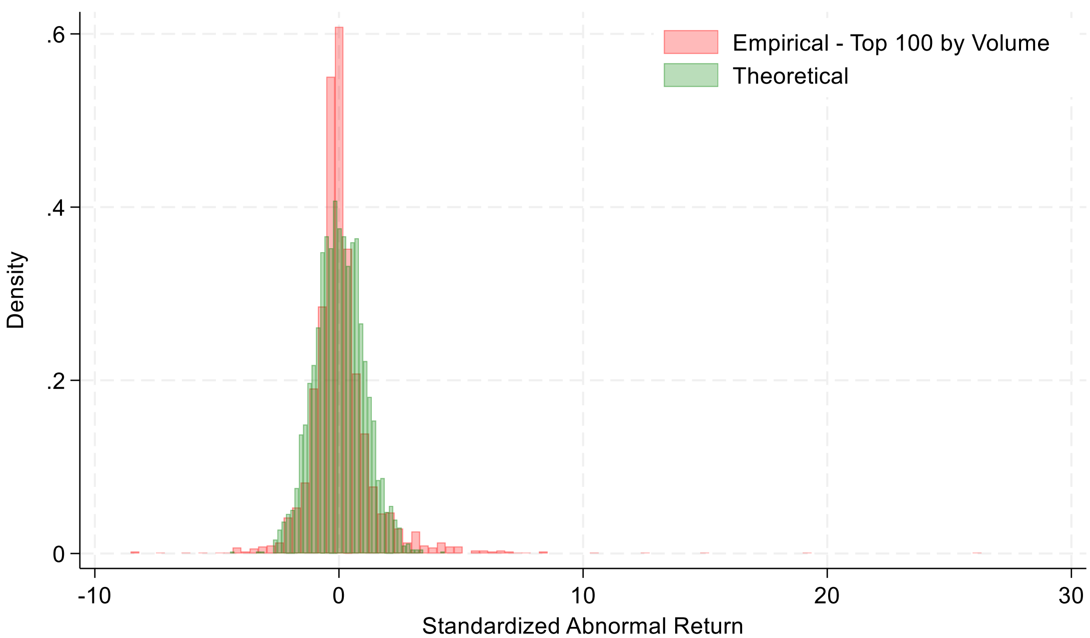

Figure 2. 3: Empirical versus Theoretical distribution of standardized abnormal returns (SAR) for the Cryptocurrencies with Market Capitalization above $25 Million

Figure 2. 4: Empirical versus Theoretical distribution of standardized abnormal returns (SAR) for the Cryptocurrencies with Market Capitalization less than $25 Million

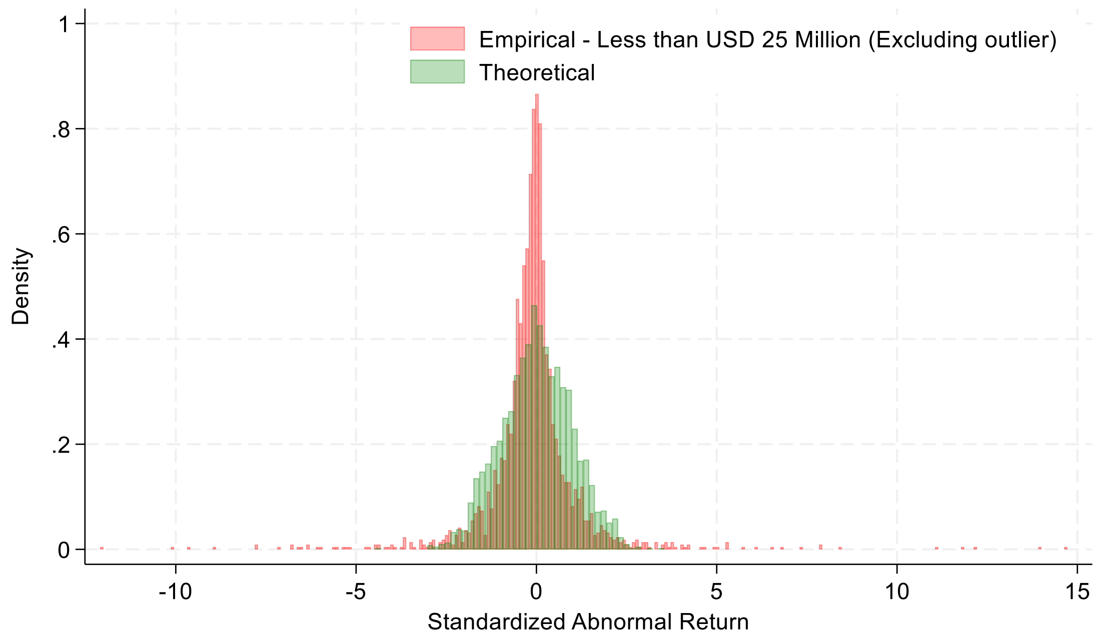

Table 2. 1: Sample Description

Panel A: Sample Cryptocurrency Counts by Year and Subsample

This panel displays the annual count of sample cryptocurrencies across four distinct subsamples: the top 100 cryptocurrencies by trading volume (Top100 by Volume), the top 100 by market capitalization (Top100 by MCAP), cryptocurrencies with a market capitalization greater than 25 million (≥ 25M MCAP), and those with less than 25 million (< 25M MCAP).

DATE	TOP100 BY MCAP	TOP100 BY VOLUME	≥25M MCAP	< 25M MCAP	TOTAL
01/07/2015	94	94	4	90	94
01/01/2016	94	94	4	90	94
01/01/2017	100	100	14	140	154
01/01/2018	100	100	254	376	630
01/01/2019	100	100	104	1,072	1176
01/01/2020	100	100	132	1,133	1265
01/01/2021	100	100	287	1,751	2038
01/01/2022	100	100	671	3,888	4559
01/01/2023	100	100	393	3,865	4258
ALL	**794**	**794**	**1,859**	**12,315**	**14174**

Panel B: Descriptive Statistics by Sub-Sample and Year

This panel displays the summary statistics of the daily returns from 2015 to 2023 for four distinct cryptocurrency market segments and the value-weighted index. These statistics include the number of cryptocurrencies (N), the mean, median, standard deviation (SD), the 5th quintile (p5), the 95th quintile (p95), skewness (Skew) and kurtosis (Kurt) of the daily returns.

Year	N	Mean	Median	SD	p5	p95	Skewness	Kurtosis
All	5,097,332	0.4%	-0.3%	17.5%	-14.4%	15.9%	22.8	1319
Top100 by MCAP	288,327	0.8%	0.0%	14.4%	-11.2%	14.3%	32.7	2,724.8
Top100 by Volume	288,330	1.3%	0.0%	14.6%	-12.0%	17.6%	18.9	1,110.8
≥ 25M MCAP	709,379	0.6%	-0.1%	13.6%	-10.8%	13.1%	21.3	1,163.7
< 25M MCAP	4,387,849	0.4%	-0.3%	18.1%	-15.1%	16.5%	40.2	3,658.1
VW Index	2,901	0.4%	0.3%	3.9%	-6.0%	6.3%	-0.5	9.5

Table 2. 2: Average Abnormal Returns (AAR) for Simulated Events by Sub-Sample

This table displays the Average Abnormal Returns (AAR) across various sample sizes (N=100 to N=8,000) for simulated events for our four sub-samples. The first (second) row in each panel represents no event return or volatility (no event return but event volatility), while subsequent rows show the AAR for different levels of event return (1%-5%) with or without event-induced volatility.

Panel A – Top 100 by MCAP

Simulated Event		N=100	N=250	N=500	N=1,000	N=2,500	N=5,000	N=8,000
No Event	$\Delta_{i,E}$ (0,0)	-1.16%	-0.66%	-0.78%	-0.13%	0.12%	0.00%	0.04%
	$\Delta_{i,E}$ (0%, $\widehat{\theta_{\iota,E}}$)	-2.09%	-1.81%	-1.50%	-0.52%	-0.36%	-0.55%	-0.55%
Event Return but no event vola	$\Delta_{i,E}$ (1%,0)	-0.14%	0.34%	0.23%	0.87%	1.11%	1.00%	1.04%
	$\Delta_{i,E}$ (2%,0)	0.86%	1.34%	1.22%	1.86%	2.10%	1.99%	2.02%
	$\Delta_{i,E}$ (3%,0)	1.86%	2.32%	2.21%	2.84%	3.08%	2.96%	3.00%
	$\Delta_{i,E}$ (4%,0)	2.84%	3.29%	3.18%	3.81%	4.04%	3.93%	3.97%
	$\Delta_{i,E}$ (5%,0)	3.81%	4.26%	4.15%	4.78%	5.00%	4.89%	4.93%
Event Return and event vola	$\Delta_{i,E}$ (1%, $\widehat{\theta_{\iota,E}}$)	-0.70%	0.33%	-0.34%	0.43%	0.53%	0.51%	0.56%
	$\Delta_{i,E}$ (2%, $\widehat{\theta_{\iota,E}}$)	-1.08%	0.06%	0.24%	1.43%	1.58%	1.53%	1.57%
	$\Delta_{i,E}$ (3%, $\widehat{\theta_{\iota,E}}$)	2.76%	2.28%	2.44%	3.14%	2.90%	2.71%	2.48%
	$\Delta_{i,E}$ (4%, $\widehat{\theta_{\iota,E}}$)	0.58%	2.48%	2.77%	3.10%	3.57%	3.31%	3.37%
	$\Delta_{i,E}$ (5%, $\widehat{\theta_{\iota,E}}$)	3.96%	4.17%	4.18%	4.93%	4.89%	4.79%	4.67%

Panel B – Top 100 by Volume

Simulated Event		N=100	N=250	N=500	N=1,000	N=2,500	N=5,000	N=8,000
No Event	$\Delta_{i,E}$ (0,0)	0.24%	0.80%	0.72%	0.57%	0.44%	0.44%	0.38%
	$\Delta_{i,E}$ (0%, $\widehat{\theta_{\iota,E}}$)	-0.80%	0.42%	0.31%	0.38%	0.14%	-0.03%	-0.09%
Event Return but no event vola	$\Delta_{i,E}$ (1%,0)	1.23%	1.79%	1.71%	1.56%	1.43%	1.43%	1.38%
	$\Delta_{i,E}$ (2%,0)	2.21%	2.77%	2.69%	2.54%	2.42%	2.42%	2.36%
	$\Delta_{i,E}$ (3%,0)	3.18%	3.74%	3.66%	3.51%	3.39%	3.39%	3.33%
	$\Delta_{i,E}$ (4%,0)	4.14%	4.70%	4.63%	4.47%	4.35%	4.35%	4.29%
	$\Delta_{i,E}$ (5%,0)	5.09%	5.65%	5.58%	5.42%	5.30%	5.30%	5.25%
Event Return and event vola	$\Delta_{i,E}$ (1%, $\widehat{\theta_{\iota,E}}$)	1.17%	1.68%	1.20%	1.31%	0.67%	0.88%	0.83%
	$\Delta_{i,E}$ (2%, $\widehat{\theta_{\iota,E}}$)	2.59%	3.06%	2.72%	2.39%	2.26%	1.96%	1.81%
	$\Delta_{i,E}$ (3%, $\widehat{\theta_{\iota,E}}$)	2.49%	2.98%	2.44%	2.73%	2.60%	2.79%	2.76%
	$\Delta_{i,E}$ (4%, $\widehat{\theta_{\iota,E}}$)	3.79%	4.71%	4.52%	4.22%	3.90%	4.00%	3.93%
	$\Delta_{i,E}$ (5%, $\widehat{\theta_{\iota,E}}$)	5.52%	4.65%	5.09%	5.38%	4.95%	4.96%	4.97%

Panel C – MCAP ≥ 25M

	Simulated Event	N=100	N=250	N=500	N=1,000	N=2,500	N=5,000	N=8,000
No Event	$\Delta_{i,E}$ (0,0)	-0.76%	-0.56%	-0.43%	-0.31%	-0.05%	-0.13%	-0.03%
	$\Delta_{i,E}$ (0%, $\widehat{\theta_{i,E}}$)	-1.60%	-1.57%	-1.19%	-0.84%	-0.27%	-0.39%	-0.25%
Event Return but no event vola	$\Delta_{i,E}$ (1%,0)	0.25%	0.45%	0.57%	0.69%	0.95%	0.87%	0.97%
	$\Delta_{i,E}$ (2%,0)	1.25%	1.44%	1.56%	1.68%	1.94%	1.86%	1.95%
	$\Delta_{i,E}$ (3%,0)	2.24%	2.43%	2.54%	2.66%	2.91%	2.84%	2.93%
	$\Delta_{i,E}$ (4%,0)	3.21%	3.40%	3.51%	3.63%	3.88%	3.81%	3.90%
	$\Delta_{i,E}$ (5%,0)	4.18%	4.36%	4.48%	4.59%	4.84%	4.76%	4.86%
Event Return and event vola	$\Delta_{i,E}$ (1%, $\widehat{\theta_{i,E}}$)	-0.55%	-0.36%	0.24%	0.52%	0.70%	0.54%	0.83%
	$\Delta_{i,E}$ (2%, $\widehat{\theta_{i,E}}$)	1.33%	0.60%	0.81%	1.22%	1.52%	1.45%	1.48%
	$\Delta_{i,E}$ (3%, $\widehat{\theta_{i,E}}$)	2.40%	1.67%	2.28%	2.28%	2.72%	2.43%	2.54%
	$\Delta_{i,E}$ (4%, $\widehat{\theta_{i,E}}$)	1.72%	3.00%	3.46%	3.57%	3.86%	3.77%	3.62%
	$\Delta_{i,E}$ (5%, $\widehat{\theta_{i,E}}$)	3.50%	3.61%	4.07%	4.21%	4.39%	4.41%	4.54%

Panel D – MCAP < 25M

	Simulated Event	N=100	N=250	N=500	N=1,000	N=2,500	N=5,000	N=8,000
No Event	$\Delta_{i,E}$ (0,0)	-0.99%	-1.06%	-0.32%	-0.68%	-0.92%	-0.68%	-0.74%
	$\Delta_{i,E}$ (0%, $\widehat{\theta_{i,E}}$)	-3.44%	-2.38%	-1.84%	-1.75%	-1.92%	-1.52%	-1.67%
Event Return but no event vola	$\Delta_{i,E}$ (1%,0)	0.04%	-0.03%	0.70%	0.33%	0.09%	0.33%	0.27%
	$\Delta_{i,E}$ (2%,0)	1.05%	0.98%	1.70%	1.34%	1.09%	1.33%	1.27%
	$\Delta_{i,E}$ (3%,0)	2.06%	1.98%	2.69%	2.33%	2.09%	2.32%	2.26%
	$\Delta_{i,E}$ (4%,0)	3.05%	2.97%	3.68%	3.32%	3.07%	3.30%	3.24%
	$\Delta_{i,E}$ (5%,0)	4.04%	3.96%	4.65%	4.29%	4.04%	4.27%	4.21%
Event Return and event vola	$\Delta_{i,E}$ (1%, $\widehat{\theta_{i,E}}$)	0.45%	0.76%	1.20%	0.17%	-0.69%	-0.47%	-0.64%
	$\Delta_{i,E}$ (2%, $\widehat{\theta_{i,E}}$)	-0.95%	-0.16%	0.65%	0.24%	-0.07%	0.15%	0.10%
	$\Delta_{i,E}$ (3%, $\widehat{\theta_{i,E}}$)	-0.58%	0.46%	2.19%	1.93%	1.20%	1.44%	1.25%
	$\Delta_{i,E}$ (4%, $\widehat{\theta_{i,E}}$)	4.85%	2.83%	4.12%	3.05%	3.13%	2.85%	2.63%
	$\Delta_{i,E}$ (5%, $\widehat{\theta_{i,E}}$)	0.74%	2.18%	2.34%	2.51%	2.85%	3.32%	3.33%

Table 2. 3: Performance Tests for Event Study Methods (No Event)

This table shows the AAR (see also Table 2) for different sample sizes, along with the corresponding p-values for the ten tests mentioned in the methodology section. The results are presented for two simulated conditions: no event return and no volatility, and no event return but with event-induced volatility. Under these conditions, the AARs should not significantly differ from zero, as no event return was simulated. The null hypothesis (H_0) being tested is that AAR = 0, meaning there is no abnormal return. If the p-value is greater than the chosen significance level (e.g., 10%), we fail to reject the null hypothesis, as expected in the absence of an event return. p-values that support this conclusion are highlighted in green.

Panel A – Top 100 by MCAP

	AAR	t-test	CDA T	Patell Z	Adj. Patell Z	Std-Csect Z	Adj. Std-Csect Z	Rank	Rank Z	Gen. Sign Z	Will-coxon
$\Delta_{i,E}$ (0%,0)											
N=100	-1.16%	***0.11***	0.08	***0.35***	***0.29***	***0.47***	***0.41***	***0.52***	***0.85***	***0.49***	0.03
N=250	-0.66%	***0.21***	***0.17***	***0.26***	***0.24***	***0.35***	***0.33***	***0.89***	***0.56***	***0.98***	0.03
N=500	-0.78%	0.02	0.02	0.01	0.01	0.05	0.03	***0.48***	***0.88***	***0.50***	0.00
N=1,000	-0.13%	***0.63***	***0.62***	0.00	0.00	0.01	0.01	***0.63***	***0.64***	***0.65***	0.00
N=2,500	0.12%	***0.47***	***0.46***	***0.39***	***0.35***	***0.47***	***0.43***	***0.20***	0.01	***0.59***	0.00
$\Delta_{i,E}$ (0%, $\widehat{\theta_{i,E}}$)											
N=100	-2.09%	0.00	0.00	0.01	0.00	***0.17***	***0.12***	0.03	***0.31***	***0.90***	0.04
N=250	-1.81%	0.00	0.00	0.00	0.00	0.05	0.04	0.07	***0.47***	***0.63***	0.02
N=500	-1.50%	0.00	0.00	0.00	0.00	0.01	0.00	***0.13***	***0.94***	***0.13***	0.02
N=1,000	-0.52%	0.04	0.04	0.00	0.00	0.01	0.01	***0.63***	***0.20***	0.00	0.02
N=2,500	-0.36%	0.03	0.03	0.00	0.00	0.06	0.04	***0.31***	0.00	0.00	0.05

Panel B – Top 100 by Volume

	AAR	t-test	CDA T	Patell Z	Adj. Patell Z	Std-Csect Z	Adj. Std-Csect Z	Rank	Rank Z	Gen. Sign Z	Will-coxon
$\underline{\Delta_{i,E}\ (0\%,0)}$											
N=100	0.24%	***0.70***	***0.70***	***0.94***	***0.94***	***0.94***	***0.94***	***0.80***	***0.80***	***0.89***	***0.42***
N=250	0.80%	***0.11***	0.09	0.05	0.06	***0.26***	***0.28***	***0.12***	0.01	***0.25***	***0.77***
N=500	0.72%	0.05	0.04	0.02	0.02	***0.13***	***0.14***	***0.17***	0.01	***0.11***	***0.48***
N=1,000	0.57%	0.02	0.02	0.01	0.02	0.07	0.09	0.04	0.00	0.01	***0.28***
N=2,500	0.44%	0.01	0.01	0.00	0.00	0.01	0.02	0.00	0.00	0.00	0.03
$\underline{\Delta_{i,E}\ (0\%,\ \widehat{\theta_{i,E}})}$											
N=100	-0.80%	***0.20***	***0.21***	***0.16***	***0.20***	***0.36***	***0.40***	***0.23***	***0.75***	***0.89***	***0.52***
N=250	0.42%	***0.40***	***0.37***	0.07	0.08	***0.37***	***0.40***	***0.20***	0.01	0.01	***0.50***
N=500	0.31%	***0.38***	***0.38***	0.03	0.04	***0.26***	***0.27***	***0.12***	0.00	0.00	***0.36***
N=1,000	0.38%	0.10	***0.13***	0.00	0.00	0.07	0.09	0.00	0.00	0.00	***0.23***
N=2,500	0.14%	***0.36***	***0.39***	0.00	0.01	0.07	***0.11***	0.00	0.00	0.00	***0.22***

<u>Panel C – MCAP ≥ 25M</u>

	AAR	t-test	CDA T	Patell Z	Adj. Patell Z	Std-Csect Z	Adj. Std-Csect Z	Rank	Rank Z	Gen. Sign Z	Will-coxon
$\underline{\Delta_{i,E}\ (0\%,0)}$											
N=100	-0.76%	***0.28***	***0.27***	***0.39***	***0.39***	***0.35***	***0.35***	***0.89***	***0.80***	***0.83***	0.03
N=250	-0.56%	***0.22***	***0.20***	***0.50***	***0.50***	***0.54***	***0.54***	***0.91***	***0.71***	***0.97***	0.02
N=500	-0.43%	***0.22***	***0.23***	***0.31***	***0.30***	***0.35***	***0.35***	***0.50***	***0.33***	***0.77***	0.01
N=1,000	-0.31%	***0.20***	***0.20***	***0.51***	***0.49***	***0.55***	***0.54***	***0.28***	***0.11***	***0.33***	0.00
N=2,500	-0.05%	***0.77***	***0.78***	***0.43***	***0.41***	***0.48***	***0.46***	***0.57***	***0.16***	***0.79***	0.00
$\underline{\Delta_{i,E}\ (0\%,\ \widehat{\theta_{i,E}})}$											
N=100	-1.60%	0.02	0.02	0.04	0.04	0.06	0.06	0.09	***0.17***	***0.54***	0.06
N=250	-1.57%	0.00	0.00	0.01	0.01	0.05	0.06	***0.15***	***0.47***	***0.67***	0.02
N=500	-1.19%	0.00	0.00	0.01	0.01	0.06	0.06	***0.52***	***0.70***	0.06	0.06
N=1,000	-0.84%	0.00	0.00	0.04	0.04	***0.19***	***0.18***	***0.94***	***0.13***	0.00	0.07
N=2,500	-0.27%	***0.11***	***0.13***	0.02	0.02	***0.14***	***0.12***	***0.87***	0.03	0.00	0.02

<u>Panel D – MCAP < 25M</u>

	AAR	t-test	CDA T	Patell Z	Adj. Patell Z	Std-Csect Z	Adj. Std-Csect Z	Rank	Rank Z	Gen. Sign Z	Will-coxon
$\Delta_{i,E}$ (0%,0)											
N=100	-0.99%	***0.53***	***0.52***	0.01	0.01	***0.22***	***0.19***	***0.83***	***0.48***	***0.72***	***0.67***
N=250	-1.06%	***0.22***	***0.19***	0.02	0.02	***0.17***	***0.15***	***0.85***	***0.43***	***0.60***	***0.21***
N=500	-0.32%	***0.57***	***0.57***	***0.18***	***0.20***	***0.41***	***0.43***	***0.97***	***0.24***	***0.97***	0.03
N=1,000	-0.68%	0.09	0.07	0.00	0.00	0.03	0.03	***0.56***	***0.52***	***0.68***	0.00
N=2,500	-0.92%	0.00	0.00	0.00	0.00	0.00	0.00	***0.48***	***0.76***	***0.62***	0.00
$\Delta_{i,E}$ (0%, $\widehat{\theta_{i,E}}$)											
N=100	-3.44%	0.03	0.03	0.00	0.00	***0.13***	***0.11***	***0.94***	***0.67***	***0.45***	***0.74***
N=250	-2.38%	0.01	0.00	0.00	0.00	0.09	0.07	***0.73***	***0.61***	***0.25***	***0.42***
N=500	-1.84%	0.00	0.00	0.00	0.00	***0.12***	***0.14***	***0.90***	***0.40***	0.05	***0.21***
N=1,000	-1.75%	0.00	0.00	0.00	0.00	0.00	0.00	***0.34***	***0.64***	0.07	0.03
N=2,500	-1.92%	0.00	0.00	0.00	0.00	0.00	0.00	***0.11***	***0.77***	0.00	0.00

Table 2. 4: Performance Tests for Event Study Methods (with Event Returns)

This table shows the AAR (see also Table 2) for different sample sizes, along with the corresponding p-values for the ten tests mentioned in the methodology section. The results are presented for event-induced returns ranging from 1% to 5% and no volatility. Under these conditions, the AARs should significantly differ from zero, as event return was simulated. If the p-value is greater than the chosen significance level (e.g., 10%), we fail to reject the null hypothesis and falsely assume the absence of an event return. For brevity, the results presented in this table include only iterations where notable changes in p-values are observed. Rows with results that closely mirror previous iterations, exhibiting minimal variation, have been omitted to avoid redundancy. p-values that support this conclusion are highlighted in green.

Panel A – Top 100 by MCAP

	AAR	t-test	CDA T	Patell Z	Adj. Patell Z	Std-Csect Z	Adj. Std-Csect Z	Rank	Rank Z	Gen. Sign Z	Will-coxon
$\Delta_{i,E}$ (1%,0)											
N=100	-0.14%	84.2%	82.8%	24.4%	18.0%	37.0%	30.3%	***2.2%***	***1.6%***	***0.6%***	70.0%
N=250	0.34%	51.1%	47.0%	***6.1%***	***5.1%***	11.9%	10.5%	***0.0%***	***0.0%***	***0.0%***	10.3%
N=500	0.23%	51.1%	48.3%	***8.0%***	***6.1%***	14.9%	12.4%	***0.0%***	***0.0%***	***0.0%***	13.0%
N=1,000	0.87%	***0.1%***	***0.1%***	***0.0%***	***0.0%***	***0.0%***	***0.0%***	***0.0%***	***0.0%***	***0.0%***	***0.0%***
$\Delta_{i,E}$ (2%,0)											
N=100	0.86%	22.8%	18.9%	***0.1%***	***0.0%***	***1.4%***	***0.5%***	***0.0%***	***0.0%***	***0.0%***	***1.5%***
N=250	1.34%	***1.1%***	***0.5%***	***0.0%***	***0.0%***	***0.0%***	***0.0%***	***0.0%***	***0.0%***	***0.0%***	***0.0%***
$\Delta_{i,E}$ (3%,0)											
N=100	1.86%	***1.0%***	***0.5%***	***0.0%***	***0.0%***	***0.0%***	***0.0%***	***0.0%***	***0.0%***	***0.0%***	***0.0%***

Panel B – Top 100 by Volume

	AAR	t-test	CDA T	Patell Z	Adj. Patell Z	Std-Csect Z	Adj. Std-Csect Z	Rank	Rank Z	Gen. Sign Z	Will-coxon
$\Delta_{i,E}$ (1%,0)											
N=100	1.23%	*5.0%*	*5.4%*	*3.4%*	*4.9%*	*3.3%*	*4.9%*	*0.6%*	*0.6%*	*1.7%*	14.8%
N=250	1.79%	*0.0%*	*0.0%*	*0.0%*	*0.0%*	*0.4%*	*0.7%*	*0.0%*	*0.0%*	*0.0%*	*0.3%*
N=500	1.71%	*0.0%*	*0.0%*	*0.0%*	*0.0%*	*0.0%*	*0.0%*	*0.0%*	*0.0%*	*0.0%*	*0.1%*
N=1,000	1.56%	*0.0%*	*0.0%*	*0.0%*	*0.0%*	*0.0%*	*0.0%*	*0.0%*	*0.0%*	*0.0%*	*0.0%*
$\Delta_{i,E}$ (2%,0)											
N=100	2.21%	*0.1%*	*0.1%*	*0.0%*	*0.0%*	*0.0%*	*0.0%*	*0.0%*	*0.0%*	*0.0%*	*0.0%*
N=250	2.77%	*0.0%*	*0.0%*	*0.0%*	*0.0%*	*0.0%*	*0.0%*	*0.0%*	*0.0%*	*0.0%*	*0.0%*
$\Delta_{i,E}$ (3%,0)											
N=100	3.18%	*0.0%*	*0.0%*	*0.0%*	*0.0%*	*0.0%*	*0.0%*	*0.0%*	*0.0%*	*0.0%*	*0.0%*

Panel C – MCAP ≥ 25M

	AAR	t-test	CDA T	Patell Z	Adj. Patell Z	Std-Csect Z	Adj. Std-Csect Z	Rank	Rank Z	Gen. Sign Z	Will-coxon
$\Delta_{i,E}$ (1%,0)											
N=100	0.25%	72.3%	71.6%	24.3%	24.2%	20.3%	20.2%	*1.4%*	*1.6%*	*2.7%*	49.6%
N=250	0.45%	31.9%	30.7%	*1.5%*	*1.6%*	*2.9%*	*3.0%*	*0.0%*	*0.0%*	*0.0%*	15.1%
N=500	0.57%	11.2%	11.6%	*0.1%*	*0.1%*	*0.3%*	*0.2%*	*0.0%*	*0.0%*	*0.0%*	*0.6%*
N=1,000	0.69%	*0.5%*	*0.6%*	*0.0%*	*0.0%*	*0.0%*	*0.0%*	*0.0%*	*0.0%*	*0.0%*	*0.0%*
$\Delta_{i,E}$ (2%,0)											
N=100	1.25%	*7.9%*	*7.1%*	*0.2%*	*0.1%*	*0.1%*	*0.1%*	*0.0%*	*0.0%*	*0.0%*	*0.1%*
N=250	1.44%	*0.2%*	*0.1%*	*0.0%*	*0.0%*	*0.0%*	*0.0%*	*0.0%*	*0.0%*	*0.0%*	*0.0%*
$\Delta_{i,E}$ (3%,0)											
N=100	2.24%	*0.2%*	*0.1%*	*0.0%*	*0.0%*	*0.0%*	*0.0%*	*0.0%*	*0.0%*	*0.0%*	*0.0%*

Panel D – MCAP < 25M

	AAR	t-test	CDA T	Patell Z	Adj. Patell Z	Std-Csect Z	Adj. Std-Csect Z	Rank	Rank Z	Gen. Sign Z	Will-coxon
$\Delta_{i,E}$ (1%,0)											
N=100	0.04%	98.1%	98.1%	*8.7%*	*6.9%*	40.3%	37.4%	16.0%	15.0%	17.3%	61.0%
N=250	-0.03%	96.8%	96.6%	67.9%	66.5%	79.9%	79.0%	*2.4%*	*0.7%*	*0.7%*	49.7%
N=500	0.70%	21.8%	21.8%	12.5%	14.3%	34.0%	36.1%	*0.0%*	*0.0%*	*0.0%*	13.6%
N=1,000	0.33%	40.4%	38.2%	29.0%	28.3%	44.2%	43.5%	*0.0%*	*0.0%*	*0.0%*	17.3%
N=2,500	0.09%	72.2%	72.6%	*7.2%*	*8.3%*	13.1%	14.4%	*0.0%*	*0.0%*	*0.0%*	*6.1%*
$\Delta_{i,E}$ (2%,0)											
N=100	1.05%	50.5%	49.2%	40.1%	37.2%	67.5%	65.6%	1.3%	2.7%	1.0%	12.2%
N=250	0.98%	25.1%	22.0%	15.0%	13.1%	37.0%	34.8%	*0.0%*	*0.0%*	*0.0%*	*0.7%*
N=500	1.70%	*0.3%*	*0.3%*	*0.0%*	*0.0%*	*0.7%*	*0.9%*	*0.0%*	*0.0%*	*0.0%*	*0.0%*
N=1,000	1.34%	*0.1%*	*0.1%*	*0.0%*	*0.0%*	*0.0%*	*0.0%*	*0.0%*	*0.0%*	*0.0%*	*0.0%*
$\Delta_{i,E}$ (3%,0)											
N=100	2.06%	19.3%	18.1%	98.3%	98.2%	99.1%	99.1%	*0.0%*	*0.3%*	*0.1%*	*1.3%*
N=250	1.98%	*2.1%*	*1.4%*	*0.1%*	*0.1%*	*4.0%*	*3.2%*	*0.0%*	*0.0%*	*0.0%*	*0.0%*
N=500	2.69%	*0.0%*	*0.0%*	*0.0%*	*0.0%*	*0.0%*	*0.0%*	*0.0%*	*0.0%*	*0.0%*	*0.0%*
$\Delta_{i,E}$ (4%,0)											
N=100	3.05%	*5.4%*	*4.8%*	38.3%	35.4%	64.9%	62.9%	*0.0%*	*0.0%*	*0.0%*	*0.1%*
N=250	2.97%	*0.1%*	*0.0%*	*0.0%*	*0.0%*	*0.1%*	*0.1%*	*0.0%*	*0.0%*	*0.0%*	*0.0%*
$\Delta_{i,E}$ (5%,0)											
N=100	4.04%	*1.1%*	*0.9%*	*8.6%*	*6.8%*	36.2%	33.3%	*0.0%*	*0.0%*	*0.0%*	*0.0%*
N=250	3.96%	*0.0%*	*0.0%*	*0.0%*	*0.0%*	*0.0%*	*0.0%*	*0.0%*	*0.0%*	*0.0%*	*0.0%*

Table 2. 5: Performance Tests for Event Study Methods (with Event Returns and Volatility)

This table shows the AAR (see also table 2) for different sample sizes, along with the corresponding p-values for the ten tests mentioned in the methodology section. The results are presented for event returns ranging from 1% to 5% and event volatility. Under these conditions, the AARs should significantly differ from zero, as event return was simulated. If the p-value is greater than the chosen significance level (e.g., 10%), we fail to reject the null hypothesis and falsely assume the absence of an event return. For brevity, the results presented in this table include only iterations where notable changes in p-values are observed. Rows with results that closely mirror previous iterations, exhibiting minimal variation, have been omitted to avoid redundancy. p-values that support this conclusion are highlighted in green.

<u>Panel A – Top 100 by MCAP</u>

	AAR	**t-test**	**CDA T**	**Patell Z**	**Adj. Patell Z**	**Std-CSect Z**	**Adj. Std-CSect Z**	**Rank**	**Rank Z**	**Gen. Sign Z**	**Will-coxon**
$\Delta_{i,E}$ $(1\%, \widehat{\theta_{\iota,E}})$											
N=100	-0.70%	32.4%	28.3%	89.7%	88.2%	93.6%	92.6%	98.6%	62.8%	18.2%	61.1%
N=250	0.33%	52.9%	48.9%	***3.3%***	***2.7%***	19.0%	17.2%	***0.9%***	***0.3%***	***0.1%***	17.7%
N=500	-0.34%	32.6%	29.5%	77.2%	75.8%	85.6%	84.6%	38.1%	***3.7%***	***1.0%***	76.4%
N=1,000	0.43%	***9.6%***	***8.6%***	***0.0%***	***0.0%***	***0.3%***	***0.1%***	***0.0%***	***0.0%***	***0.0%***	21.0%
$\Delta_{i,E}$ $(2\%, \widehat{\theta_{\iota,E}})$											
N=100	-1.08%	13.1%	10.1%	19.5%	13.6%	46.8%	40.4%	***2.0%***	***1.3%***	***0.6%***	44.3%
N=250	0.06%	91.5%	90.6%	***0.5%***	***0.3%***	***8.0%***	***6.8%***	***0.0%***	***0.0%***	***0.0%***	11.0%
N=500	0.24%	49.2%	46.3%	***0.1%***	***0.0%***	***5.4%***	***4.0%***	***0.0%***	***0.0%***	***0.0%***	***1.1%***
$\Delta_{i,E}$ $(3\%, \widehat{\theta_{\iota,E}})$											
N=100	2.76%	***0.0%***	***0.0%***	***0.0%***	***0.0%***	***0.0%***	***0.0%***	***0.0%***	***0.0%***	***0.0%***	***0.1%***

Panel B – Top 100 by Volume

	AAR	t-test	CDA T	Patell Z	Adj. Patell Z	Std-CSect Z	Adj. Std-CSect Z	Rank Z	Sign Z	Gen. Sign Z	Will-coxon
$\Delta_{i,E}$ (1%, $\widehat{\theta_{i,E}}$)											
N=100	1.17%	***6.3%***	***6.7%***	16.3%	19.7%	35.1%	38.8%	***9.6%***	***5.6%***	***1.7%***	34.5%
N=250	1.68%	***0.1%***	***0.0%***	***0.0%***	***0.0%***	***3.1%***	***4.1%***	***0.1%***	***0.0%***	***0.0%***	***4.5%***
N=500	1.20%	***0.1%***	***0.1%***	***0.0%***	***0.0%***	***0.7%***	***0.9%***	***0.0%***	***0.0%***	***0.0%***	***1.6%***
N=1,000	1.31%	***0.0%***	***0.0%***	***0.0%***	***0.0%***	***0.0%***	***0.0%***	***0.0%***	***0.0%***	***0.0%***	***0.0%***
$\Delta_{i,E}$ (2%, $\widehat{\theta_{i,E}}$)											
N=100	2.59%	***0.0%***	***0.0%***	***0.0%***	***0.0%***	***0.7%***	***1.2%***	***0.0%***	***0.0%***	***0.0%***	***1.4%***
N=250	3.06%	***0.0%***	***0.0%***	***0.0%***	***0.0%***	***0.0%***	***0.1%***	***0.0%***	***0.0%***	***0.0%***	***0.0%***
$\Delta_{i,E}$ (3%, $\widehat{\theta_{i,E}}$)											
N=100	2.49%	***0.0%***	***0.0%***	***0.0%***	***0.0%***	***0.0%***	***0.0%***	***0.0%***	***0.0%***	***0.0%***	***0.1%***

Panel C – MCAP ≥ 25M

	AAR	t-test	CDA T	Patell Z	Adj. Patell Z	Std-CSect Z	Adj. Std-CSect Z	Rank Z	Sign Z	Gen. Sign Z	Will-coxon
$\Delta_{i,E}$ (1%, $\widehat{\theta_{i,E}}$)											
N=100	-0.55%	43.8%	42.4%	60.8%	60.6%	69.4%	69.3%	***5.7%***	***4.8%***	***0.1%***	60.4%
N=250	-0.36%	41.7%	40.6%	22.0%	22.5%	38.8%	39.3%	***2.9%***	***1.4%***	***0.0%***	80.9%
N=500	0.24%	50.4%	50.9%	***0.4%***	***0.4%***	***4.8%***	***4.6%***	***0.0%***	***0.0%***	***0.0%***	***5.9%***
N=1,000	0.52%	***3.4%***	***3.5%***	***0.0%***	***0.0%***	***0.1%***	***0.1%***	***0.0%***	***0.0%***	***0.0%***	***0.7%***
$\Delta_{i,E}$ (2%, $\widehat{\theta_{i,E}}$)											
N=100	1.33%	***6.0%***	***5.3%***	***0.1%***	***0.1%***	***0.4%***	***0.4%***	***0.0%***	***0.0%***	***0.0%***	***0.6%***
N=250	0.60%	18.4%	17.3%	***0.1%***	***0.1%***	***3.1%***	***3.3%***	***0.0%***	***0.0%***	***0.0%***	***2.4%***
N=500	0.81%	***2.5%***	***2.6%***	***0.0%***	***0.0%***	***0.0%***	***0.0%***	***0.0%***	***0.0%***	***0.0%***	***0.0%***
$\Delta_{i,E}$ (3%, $\widehat{\theta_{i,E}}$)											
N=100	2.40%	***0.1%***	***0.1%***	***0.0%***	***0.0%***	***0.0%***	***0.0%***	***0.0%***	***0.0%***	***0.0%***	***0.1%***

Panel D – MCAP < 25M

	AAR	t-test	CDA T	Patell Z	Adj. Patell Z	Std-CSect Z	Adj. Std-CSect Z	Rank Z	Sign Z	Gen. Sign Z	Will-coxon
$\Delta_{i,E}$ (1%,$\widehat{\theta_{i,E}}$)											
N=100	0.45%	77.8%	77.1%	11.2%	***9.1%***	43.7%	40.9%	43.0%	28.2%	45.0%	93.0%
N=250	0.76%	37.7%	34.3%	69.6%	68.3%	82.9%	82.1%	***0.3%***	***0.2%***	***0.1%***	22.4%
N=500	1.20%	***3.4%***	***3.4%***	***1.7%***	***2.3%***	19.5%	21.5%	***0.0%***	***0.0%***	***0.0%***	***8.6%***
N=1,000	0.17%	67.4%	65.8%	27.1%	26.4%	52.7%	52.1%	***0.0%***	***0.0%***	***0.0%***	***2.2%***
N=2,500	-0.69%	***0.7%***	***0.8%***	79.9%	80.6%	87.7%	88.1%	***0.0%***	***0.0%***	***0.0%***	***5.3%***
$\Delta_{i,E}$ (2%,$\widehat{\theta_{i,E}}$)											
N=100	-0.95%	54.8%	53.6%	***4.1%***	***3.0%***	37.8%	34.9%	12.3%	13.6%	***7.8%***	49.8%
N=250	-0.16%	84.9%	83.8%	65.5%	63.9%	82.0%	81.1%	***0.0%***	***0.0%***	***0.0%***	***2.5%***
N=500	0.65%	24.9%	24.8%	***0.2%***	***0.3%***	10.2%	11.8%	***0.0%***	***0.0%***	***0.0%***	***0.5%***
N=1,000	0.24%	55.4%	53.4%	***0.7%***	***0.6%***	12.8%	12.2%	***0.0%***	***0.0%***	***0.0%***	***0.2%***
N=2,500	-0.07%	79.1%	79.4%	***0.0%***	***0.0%***	***0.4%***	***0.5%***	***0.0%***	***0.0%***	***0.0%***	***0.0%***
$\Delta_{i,E}$ (3%,$\widehat{\theta_{i,E}}$)											
N=100	-0.58%	71.1%	70.3%	20.0%	17.3%	53.8%	51.3%	12.8%	10.2%	45.0%	71.1%
N=250	0.46%	58.9%	56.0%	***3.0%***	***2.3%***	23.9%	21.7%	***0.0%***	***0.0%***	***0.0%***	***4.2%***
N=500	2.19%	***0.0%***	***0.0%***	***0.0%***	***0.0%***	***0.0%***	***0.0%***	***0.0%***	***0.0%***	***0.0%***	***0.0%***
$\Delta_{i,E}$ (4%,$\widehat{\theta_{i,E}}$)											
N=100	4.85%	***0.2%***	***0.2%***	10.2%	***8.2%***	46.1%	43.4%	***0.0%***	***0.0%***	***0.1%***	***0.1%***
N=250	2.83%	***0.1%***	***0.0%***	***0.0%***	***0.0%***	***1.5%***	***1.1%***	***0.0%***	***0.0%***	***0.0%***	***0.0%***
$\Delta_{i,E}$ (5%, $\widehat{\theta_{i,E}}$)											
N=100	0.74%	63.8%	62.8%	59.4%	57.2%	80.6%	79.4%	***0.5%***	***1.9%***	***1.0%***	20.5%
N=250	2.18%	***1.2%***	***0.7%***	***0.0%***	***0.0%***	***1.2%***	***0.9%***	***0.0%***	***0.0%***	***0.0%***	***0.0%***

Table 2. 6: Heat Map —— N=100 Samples Drawn 80 Times, p-level 10%

This table presents the results for the ten tests, with N=100 samples drawn 80 times, representing a total of 8,000 randomly drawn events for each of the four sub-samples. The results encompass all scenarios: no event (with and without volatility), event without volatility, and event with both return and volatility. The percentages in the table indicate how often each respective test correctly identified an event (or non-event in the case of no-event scenarios) at the **10% level** (other tested levels can be found in the online appendix). The last row reports the average percentage of correct (Avg.Pct.Correct) identifications for each test across different scenarios. Percentages that meet or exceed the usual significance threshold of 90% are highlighted in red to draw attention to particularly robust test performance.

Panel A – Top 100 by MCAP

		t-test	CDA T	Patell Z	Adj. Patell Z	Std-Csect Z	Adj. Std-Csect Z	Rank	Rank Z	Gen. Sign Z	Will-coxon
	Avg.Pct. Correct	***92%***	***93%***	77%	77%	85%	85%	84%	84%	***93%***	***94%***
No Event	$\Delta_{i,E}$ (0,0)	***93%***	***95%***	89%	84%	88%	88%	***91%***	89%	88%	88%
	$\Delta_{i,E}$ (0%, $\widehat{\theta_{i,E}}$)	***90%***	84%	60%	60%	65%	64%	88%	88%	83%	86%
Event Return but no event vola	$\Delta_{i,E}$ (1%,0)	84%	81%	36%	36%	56%	56%	53%	56%	***90%***	***91%***
	$\Delta_{i,E}$ (2%,0)	***100%***	***99%***	81%	80%	***96%***	***96%***	***94%***	***94%***	***100%***	***100%***
	$\Delta_{i,E}$ (3%,0)	***100%***	***100%***	***98%***	***98%***	***100%***	***100%***	***98%***	***98%***	***100%***	***100%***
	$\Delta_{i,E}$ (4%,0)	***100%***	***100%***	***99%***	***99%***	***100%***	***100%***	***100%***	***100%***	***100%***	***100%***
	$\Delta_{i,E}$ (5%,0)	***100%***	***100%***	***100%***	***100%***	***100%***	***100%***	***100%***	***100%***	***100%***	***100%***
Event Return and event vola	$\Delta_{i,E}$ (1%, $\widehat{\theta_{i,E}}$)	56%	68%	35%	35%	40%	39%	21%	24%	63%	66%
	$\Delta_{i,E}$ (2%, $\widehat{\theta_{i,E}}$)	85%	***90%***	60%	60%	84%	84%	70%	73%	89%	***94%***
	$\Delta_{i,E}$ (3%, $\widehat{\theta_{i,E}}$)	***98%***	***99%***	80%	79%	***96%***	***96%***	***91%***	***91%***	***99%***	***99%***
	$\Delta_{i,E}$ (4%, $\widehat{\theta_{i,E}}$)	***100%***	***100%***	89%	89%	***99%***	***99%***	***99%***	***99%***	***100%***	***100%***
	$\Delta_{i,E}$ (5%, $\widehat{\theta_{i,E}}$)	***100%***	***100%***	***100%***	***100%***	***100%***	***100%***	***100%***	***100%***	***100%***	***100%***

Panel B – Top 100 by Volume

		t-test	CDA T	Patell Z	Adj. Patell Z	Std-Csect Z	Adj. Std-Csect Z	Rank	Rank Z	Gen. Sign Z	Will-coxon
	Avg.Pct. Correct	***93%***	***92%***	84%	84%	88%	88%	87%	88%	***93%***	***92%***
No Event	$\Delta_{i,E}$ (0,0)	84%	***90%***	89%	88%	74%	74%	86%	86%	84%	79%
	$\Delta_{i,E}$ (0%, $\widehat{\theta_{i,E}}$)	83%	68%	73%	71%	69%	68%	89%	89%	76%	69%
Event Return but no event vola	$\Delta_{i,E}$ (1%,0)	85%	75%	55%	58%	76%	76%	65%	66%	***91%***	***91%***
	$\Delta_{i,E}$ (2%,0)	***100%***	***100%***	***93%***	***94%***	***98%***	***98%***	***98%***	***98%***	***100%***	***100%***
	$\Delta_{i,E}$ (3%,0)	***100%***	***100%***	***99%***	***99%***	***100%***	***100%***	***100%***	***100%***	***100%***	***100%***
	$\Delta_{i,E}$ (4%,0)	***100%***	***100%***	***100%***	***100%***	***100%***	***100%***	***100%***	***100%***	***100%***	***100%***
	$\Delta_{i,E}$ (5%,0)	***100%***	***100%***	***100%***	***100%***	***100%***	***100%***	***100%***	***100%***	***100%***	***100%***
Event Return and event vola	$\Delta_{i,E}$ (1%, $\widehat{\theta_{i,E}}$)	65%	71%	48%	48%	60%	59%	41%	43%	65%	71%
	$\Delta_{i,E}$ (2%, $\widehat{\theta_{i,E}}$)	***94%***	***95%***	71%	69%	89%	89%	76%	79%	***95%***	***98%***
	$\Delta_{i,E}$ (3%, $\widehat{\theta_{i,E}}$)	***100%***	***100%***	88%	88%	***98%***	***98%***	***94%***	***95%***	***100%***	***100%***
	$\Delta_{i,E}$ (4%, $\widehat{\theta_{i,E}}$)	***100%***	***100%***	***99%***	***99%***	***99%***	***100%***	***99%***	***99%***	***100%***	***100%***
	$\Delta_{i,E}$ (5%, $\widehat{\theta_{i,E}}$)	***100%***	***100%***	***99%***	***99%***	***100%***	***100%***	***100%***	***100%***	***100%***	***100%***

Panel C – MCAP ≥ 25M

		t-test	CDA T	Patell Z	Adj. Patell Z	Std-Csect Z	Adj. Std-Csect Z	Rank	Rank Z	Gen. Sign Z	Will-coxon
	Avg.Pct. Correct	***93%***	***93%***	79%	79%	86%	86%	84%	84%	***93%***	***93%***
No Event	$\Delta_{i,E}$ (0,0)	***93%***	***98%***	89%	86%	84%	83%	83%	80%	89%	85%
	$\Delta_{i,E}$ (0%, $\widehat{\theta_{i,E}}$)	***91%***	81%	66%	66%	68%	68%	83%	85%	83%	83%
Event Return but no event vola	$\Delta_{i,E}$ (1%,0)	83%	83%	38%	38%	53%	51%	49%	49%	88%	88%
	$\Delta_{i,E}$ (2%,0)	***100%***	***100%***	69%	71%	***94%***	***94%***	***96%***	***96%***	***100%***	***100%***
	$\Delta_{i,E}$ (3%,0)	***100%***	***100%***	***99%***	***99%***	***100%***	***100%***	***100%***	***100%***	***100%***	***100%***
	$\Delta_{i,E}$ (4%,0)	***100%***	***100%***	***100%***	***100%***	***100%***	***100%***	***100%***	***100%***	***100%***	***100%***
	$\Delta_{i,E}$ (5%,0)	***100%***	***100%***	***100%***	***100%***	***100%***	***100%***	***100%***	***100%***	***100%***	***100%***
Event Return and event vola	$\Delta_{i,E}$ (1%, $\widehat{\theta_{i,E}}$)	60%	66%	45%	44%	58%	60%	34%	30%	63%	69%
	$\Delta_{i,E}$ (2%, $\widehat{\theta_{i,E}}$)	88%	***91%***	60%	60%	84%	84%	70%	73%	89%	***90%***
	$\Delta_{i,E}$ (3%, $\widehat{\theta_{i,E}}$)	***99%***	***98%***	83%	84%	***93%***	***93%***	***90%***	***90%***	***100%***	***100%***
	$\Delta_{i,E}$ (4%, $\widehat{\theta_{i,E}}$)	***100%***	***100%***	***98%***	***98%***	***100%***	***100%***	***100%***	***100%***	***100%***	***100%***
	$\Delta_{i,E}$ (5%, $\widehat{\theta_{i,E}}$)	***100%***	***100%***	***100%***	***100%***	***100%***	***100%***	***100%***	***100%***	***100%***	***100%***

Panel D – MCAP < 25M

		t-test	CDA T	Patell Z	Adj. Patell Z	Std-Csect Z	Adj. Std-Csect Z	Rank	Rank Z	Gen. Sign Z	Will-coxon
	Avg.Pct. Correct	86%	87%	56%	56%	69%	70%	62%	62%	88%	89%
No Event	$\Delta_{i,E}$ (0,0)	***98%***	***96%***	79%	79%	76%	74%	76%	75%	***94%***	***94%***
	$\Delta_{i,E}$ (0%, $\widehat{\theta_{i,E}}$)	***96%***	***98%***	55%	55%	60%	60%	78%	76%	85%	***91%***
Event Return but no event vola	$\Delta_{i,E}$ (1%,0)	49%	53%	11%	15%	16%	20%	15%	19%	60%	60%
	$\Delta_{i,E}$ (2%,0)	***96%***	***100%***	30%	29%	53%	55%	45%	45%	***99%***	***99%***
	$\Delta_{i,E}$ (3%,0)	***100%***	***100%***	51%	50%	89%	***90%***	88%	88%	***100%***	***100%***
	$\Delta_{i,E}$ (4%,0)	***100%***	***100%***	80%	81%	***96%***	***96%***	***96%***	***95%***	***100%***	***100%***
	$\Delta_{i,E}$ (5%,0)	***100%***	***100%***	***96%***	***96%***	***100%***	***100%***	***99%***	***99%***	***100%***	***100%***
Event Return and event vola	$\Delta_{i,E}$ (1%, $\widehat{\theta_{i,E}}$)	40%	40%	45%	45%	31%	33%	11%	11%	48%	50%
	$\Delta_{i,E}$ (2%, $\widehat{\theta_{i,E}}$)	73%	71%	33%	33%	51%	54%	21%	21%	76%	83%
	$\Delta_{i,E}$ (3%, $\widehat{\theta_{i,E}}$)	89%	***93%***	49%	48%	68%	68%	51%	49%	***93%***	***94%***
	$\Delta_{i,E}$ (4%, $\widehat{\theta_{i,E}}$)	***98%***	***99%***	71%	71%	***93%***	***93%***	81%	81%	***99%***	***98%***
	$\Delta_{i,E}$ (5%, $\widehat{\theta_{i,E}}$)	***99%***	***99%***	74%	74%	***95%***	***95%***	88%	88%	***99%***	***99%***

Table 2. 7: Heat Map —— N=100 Samples Drawn 80 Times, p-level 5%

This table presents the results for the ten tests, with N=100 samples drawn 80 times, representing a total of 8,000 randomly drawn events for each of the four sub-samples. The results encompass all scenarios: no event (with and without volatility), event without volatility, and event with both return and volatility. The percentages in the table indicate how often each respective test correctly identified an event (or non-event in the case of no-event scenarios) at the **5% level** (other tested levels can be found in the online appendix). The last row reports the average percentage of correct identifications for each test across different scenarios. Percentages that meet or exceed the usual significance threshold of 90% are highlighted in red to draw attention to particularly robust test performance.

Panel A – Top 100 by MCAP

		t-test	**CDA T**	**Patell Z**	**Adj. Patell Z**	**Std-Csect Z**	**Adj. Std-Csect Z**	**Rank**	**Rank Z**	**Gen. Sign Z**	**Will-coxon**
	Avg.Pct. Correct	76%	76%	85%	85%	82%	83%	***91%***	***92%***	***93%***	80%
No Event	$\Delta_{i,E}$ (0,0)	***96%***	***94%***	***91%***	***93%***	***93%***	***94%***	***93%***	***93%***	***95%***	83%
	$\Delta_{i,E}$ (0%, $\widehat{\theta_{i,E}}$)	76%	74%	74%	74%	***93%***	***91%***	86%	***90%***	84%	89%
Event Return but no event vola	$\Delta_{i,E}$ (1%,0)	28%	30%	50%	50%	44%	46%	83%	84%	81%	34%
	$\Delta_{i,E}$ (2%,0)	71%	70%	***95%***	***95%***	***94%***	***94%***	***100%***	***100%***	***99%***	***94%***
	$\Delta_{i,E}$ (3%,0)	***98%***	***98%***	***99%***	***99%***	***98%***	***98%***	***100%***	***100%***	***100%***	***100%***
	$\Delta_{i,E}$ (4%,0)	***99%***	***99%***	***100%***	***100%***	***100%***	***100%***	***100%***	***100%***	***100%***	***100%***
	$\Delta_{i,E}$ (5%,0)	***100%***	***100%***	***100%***	***100%***	***100%***	***100%***	***100%***	***100%***	***100%***	***100%***
Event Return and event vola	$\Delta_{i,E}$ (1%, $\widehat{\theta_{i,E}}$)	28%	30%	36%	34%	20%	20%	53%	56%	68%	24%
	$\Delta_{i,E}$ (2%, $\widehat{\theta_{i,E}}$)	53%	51%	80%	81%	63%	64%	84%	85%	90%	63%
	$\Delta_{i,E}$ (3%, $\widehat{\theta_{i,E}}$)	75%	76%	***91%***	***93%***	88%	88%	***98%***	***98%***	***99%***	84%
	$\Delta_{i,E}$ (4%, $\widehat{\theta_{i,E}}$)	88%	88%	***99%***	***99%***	***96%***	***96%***	***100%***	***100%***	***100%***	***95%***
	$\Delta_{i,E}$ (5%, $\widehat{\theta_{i,E}}$)	***98%***	***98%***	***100%***	***100%***	***100%***	***100%***	***100%***	***100%***	***100%***	***100%***

<u>Panel B – Top 100 by Volume</u>

		t-test	CDA T	Patell Z	Adj. Patell Z	Std-Csect Z	Adj. Std-Csect Z	Rank	Rank Z	Gen. Sign Z	Will-coxon
	Avg.Pct. Correct	82%	81%	88%	88%	85%	84%	***92%***	***93%***	***92%***	83%
No Event	$\Delta_{i,E}$ (0,0)	***91%***	***91%***	83%	83%	***91%***	***90%***	***93%***	84%	***90%***	89%
	$\Delta_{i,E}$ (0%, $\widehat{\theta_{\iota,E}}$)	81%	78%	78%	78%	***93%***	***91%***	85%	83%	68%	***95%***
Event Return but no event vola	$\Delta_{i,E}$ (1%,0)	41%	43%	66%	68%	56%	56%	84%	85%	75%	45%
	$\Delta_{i,E}$ (2%,0)	86%	85%	***98%***	***98%***	***93%***	***94%***	***100%***	***100%***	***100%***	***93%***
	$\Delta_{i,E}$ (3%,0)	***98%***	***99%***	***100%***	***100%***	***100%***	***100%***	***100%***	***100%***	***100%***	***100%***
	$\Delta_{i,E}$ (4%,0)	***99%***	***99%***	***100%***	***100%***	***100%***	***100%***	***100%***	***100%***	***100%***	***100%***
	$\Delta_{i,E}$ (5%,0)	***100%***	***100%***	***100%***	***100%***	***100%***	***100%***	***100%***	***100%***	***100%***	***100%***
Event Return and event vola	$\Delta_{i,E}$ (1%, $\widehat{\theta_{\iota,E}}$)	41%	41%	51%	51%	30%	29%	53%	65%	71%	21%
	$\Delta_{i,E}$ (2%, $\widehat{\theta_{\iota,E}}$)	61%	61%	81%	84%	63%	63%	***93%***	***94%***	***95%***	65%
	$\Delta_{i,E}$ (3%, $\widehat{\theta_{\iota,E}}$)	83%	81%	***96%***	***96%***	***94%***	***93%***	***99%***	***100%***	***100%***	86%
	$\Delta_{i,E}$ (4%, $\widehat{\theta_{\iota,E}}$)	***99%***	***99%***	***99%***	***99%***	***99%***	***99%***	***100%***	***100%***	***100%***	***98%***
	$\Delta_{i,E}$ (5%, $\widehat{\theta_{\iota,E}}$)	***99%***	***99%***	***100%***	***100%***	***100%***	***100%***	***100%***	***100%***	***100%***	***100%***

<u>Panel C – MCAP ≥ 25M</u>

		t-test	CDA T	Patell Z	Adj. Patell Z	Std-Csect Z	Adj. Std-Csect Z	Rank	Rank Z	Gen. Sign Z	Will-coxon
	Avg.Pct. Correct	76%	76%	85%	85%	81%	82%	***92%***	***93%***	***93%***	80%
No Event	$\Delta_{i,E}$ (0,0)	***94%***	***94%***	***90%***	***91%***	***91%***	***90%***	***96%***	***93%***	***98%***	76%
	$\Delta_{i,E}$ (0%, $\widehat{\theta_{i,E}}$)	74%	75%	73%	74%	***94%***	***93%***	***91%***	***91%***	81%	***95%***
Event Return but no event vola	$\Delta_{i,E}$ (1%,0)	26%	26%	44%	44%	41%	43%	81%	83%	83%	25%
	$\Delta_{i,E}$ (2%,0)	66%	66%	90%	90%	88%	88%	***100%***	***100%***	***100%***	***94%***
	$\Delta_{i,E}$ (3%,0)	***96%***	***94%***	***100%***	***100%***	***100%***	***100%***	***100%***	***100%***	***100%***	***100%***
	$\Delta_{i,E}$ (4%,0)	***100%***	***100%***	***100%***	***100%***	***100%***	***100%***	***100%***	***100%***	***100%***	***100%***
	$\Delta_{i,E}$ (5%,0)	***100%***	***100%***	***100%***	***100%***	***100%***	***100%***	***100%***	***100%***	***100%***	***100%***
Event Return and event vola	$\Delta_{i,E}$ (1%, $\widehat{\theta_{i,E}}$)	36%	35%	50%	50%	21%	23%	53%	60%	66%	23%
	$\Delta_{i,E}$ (2%, $\widehat{\theta_{i,E}}$)	51%	54%	80%	80%	59%	59%	85%	88%	***91%***	59%
	$\Delta_{i,E}$ (3%, $\widehat{\theta_{i,E}}$)	76%	76%	***90%***	***90%***	86%	86%	***99%***	***99%***	***98%***	86%
	$\Delta_{i,E}$ (4%, $\widehat{\theta_{i,E}}$)	***95%***	***95%***	***100%***	***100%***	***98%***	***99%***	***100%***	***100%***	***100%***	***98%***
	$\Delta_{i,E}$ (5%, $\widehat{\theta_{i,E}}$)	***100%***	***100%***	***100%***	***100%***	***100%***	***100%***	***100%***	***100%***	***100%***	***100%***

<u>Panel D – MCAP < 25M</u>

		t-test	CDA T	Patell Z	Adj. Patell Z	Std-Csect Z	Adj. Std-Csect Z	Rank	Rank Z	Gen. Sign Z	Will-coxon
	Avg.Pct. Correct	50%	50%	66%	66%	59%	58%	84%	86%	87%	63%
No Event	$\Delta_{i,E}$ (0,0)	***90%***	***91%***	84%	83%	86%	85%	***98%***	***98%***	***96%***	75%
	$\Delta_{i,E}$ (0%, $\widehat{\theta_{i,E}}$)	63%	63%	65%	65%	86%	85%	***90%***	***96%***	***98%***	***91%***
Event Return but no event vola	$\Delta_{i,E}$ (1%,0)	4%	4%	13%	13%	9%	10%	46%	49%	53%	5%
	$\Delta_{i,E}$ (2%,0)	20%	19%	40%	40%	40%	40%	***95%***	***96%***	***100%***	56%
	$\Delta_{i,E}$ (3%,0)	44%	44%	85%	86%	83%	83%	***100%***	***100%***	***100%***	***94%***
	$\Delta_{i,E}$ (4%,0)	71%	69%	***96%***	***96%***	***95%***	***95%***	***100%***	***100%***	***100%***	***99%***
	$\Delta_{i,E}$ (5%,0)	***93%***	***93%***	***99%***	***99%***	***99%***	***99%***	***100%***	***100%***	***100%***	***100%***
Event Return and event vola	$\Delta_{i,E}$ (1%, $\widehat{\theta_{i,E}}$)	28%	28%	20%	19%	4%	5%	34%	40%	40%	8%
	$\Delta_{i,E}$ (2%, $\widehat{\theta_{i,E}}$)	23%	21%	36%	39%	8%	5%	66%	73%	71%	9%
	$\Delta_{i,E}$ (3%, $\widehat{\theta_{i,E}}$)	41%	43%	64%	64%	39%	39%	88%	89%	***93%***	44%
	$\Delta_{i,E}$ (4%, $\widehat{\theta_{i,E}}$)	55%	56%	***90%***	***90%***	73%	71%	***98%***	***98%***	***99%***	81%
	$\Delta_{i,E}$ (5%, $\widehat{\theta_{i,E}}$)	70%	68%	***95%***	***95%***	83%	83%	***99%***	***99%***	***99%***	89%

Table 2. 8: Heat Map —— N=100 Samples Drawn 80 Times, p-level 1%

This table presents the results for the ten tests, with N=100 samples drawn 80 times, representing a total of 8,000 randomly drawn events for each of the four sub-samples. The results encompass all scenarios: no event (with and without volatility), event without volatility, and event with both return and volatility. The percentages in the table indicate how often each respective test correctly identified an event (or non-event in the case of no-event scenarios) at the **1% level** (other tested levels can be found in the online appendix). The last row reports the average percentage of correct identifications for each test across different scenarios. Percentages that meet or exceed the usual significance threshold of 90% are highlighted in red to draw attention to particularly robust test performance.

Panel A – Top 100 by MCAP

		t-test	CDA T	Patell Z	Adj. Patell Z	Std-Csect Z	Adj. Std-Csect Z	Rank	Rank Z	Gen. Sign Z	Will-coxon
	Avg.Pct. Correct	69%	69%	81%	82%	76%	76%	88%	88%	89%	75%
No Event	$\Delta_{i,E}$ (0,0)	***98%***	***98%***	***98%***	***96%***	***100%***	***100%***	***100%***	***100%***	***100%***	***95%***
	$\Delta_{i,E}$ (0%, $\widehat{\theta_{i,E}}$)	88%	86%	89%	89%	***99%***	***99%***	***94%***	***95%***	***94%***	***100%***
Event Return but no event vola	$\Delta_{i,E}$ (1%,0)	10%	10%	25%	30%	21%	24%	66%	66%	56%	15%
	$\Delta_{i,E}$ (2%,0)	48%	48%	89%	90%	81%	83%	***98%***	***98%***	***98%***	80%
	$\Delta_{i,E}$ (3%,0)	85%	86%	***96%***	***98%***	***96%***	***96%***	***100%***	***100%***	***100%***	***98%***
	$\Delta_{i,E}$ (4%,0)	***98%***	***98%***	***100%***	***100%***	***99%***	***99%***	***100%***	***100%***	***100%***	***100%***
	$\Delta_{i,E}$ (5%,0)	***99%***	***99%***	***100%***	***100%***	***100%***	***100%***	***100%***	***100%***	***100%***	***100%***
Event Return and event vola	$\Delta_{i,E}$ (1%, $\widehat{\theta_{i,E}}$)	11%	13%	20%	21%	6%	6%	35%	31%	48%	9%
	$\Delta_{i,E}$ (2%, $\widehat{\theta_{i,E}}$)	43%	43%	70%	70%	40%	43%	76%	76%	79%	39%
	$\Delta_{i,E}$ (3%, $\widehat{\theta_{i,E}}$)	68%	68%	***91%***	***91%***	78%	78%	***93%***	***93%***	***93%***	74%
	$\Delta_{i,E}$ (4%, $\widehat{\theta_{i,E}}$)	83%	84%	***99%***	***99%***	***93%***	***91%***	***100%***	***100%***	***100%***	***93%***
	$\Delta_{i,E}$ (5%, $\widehat{\theta_{i,E}}$)	***95%***	***95%***	***100%***	***100%***	***98%***	***99%***	***100%***	***100%***	***100%***	***100%***

Panel B – Top 100 by Volume

		t-test	CDA T	Patell Z	Adj. Patell Z	Std-Csect Z	Adj. Std-Csect Z	Rank	Rank Z	Gen. Sign Z	Will-coxon
	Avg.Pct. Correct	76%	76%	85%	86%	78%	78%	89%	***90%***	89%	76%
No Event	$\Delta_{i,E}$ (0,0)	***96%***	***96%***	88%	88%	***99%***	***99%***	***99%***	***91%***	***98%***	***95%***
	$\Delta_{i,E}$ (0%, $\widehat{\theta_{i,E}}$)	***90%***	***91%***	86%	85%	***96%***	***98%***	***93%***	***91%***	86%	***98%***
Event Return but no event vola	$\Delta_{i,E}$ (1%,0)	25%	24%	46%	50%	33%	31%	65%	70%	56%	23%
	$\Delta_{i,E}$ (2%,0)	59%	60%	88%	88%	85%	85%	***99%***	***99%***	***96%***	85%
	$\Delta_{i,E}$ (3%,0)	***95%***	***95%***	***100%***	***100%***	***99%***	***99%***	***100%***	***100%***	***100%***	***100%***
	$\Delta_{i,E}$ (4%,0)	***99%***	***99%***	***100%***	***100%***	***100%***	***100%***	***100%***	***100%***	***100%***	***100%***
	$\Delta_{i,E}$ (5%,0)	***100%***	***100%***	***100%***	***100%***	***100%***	***100%***	***100%***	***100%***	***100%***	***100%***
Event Return and event vola	$\Delta_{i,E}$ (1%, $\widehat{\theta_{i,E}}$)	28%	28%	43%	45%	10%	13%	41%	43%	50%	9%
	$\Delta_{i,E}$ (2%, $\widehat{\theta_{i,E}}$)	51%	50%	76%	78%	45%	45%	83%	86%	85%	40%
	$\Delta_{i,E}$ (3%, $\widehat{\theta_{i,E}}$)	73%	76%	***95%***	***95%***	76%	78%	***94%***	***96%***	***99%***	74%
	$\Delta_{i,E}$ (4%, $\widehat{\theta_{i,E}}$)	***96%***	***96%***	***99%***	***99%***	***94%***	***94%***	***99%***	***99%***	***99%***	***91%***
	$\Delta_{i,E}$ (5%, $\widehat{\theta_{i,E}}$)	***95%***	***95%***	***100%***	***100%***	***99%***	***99%***	***100%***	***100%***	***100%***	***99%***

Panel C – MCAP ≥ 25M

		t-test	CDA T	Patell Z	Adj. Patell Z	Std-Csect Z	Adj. Std-Csect Z	Rank	Rank Z	Gen. Sign Z	Will-coxon
	Avg.Pct. Correct	70%	70%	82%	82%	76%	77%	89%	***90%***	89%	74%
No Event	$\Delta_{i,E}$ (0,0)	***96%***	***98%***	***99%***	***99%***	***99%***	***98%***	***100%***	***100%***	***99%***	***91%***
	$\Delta_{i,E}$ (0%, $\widehat{\theta_{i,E}}$)	86%	86%	89%	85%	***100%***	***100%***	***99%***	***99%***	***95%***	***99%***
Event Return but no event vola	$\Delta_{i,E}$ (1%,0)	13%	11%	30%	33%	20%	21%	61%	65%	58%	10%
	$\Delta_{i,E}$ (2%,0)	46%	46%	79%	78%	78%	80%	***99%***	***99%***	***100%***	81%
	$\Delta_{i,E}$ (3%,0)	80%	84%	***100%***	***100%***	***100%***	***100%***	***100%***	***100%***	***100%***	***100%***
	$\Delta_{i,E}$ (4%,0)	***99%***	***99%***	***100%***	***100%***	***100%***	***100%***	***100%***	***100%***	***100%***	***100%***
	$\Delta_{i,E}$ (5%,0)	***100%***	***100%***	***100%***	***100%***	***100%***	***100%***	***100%***	***100%***	***100%***	***100%***
Event Return and event vola	$\Delta_{i,E}$ (1%, $\widehat{\theta_{i,E}}$)	25%	28%	30%	30%	8%	6%	34%	41%	40%	9%
	$\Delta_{i,E}$ (2%, $\widehat{\theta_{i,E}}$)	33%	33%	70%	73%	43%	45%	76%	79%	78%	33%
	$\Delta_{i,E}$ (3%, $\widehat{\theta_{i,E}}$)	73%	73%	88%	88%	75%	78%	***94%***	***94%***	***95%***	71%
	$\Delta_{i,E}$ (4%, $\widehat{\theta_{i,E}}$)	***91%***	***90%***	***100%***	***100%***	***96%***	***96%***	***100%***	***100%***	***100%***	***96%***
	$\Delta_{i,E}$ (5%, $\widehat{\theta_{i,E}}$)	***98%***	***98%***	***100%***	***100%***	***100%***	***100%***	***100%***	***100%***	***100%***	***100%***

Panel D – MCAP < 25M

		t-test	CDA T	Patell Z	Adj. Patell Z	Std-Csect Z	Adj. Std-Csect Z	Rank	Rank Z	Gen. Sign Z	Will-coxon
	Avg.Pct. Correct	39%	40%	58%	58%	50%	51%	78%	78%	80%	56%
No Event	$\Delta_{i,E}$ (0,0)	***96%***	***98%***	***93%***	***91%***	***93%***	***95%***	***100%***	***100%***	***100%***	***90%***
	$\Delta_{i,E}$ $(0\%, \widehat{\theta_{i,E}})$	81%	81%	79%	73%	***96%***	***95%***	***98%***	***100%***	***100%***	***96%***
Event Return but no event vola	$\Delta_{i,E}$ (1%,0)	1%	1%	3%	3%	0%	0%	30%	33%	28%	0%
	$\Delta_{i,E}$ (2%,0)	8%	9%	26%	26%	23%	24%	89%	86%	***94%***	41%
	$\Delta_{i,E}$ (3%,0)	24%	25%	65%	65%	59%	61%	***99%***	***99%***	***100%***	86%
	$\Delta_{i,E}$ (4%,0)	49%	48%	***93%***	***93%***	88%	***90%***	***100%***	***100%***	***100%***	***99%***
	$\Delta_{i,E}$ (5%,0)	75%	78%	***98%***	***96%***	***96%***	***95%***	***100%***	***100%***	***100%***	***100%***
Event Return and event vola	$\Delta_{i,E}$ $(1\%, \widehat{\theta_{i,E}})$	11%	15%	10%	10%	0%	1%	16%	15%	28%	1%
	$\Delta_{i,E}$ $(2\%, \widehat{\theta_{i,E}})$	14%	14%	19%	19%	1%	1%	40%	41%	45%	0%
	$\Delta_{i,E}$ $(3\%, \widehat{\theta_{i,E}})$	21%	21%	43%	45%	18%	21%	74%	71%	80%	23%
	$\Delta_{i,E}$ $(4\%, \widehat{\theta_{i,E}})$	40%	40%	84%	83%	54%	54%	***94%***	***94%***	***93%***	61%
	$\Delta_{i,E}$ $(5\%, \widehat{\theta_{i,E}})$	54%	55%	88%	88%	70%	73%	***99%***	***96%***	***98%***	80%

Table 2A. 1: Summary of Event Study Research

Authors	Events	Period	Token Sample	Estimation Window	Event Window	Abnormal Return	Event Study Tests	Findings
Weak-form Efficiency Test / Cross-sectional Approach								
Ante and Fiedler (2021)	2,132 Large Bitcoins Transfers	06 Sep 2018 – 14 Nov 2019	Bitcoin	Minutes (-141, -21)	Minutes (-15, 15)	Mean Return Model	Standard t-test; Wilcoxon sign-rank test	Significant market reactions to large Bitcoin transfers
Semi-strong Form Efficiency Test / Cross-sectional Approach								
Ante (2019)	327 exchange listings	2017 – 2019	180 cryptos on 22 different exchanges	Day (-30, -10)	Day (-3, +3), (-7, +7)	Constant Mean Return Model; Market Model (Bitcoin)	Standard t-test; Wilcoxon sign-rank test	Cryptocurrency markets respond strongly to new exchange listings.
Joo et al., (2020)	Major positive/negative news announcements	2015 – 2018	3 primary cryptos: Bitcoin, Ethereum and Ripple	60, 180 or 365 days	Day (0, 0), (-3, 6), (0, 6)	Mean-Adjusted Returns Model	Nonparametric Tests: Corrado (1989), Kolar and Pynnonen (2011)	Larger magnitudes of CARs are observed for negative events compared to positive ones.
Tomić (2020)	Three Bitcoin forks: Bitcoin Cash (BCH), Bitcoin Gold (BTG), and Bitcoin Satoshi Vision (BSV)	2016, 2017, 2018	8 cryptos: BTC, ETH, XRP, LTC, ETC, XMR, XLM, and DASH	8 months prior to events	Day (0, +3)	Market Model	Standard t-test, Rank and Sign Tests	The forks of Bitcoin Gold and Bitcoin SV resulted in significant negative effects on the crypto market.
Jumah and Karri (2020)	Major cryptocurrency-related events	N/A	4 major cryptocurrencies: Bitcoin, Ripple, Litecoin, and	230 days prior to events	Day (-20, +20)	Market Risk-Adjusted Excess	Standard t-test and other parametric tests	External events significantly impact firm performance,

			Etheereum			Return		particularly in terms of stock price reactions to regulatory and security-related events.
Abraham (2021)	COVID-19 pandemic announcements	January 1, 2018 – July 17, 2020	Bitcoin and 14 Altcoins	Day (-250, -10)	Day (-10, 10)	Market Model	Standard t-test	While all cryptocurrencies experienced negative impacts due to COVID-19, Altcoins were more adversely affected than Bitcoin.
Yue et al., (2021)	5 positive & 5 negative news in the crypto market	2013 – 2019	Top 5 and Top 100 cryptos based on market capitalization	N/A	Day 0, (-1, +1) … (-5, +5), (0, +10) & (0, +20)	N/A	Standard t-test	The effects of positive news persist longer
Öget (2022)	Major listing and airdrop announcements. Major delisting announcement and SEC enforcements.	2020, 2021	Specific cryptocurrencies associated with the events (e.g., Ripple for SEC enforcement, Celo for listing).	120 days	Day (-5, +10)	Market Model (Bitcoin as the market proxy)	Standard t-test	Negative events have a more substantial and lasting impact on prices than positive events.
Ante (2023)	Twitter activity by Elon Mush	April 2019 – July 2021	Bitcoin and Dogecoin	Minutes (−360, −60)	The time of the tweets be posted	Constant Mean Return Model	Standard t-test, Wilcoxon sign rank tests	Musk's tweets lead to significant positive abnormal returns and increased

								trading volumes, particularly with Dogecoin. The impact on Bitcoin is less pronounced and varies depending on the sentiment of the tweet.
Yousaf et al., (2023)	The collapse of the cryptocurrency exchange FTX	November 2021 – November 2022	Bitcoin, Ethereum, and Binance Coin	235 days prior the event	Day (-4, +7)	Market Model	OLS regression	The collapse notably affected cryptocurrencies with Bitcoin, Ethereum, and Binance Coin showing significant negative abnormal returns.
Semi-strong Form Efficiency Test / Pooled Analysis								
Shanaev et al., (2019)	14 individual 51% attacks	2013, 2016, 2018	13 (PoW) Cryptocurrencies	30 days pre-event	Day (0, 0), (-3, 0), (-1, 0), (0, 1), (0, 3), (0, 6).	Market Model	F-tests	51% attacks lead to a significant decline in the value.
Ante et al., (2021)	565 issuances of stablecoins	April 2019 – March 2020	7 stablecoins: USDC, HUSD, USDT, PAX, BUSD, DAI, and GUSD	Hours (-150, -30)	Hours (-24, -24)	Mean-Adjusted Returns Model	Standard t-test, Wilcoxon Sign Rank test, and the adjusted BMP test	The market experiences downturns in the week before an issuance and generally shows positive abnormal

								returns within twenty-four hours around the issuance.
Ramos et al., (2021)	Specific cyber attacks: 51% attacks, hard forks and wallet attacks	2017, 2018, 2019, 2020	PoW cryptocurrencies	80 days prior to events	Day (-14, 5), (-5, 5), (0, 1), (0, 10)	Market Model	Standard T-test	Different types of cyber attacks have varying impacts on cryptocurrency returns, with some leading to significant negative CARs.
Chokor and Alfieri (2021)	The events that signal the likelihood of increased regulation in the cryptocurrency market	2015 – 2019	N/A	Day (-120, -5)	Day (-1, +1)	Market Model	Standard T-tests and non-parametric tests	Regulatory events generally lead to negative abnormal returns.
Almaqableh et al. (2022)	21 specific terrorist attacks	April 2013 – February 2018	100 largest cryptocurrencies	260 days prior to events	Day (-180, +180)	Market Model	Standard T-test	Terrorist attacks generally lead to positive abnormal returns.

Chapter 3: Deciphering Cryptocurrency Returns: Novel Factors and Insights

Abstract

We explore various factors aimed at capturing cross-sectional expected returns in the cryptocurrency market, utilizing a substantial sample comprising solely over 1,000 ERC-20 tokens. Beyond established factors such as size and momentum, we introduce additional factors derived from on-chain variables, including the dollar-value of transactions, transfer counts, and unique active addresses. These novel factors seek to serve as proxies for real economic activity on the blockchain and to elucidate the intrinsic values of the tokens.

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Key Words: Blockchain, Cryptocurrency, ERC-20, Factor
JEL Classification: G17, G23, P18, Q41

3.1. Introduction

Since the emergence of blockchain technology in 2008, attributed to an enigmatic figure or group known as Satoshi Nakamoto, global anticipation has surrounded its potential. Originally conceived as a decentralized ledger system to underpin the digital currency Bitcoin, blockchain has since fostered the creation of numerous cryptocurrencies in the form of tokens and coins over the past decade. A pivotal moment arrived in January 2024 when Bitcoin exchange-traded funds (ETFs) debuted on US stock exchanges, signaling a shift towards mainstream acceptance.

To ensure decentralized consensus on the blockchain, two primary consensus mechanisms have been employed to verify transactions and prevent double-spending without reliance on a central authority. The first, Proof of Work (PoW), mandates miners to contribute substantial processing power to solve complex cryptographic puzzles for transaction verification and block addition to the blockchain. In return, the successful miner is rewarded with a predetermined amount of cryptocurrency. Alternatively, Proof of Stake (PoS) selects validators for the latest block based on their staked crypto funds within the network.

These cryptocurrencies, typically hosted on their own blockchains, are generated through transaction confirmations and serve as units of account for storing value to sustain their respective blockchains. Termed "Coins," they have been instrumental in fueling blockchain ecosystems (Bariviera et al., 2017). Moreover, blockchain technology enables the decentralization of not only currency but also various scarce assets such as currencies, securities, properties, loyalty points, and gift certificates (Tapscott, 2016; Buterin, 2014). These assets can be tokenized through initial coin offerings (ICOs), akin to initial public offerings (IPOs) for stocks, atop existing blockchains. Referred to as "Tokens," they often possess utility tied to the products or services offered by a company or represent ownership stakes in a company's ventures.

Since the emergency of the cryptocurrency, research has focused on developing theoretical models of cryptocurrencies. Weber (2016) imagines a monetary system depending on Bitcoin standards and investigates the similarities and differences between the new standards and the gold standard. Even though the Bitcoin standard dominates the fiat standards, the author still believes that the cryptocurrency standard will not come into existence. Huberman et al. (2017) establish a model of the decentralized payment system of Bitcoin and find that this system can avoid monopoly pricing. They also use computational power as an exogenous variable in the model to build the equilibrium. Chiu and Koeppl (2017) consider bitcoin as a means of payment and formalize the system from the feasibility and security for example double-spending.

The primary challenge in digital record-keeping lies in establishing consensus on ledger updates (Abadi and Brunnermeier, 2018). Due to the perceived efficiency and security advantages of decentralized consensus over centralized authority, scholars explore whether decentralized consensus mechanisms can enhance social welfare and consumer surplus. Cong and He (2018) investigate blockchain mechanisms for decentralized consensus generation and explore potential economic outcomes, including market equilibria and implications for industrial organization and competition. Schilling and Uhlig (2019) model an endowment economy with competing but inherently valueless currencies (Dollar, Bitcoin), while Biais et al. (2023) analyze the proof-of-work blockchain protocol as a stochastic mining game, discussing multiple equilibria. Pagnotta and Buraschi (2018) and Pagnotta (2018) examine Bitcoin as a decentralized network asset, linking equilibrium price to demand-supply fundamentals and network security.

There is other research in cryptocurrencies from the perspective of empirical asset pricing. Liu and Tsyvinski (2021) pioneeringly conduct a comprehensive analysis of to examine cryptocurrencies' returns. They investigate how do major cryptocurrencies comove with traditional assets, macroeconomic factors, and the cryptocurrency market specific factors and conclude that the variations of crypto returns can only be explained by the crypto specific factors such as momentum and investor attention.

Our research is in the line of exploiting empirical patterns in cryptocurrencies returns. The previous empirical analyses in the pricing drivers of cryptocurrency either have small samples (Liu and Tsyvinski, 2021; Bhambhwani et al., 2019) or big samples without distinguishing between coins and tokens (Liu, Tsyvinski and Wu, 2021). Coins are usually used as a store of value, while tokens are used to power decentralized applications. Thus, the price of a coin should be driven by demand for storing value, while the price of a token is often determined by demand for utility. Since coins and tokens may share different fundamentals, we intend to apply empirical pricing research solely on crypto tokens.

The reason for choosing ERC-20 tokens is first of all, the ERC20 standard has been a dominant pathway for the creation of new tokens in the cryptocurrency space for some time. It has been particularly popular with ICOs and crowdfunding companies. There have now been tens of thousands of distinct tokens that have been issued and are operating according to the ERC20 standard. This will provide us with a large sample base. Meanwhile, ERC-20 tokens are solely issued on Ethereum blockchain, which is one of the most successful blockchain. These ERC20 tokens have well-established properties and the contract code is straightforward to read, which may reassure investors (Howell, Niessner, and Yermack, 2018).

With the support of Ethereum block scanners (i.e., Ethereum.io), we can access to the on-chain information of each ERC-20 tokens such as the dollar value of transactions, the counts of transactions and the daily active unique addresses, which may reflect the true economic activity happened on the blockchain. Thus, besides the traditional return predictors, we can construct crypto-specific predictors by using those on-chain characteristics and test the cross-sectional relationship between them and token returns. More importantly, the on-chain characteristics can be used as proxies of the intrinsic value of tokens, with which we can construct the counterpart of the value factor (BE/ME) in the equity market.

In the following sections, we begin by constructing the characteristics of ERC-20 utility tokens and assess their efficacy in elucidating cross-sectional returns within our sample. We examine a total of 19 characteristics, encompassing market-related predictors, six on-chain predictors, and two quasi-value predictors. Subsequently, we employ a zero-investment strategy, executing long-short positions based on the spread between the first and fifth quintiles for each characteristic.

Traditional asset pricing literature has extensively analyzed equity market returns, identifying several established factors for explaining cross-sectional variations in stock returns. Drawing from this literature, we select predictors that can be derived solely from market information, including price, market capitalization, and trading volume, and develop their cryptocurrency analogs. Tokens are reallocated into quintile portfolios based on a chosen predictor value every Sunday, with each quintile held for one week. We then compute the weekly value-weighted and equal-weighted time-series average excess returns over the risk-free rate for each quintile. Employing a long position in the fifth quintile and a short position in the first quintile, we calculate the risk premium of the zero-investment strategy for each cross-sectional return predictor.

Our findings reveal statistically significant long-short strategies related to size, volume, and liquidity. However, among the eight momentum predictors examined, only three exhibit significant long-short strategies associated with past two-week (r_{-2}), three-week (r_{-3}), and four-week (r_{-4}) returns.

The two quasi-value predictors serve as analogs to the widely-used book-to-market equity ratio prevalent in equity market analysis. Adopting the perspective that on-chain transactions reflect genuine economic activity occurring within the blockchain (Hubrich, 2017), we utilize the dollar value of on-chain transactions as a substitute for book equity, forming the ratio of on-chain transaction value to market capitalization (VTM). Additionally, given that tokens underpin the corresponding peer-to-peer networks, with token price positively correlated to network user base (Cong, Li, and Wang, 2018), we regard the number of active unique addresses as an approximation of the network's intrinsic value. Consequently, we construct the ratio of active unique addresses to market capitalization as another "value" predictor.

Diverging from coins, crypto tokens can be viewed as venture capital investments for projects, thus warranting treatment as assets and adherence to asset pricing principles. Consequently, in the ensuing section, we aim to assess whether a select few characteristics can encapsulate other cross-sectional predictors of token returns. Embracing the beta-pricing model, a variant of the Arbitrage Pricing Theory (APT), we proceed to construct four pricing factors: the crypto market factor, size factor, "value" factor, and momentum factor.

The crypto market factor is derived from the S&P broad index, serving as a proxy for the entire cryptocurrency market, with excess returns calculated relative to the risk-free rate ($R_{CM}-R_f$). The size factor is predicated on market capitalization, while the "value" factor is crafted using network valuation as the benchmark. Lastly, the momentum factor is based on the past two-week return ($rr-2$), chosen for its superior performance in zero-investment strategies.

To evaluate the efficacy of these crypto-specific factors, we analyze cross-sectional zero-investment premiums and conduct double-sorting on 25 Size – NTM ratio portfolios. Additionally, drawing from Huang et al. (2019), further research is undertaken to assess the fundamental momentum of on-chain variables.

Our paper proceeds as follows: Section 3.2 describes the sample data of the selected ERC-20 tokens including the characteristics of the sample distribution. Section 3.3 presents the methodology of factors' formations and zero-investment long-short strategies coupled with corresponding results. We conclude in Section 3.4.

3.2. Data

Our sample consists of all active ERC-20 utility tokens listed on Coingecko.com with an average market capitalization of over one million dollars from 2016 to the beginning of 2023. We collected data on all ERC-20 utility tokens available through the API provided by Coingecko.com. After excluding tokens with missing values and those with insufficient data periods, we retained a total of 1,020 tokens.

Using the complete list of these 1,020 tokens, we further collected data on on-chain characteristics, including the dollar value of transactions, transaction counts, the number of unique receivers, the number of unique senders, and the total number of unique addresses, from the Ethereum blockchain scanner etherscan.io. The summary statistics of all variables, as presented in Table 1, indicate a high level of skewness. Therefore, we applied winsorization to the dataset at the 1% level to limit extreme values and mitigate the potential impact of outliers.

The daily close price represents the last traded price at the end of the trading day and is commonly regarded as a reliable indicator of daily trading activity. We calculate daily returns $r_{i,t}^{D}$ using the formula:

$$r_{i,t}^{D} = \frac{p_{i,t} - p_{i,t-1}}{p_{i,t-1}} \qquad (1)$$

To mitigate volatility and noise, we further convert daily returns $r_{i,t}^{D}$ to weekly returns using the formula

$$r_{i,t}^{W} = \prod_{t}^{T}\left(1 + r_{i,t}^{D}\right) - 1 \quad (2)$$

Given the continuous trading nature of cryptocurrencies, which operate 24/7, we have devised our own week structure based on consecutive trading days rather than traditional calendar weeks. We assign week numbers based on the initial trading day of each token and increment by 1 for every subsequent Monday. This approach aligns our "weeks" more closely with the trading dynamics of cryptocurrencies, mitigating the impact of irregularities introduced by conventional weekly boundaries.

Market capitalization (*MktCap*) denotes the total market value of a cryptocurrency, calculated by multiplying the current token price by the total circulating supply. It serves as a crucial metric for evaluating the overall size of a token in the trading market. Daily trading volume (*Volume*) reflects the total value of transactions conducted within typically 24 hours, offering insights into market activity and liquidity levels.

With assistance from the Ethereum blockchain scanner, we gather on-chain data such as transaction amount (*TxAmt*), transaction counts (*TxCnt*), and daily active unique addresses (*DAU*). Transaction amount represents the value of transactions in the native token of the involved smart contract. To provide a standardized measure of economic activity on the blockchain, we compute the dollar amount of transactions (*TxUSD*) by multiplying the transaction amount by the daily price.

Expanding our analysis to include additional dimensions of on-chain economic activities, we introduce three fundamental characteristics. These encompass the ratio of the dollar amount of transactions to the number of active unique addresses (*TVU*), the ratio of transaction counts to the number of active unique addresses (*TCU*), and the ratio of the dollar amount of transactions to transaction counts (*TVC*). These ratios offer insights into various aspects of the relationship between transactional volume, user engagement, and transaction efficiency.

The relationship between firm characteristics and stock returns has been extensively explored in the stock market. Empirical studies have consistently shown that the cross-sectional pattern of stock returns can be exemplified by firm characteristics such as size, book-to-market ratio, and past returns (momentum). Fama and French (1993) posit that the correlation between these firm characteristics and their stock returns stems from size and book-to-market ratios serving as proxies for non-diversifiable factor risk. Employing a similar methodology, we aim to uncover the cross-sectional relationship between token characteristics and weekly excess returns.

Breakpoints for portfolio formation are determined using all tokens within the sample for the specified period. To ensure an adequate number of tokens in each portfolio, we divide the sample into five portfolios based on the 20th, 40th, 60th, and 80th percentiles as the portfolio breakpoints. At the conclusion of each week (t), tokens in the sample are assigned to one of the five portfolios by comparing their values with the percentile breakpoints. These sorted portfolios are constructed or rebalanced every Sunday and held without further trading for the ensuing week ($t+1$). Subsequently, one-week-ahead excess portfolio returns (r_{t+1}) are computed as the outcome variable.

3.3. Methodology and Results

In this section, we outline the formation of long-short portfolios based on selected characteristics, aiming to determine whether these portfolios can generate significant abnormal returns during the sample period. Using characteristic-based portfolio construction, we first create single-sorted long-short portfolios and then extend this approach by employing a double-sorting technique. This allows us to more thoroughly capture interactions between different factors. Following the methodology of Fama and French (1995), we assess the explanatory power of these return predictors by testing their ability to account for excess returns in the portfolios. This approach provides a robust framework for evaluating whether the identified characteristics significantly contribute to explaining the cross-sectional variation in cryptocurrency returns.

3.3.1. Size Quintile Portfolios

The size effect has long been regarded as a significant anomaly to the classic Capital Asset Pricing Model (CAPM). This phenomenon was initially documented by Banz (1981) and Reinganum (1981). While some recent empirical studies suggest that firm size may not consistently yield a risk premium, it is still commonly regarded as a proxy for risks associated with low productivity and high financial leverage (Chan and Chen, 1991). In the cryptocurrency markets, the size effect has also been observed by Liu, Tsyvinski, and Wu (2022) based on a sample comprising over 1,000 coins and tokens. In our study, we are particularly interested in evaluating the performance of the size effect within a sample exclusively composed of Ethereum-based utility tokens (ERC-20).

We refer the log value of market capitalization as size ($Size$). Table 2 displays the outcomes of weekly excess returns across size quintiles. Both value-weighted and equal-weighted weekly average returns exhibit a monotonically decreasing trend from the small size group to the large size group. The disparities in the average returns between the smallest and largest quintiles amount to 6.1% and 4.0% respectively, demonstrating statistical significance at the 1% level. This aligns with the findings of Chan and Chen (1988), indicating that size engenders a broad spread of average returns.

– Table 2 about here –

3.3.2. Volume Quintile Portfolios

We aim to explore another sorting variable: daily trading volume, which quantifies the daily trading volume in USD. Chordia, Subrahmanyam, and Anshuman (2000) regarded trading volume as a measure of liquidity, a notion further investigated in the cryptocurrency market by researchers such as Liu, Tsyvinski, and Wu (2022). The volume variable is indicative of token liquidity, where higher trading volume signifies greater liquidity and reduced exposure to liquidity-related risks.

We construct quintile portfolios based on the log value of volume variable and present the time-series weekly excess returns in Table 3. The value-weighted returns consistently rise from the 1st quintile (low-volume portfolio) to the 5th quintile (high-volume portfolio). The average excess returns across different portfolios suggest that the low-volume portfolio outperforms the high-volume portfolio in terms of future returns.

The findings outlined in Table 3 reveal that both value-weighted and equal-weighted weekly average excess returns decline from the lowest volume quintile portfolio to the highest quintile portfolio. The disparities in average returns between the lowest and highest quintiles amount to 2.9% and 3.9% respectively, demonstrating significance at the 1% level.

– Table 3 about here –

3.3.3. Momentum Quintiles Portfolios

Since Jegadeesh and Titman (1993) first observed the tendency for stocks that performed well in previous months to continue performing well in subsequent months, the momentum effect has garnered significant attention in financial markets. Investigating whether a similar phenomenon exists in the cryptocurrency market is another key objective of this research.

The results presented in Table 4 reveal that the past one-week (r_{-1}), two-week (r_{-2}), three-week (r_{-3}), and four-week (r_{-4}) momentum quintile portfolios exhibit average excess returns that are nearly monotonic across the quintiles. All three momentum predictors demonstrate statistically significant positive returns for zero-investment strategies, where winners are longed, and losers are shorted.

– Table 4 about here –

3.3.4. Liquidity Quintile Portfolios

One of the key assumptions of CAPM is that all securities are perfectly liquid. However, Amihud and Mendelson (1989) demonstrated that the level of liquidity, measured using the bid-ask spread, exhibits a positive cross-sectional relation with future stock returns after controlling for other related variables. In our study, we also employ the liquidity measure developed by Amihud (2002), which offers the advantage of requiring only return and trading volume data for calculation.

This measure, which actually quantifies illiquidity, operates on the premise that higher values indicate lower liquidity. Its underlying concept is to estimate the extent to which returns are influenced by trading volume. If a security generates a certain absolute return from a large trading volume, it is relatively liquid. Conversely, if a security realizes a large absolute return on a small trading volume, it is deemed illiquid, as even a small volume of trading can substantially impact its price. The formula for illiquidity is defined as follows:

$$Illiquidity_t = \frac{1}{D}\sum_{d=1}^{D}\frac{|R_{i,d}|}{Volume_{i,d}} \tag{3}$$

In this formula, $R_{i,d}$ represents the daily return of security i, the denominator $Volume_{i,d}$ denotes the USD volume of security *i* traded at day *d*, and *D* represents the number of days used as the estimation period. In our calculation, we use *D=7* days, implying that the current illiquidity equals the average illiquidity of the previous 7 days.

Table 5 presents the time-series average excess returns. Both the value-weighted and equal-weighted excess returns of the low-liquidity quintile portfolio (I5) surpass those of the high-liquidity quintile portfolio (I1).

– Table 5 about here –

3.3.5. On-Chain Quintile Portfolios

In addition to market-related predictors, we have gathered data on three on-chain characteristics — namely, the dollar value of on-chain transactions (*TxUSD*), transaction counts (*TxCnt*), and the number of active unique addresses (*DAU*) from the Ethereum blockchain scanner. We then utilize the logarithm of these characteristics to construct quintile portfolios.

Tables 6 to 8 reveal that the observed patterns are consistently and mostly monotonic, with average weekly excess returns declining from the lower quintile portfolios to the higher quintile portfolios. This implies that tokens exhibiting lower log values of on-chain characteristics tend to exhibit greater exposure to underlying risk factors and consequently show higher excess returns. We find that only the dollar-value transactions quintile portfolios demonstrate a significant value-weighted return of 1.2% for the zero-investment strategy (see Table 6). However, when focusing on equally weighted returns we find that the dollar-value as well as count transactions and daily active user addresses quintile portfolios show a significant return of 2.7%, 1.5% and 1.2% return for the zero-investment strategies (see Tables 6 to 8)

– Tables 6, 7 and 8 about here –

To delve deeper into on-chain activities, we derive additional fundamental characteristics by formulating ratios that encompass various dimensions of on-chain economic activities. The ratio of dollar amount of transactions over the number of active unique addresses (*TVU*) serves as an indicator of the average transaction value per active unique address, offering insights into the average economic activity or transaction value associated with each user. A higher ratio may indicate more substantial economic activity per user, while a lower ratio could suggest smaller transaction sizes but potentially higher user engagement.

Similarly, the ratio of transaction count over the number of active unique addresses (*TCU*) reflects the average number of transactions per active unique address, providing an indication of the level of transactional activity per user. A higher ratio may imply more active participation from each user, while a lower ratio could suggest less frequent interaction. Lastly, the ratio of dollar amount of transactions over transaction counts offers insights into the efficiency or size of transactions on the network. A higher ratio may indicate larger individual transactions, whereas a lower ratio could suggest smaller but possibly more frequent transactions. By creating these normalized ratios, we aim to contextualize raw on-chain data by considering the number of active unique addresses, thereby enhancing our understanding of users' economic activities and behaviors in relation to specific on-chain metrics.

Upon constructing quintile portfolios based on these three ratios, we observe consistent monotonic patterns in excess portfolio returns across Tables 9, 10, and 11. Notably, average weekly excess returns demonstrate a discernible decline across quintile portfolios, indicating a consistent inverse relationship between the analyzed ratios and return performance over weekly intervals. With the exception of *TCU*, both *TVU* and *TVC* ratios exhibit statistically significant value-weighted long-short returns.

– Tables 9, 10 and 11 about here –

3.3.6. Quasi Value Quintile Portfolios

In traditional asset pricing factor models, the *value factor* holds significant importance in fundamental valuation. It serves to assess whether the market value of an asset is accurately reflected or mispriced by the market. Unlike traditional assets, cryptocurrencies lack conventional cash flows, posing a challenge in determining their fair value.

To address this challenge, Hubrich (2017) introduces a quasi-value factor, which is the ratio of on-chain dollar amount of transactions (*V*) to the current market capitalization (*M*). This ratio leverages the dollar value of on-chain transactions as a potential proxy for the actual economic activity facilitated by the blockchain. Hubrich contends that the "fair" value could be inferred from the value of daily on-chain transactions. Moreover, the time-series behavior of VTMs for sample cryptocurrencies suggests frequent mean-reverting, indicating market tendencies to under- or overestimate their "fair values."

In our study, we replicate this cross-sectional excess predictor using on-chain transaction volume data collected from etherscan.io. Tokens with high VTM ratios are perceived as undervalued, with higher expected returns compared to tokens with low VTM ratios. We establish breakpoints based on the z-score of VTM to construct quintile portfolios. Surprisingly, the results in Table 12 deviate from expectations, with return differences between high and low quintiles proving insignificant.

– Table 12 about here –

Network economics plays a pivotal role in understanding the adoption dynamics of technologies such as the internet and social media. Sarnoff's law posits that the value of a broadcast network is directly proportional to its viewership, while Metcalfe's law suggests a nonlinear increase in network value as more users join. Reed (2001) expands on this concept by highlighting the exponential growth in network utility, surpassing mere user or connection count.

Blockchain technology offers a decentralized communication model, facilitating peer-to-peer interactions without central servers. ERC-20 tokens, adhering to the "ERC20" scripting standard, operate exclusively within this framework. Cong, Li, and Wang (2018) develop a dynamic model of cryptocurrencies, establishing a positive relationship between user base and token price. Increased user base enhances transaction liquidity, elevating platform utility and consequently, token value.

Drawing on the network effect theorem, we employ the number of active addresses as a proxy for "fair value," constructing a value factor represented by the ratio of active addresses (N) to market capitalization (M). Tokens with promising prospects, evidenced by high market value per active address and low *NTM* ratios, are expected to yield lower returns compared to tokens with high *NTM* ratios indicating poorer prospects.

The results in Table 13 align with expectations. Both value- and equal-weighted analyses demonstrate lower expected excess returns for low *NTM* ratio quintiles compared to high ratio quintiles, with significant positive returns observed for zero-investment strategies. Results from double-sorting portfolios in Table 14 further corroborate these findings, indicating consistent patterns across *NTM* and *Size* quintiles. This suggests that size and *NTM* ratio serve as relatively independent proxies for underlying state variables in the crypto market.

– Tables 13 and 14 about here –

3.3.7. Fundamental Momentum

Cochrane (2011) highlights the potential of expected fundamentals in forecasting future stock returns, grounded in the idea that anticipated fundamentals significantly shape asset prices and, consequently, expected returns. As future expected fundamentals $F_{i,t+1}$ remain unobservable, historical fundamental values and their trends, captured by moving averages (MAs), serve as proxies for these future expectations.

The incorporation of MAs enables the model to capture historical momentum in fundamentals, potentially containing insights into future expected values. While historical values themselves may not directly impact expected returns, they are believed to reflect aspects of unobservable future expectations. Thus, utilizing MAs facilitates the integration of both current fundamental value and its historical momentum, offering a comprehensive representation of expected fundamentals and their potential influence on expected returns.

Prior financial literature often emphasizes price momentum (Huang et al., 2019), which focuses on historical price movements' ability to forecast future stock returns. This concept suggests that stocks demonstrating strong past performance are likely to continue performing well, and vice versa. In contrast, fundamental momentum pertains to historical patterns or momentum observed in a stock's fundamental values.

The rationale behind fundamental momentum lies in the belief that historical fundamental patterns may contain insights into future expected fundamentals, subsequently impacting expected returns. In our study, we adopt the methodology developed by Huang et al. (2019) to investigate the predictive power of token fundamentals.

Cochrane (2011) posits that expected fundamentals play a significant role in predicting future stock returns. The relationship is expressed as:

$$E_t[r_{i,t+1}] = \alpha_{i,t+1} + \beta E_t[F_{i,t+1}] \tag{4}$$

where $E_t[F_{i,t+1}]$ represents the market's expectation regarding future fundamentals, and β is the sensitivity coefficient of expected returns to expected fundamentals. The aim is to estimate $E_t[r_{i,t+1}]$ by integrating current and past fundamental information.

The term $E_t[F_{i,t+1}]$ captures the market's expectation about future fundamental changes, albeit unobservable. To address this, we follow Huang et al. (2019) by using the moving average (MA) of historical fundamentals as a proxy for

$$E_t\left[F_{i,t+1}\right] = MA_{i,t,L} \quad w.r.t. \;\; MA_{i,t,L} = \frac{F_{i,t} + F_{i,t-1} + \cdots + F_{i,t-L+1}}{L} \tag{5}$$

The methodology indirectly incorporates information about future expectations by leveraging historical trends as proxies, facilitating a comprehensive assessment of factors influencing expected returns.

To ascertain the appropriate value for L, we conduct tests across multiple short-term (L=1, 2, 4) and long-term (L=26, 52, 104 weeks) momentum measures. Additionally, we incorporate various token fundamentals, such as Dollar Value Transactions (*TxUSD*), Counts of Transactions (*TxCnt*), Daily Active Unique Address (*DAU*), and other blockchain-related metrics. These metrics offer insights into the activity level and efficiency of the blockchain ecosystem, positioning our research at the forefront of fundamental momentum analysis for tokens.

In our methodology, we estimate β through cross-sectional regressions of each token return $r_{i,t}$ on both short-term (ST) and long-term (LT) fundamental momentums:

$$r_{i,t}(ST) = \alpha_t^f + \sum_{L=1,2,4} \beta_{L,t}^f MA_{i,t-1,L}^f + \varepsilon_{i,t} \tag{6}$$

and

$$r_{i,t}(LT) = \alpha_t^f + \sum_{L=26,52,104} \beta_{L,t}^f MA_{i,t-1,L}^f + \varepsilon_{i,t} \tag{7}$$

The coefficients $\beta_{L,t}^f$ represent the impact of lagged fundamental variables $MA_{i,t-1,L}^f$ on current token returns at time t. These coefficients are estimated using data up to time t−1, without explicitly including the current fundamental value at time t.

In the next step, these coefficients are used to forecast the expected return for the next period,

$E_t\left[F_{i,t+1}\right]$, represented by Token's Fundamental Implied Return $TFIR_{i,t}^{f}$:

$$TFIR_{i,t}^{f} = \sum_{L=1,2,4} E_t\left[\beta_{L,t+1}^{f}\right] MA_{i,t,L}^{f} \tag{8}$$

and

$$TFIR_{i,t}^{f} = \sum_{L=26,52,104} E_t\left[\beta_{L,t+1}^{f}\right] MA_{i,t,L}^{f} \tag{9}$$

As true coefficients for time t+1 are not available, we employ estimated coefficients as proxies. This forecasting approach leverages information up to time t−1, effectively addressing concerns related to future information usage and avoiding look-forward biases. Subsequently, we construct long-short quintile portfolios based on *TFIR* to assess risk premiums.

The results, presented in Table 15, highlight that among the short-term fundamental implied returns, only the historical trend of the fundamental *TVC* (Dollar Amount of Transactions per Transaction Count) exhibits both monotonic returns and a significant long-short premium within quintile portfolios. In contrast, findings from Table 16 concerning long-term fundamental implied returns unveil divergent behavior for *DAU* (Daily Active Unique Address) and *TCU* (Transfer Count per Unique Address) compared to short-term fundamental momentum. Specifically, *DAU* and *TCU* demonstrate opposing monotonic returns, with a negative long-short premium observed when longing high fundamental quintile portfolios and shorting low quintile portfolios.

– Table 15 and 16 about here –

3.3.8. Factors Returns and Factor Regressions

One of the objectives of this study is to evaluate the performance of cryptocurrency-specific factors, which correspond to the most extensively researched pricing factors in the equity market, including size, value, and momentum factors. Following the framework outlined by Fama and French (2015), we derive factors through independent *2×3* sorts by intersecting size with quasi value (*NTM*) and momentum, respectively.

Each Sunday of week *t*, all tokens are divided into two groups based on size—small (S) and big (B)—and further classified independently into three groups based on volume—low (L), median (M), and high (H). By taking intersections, we create six *Size–NTM* portfolios. Weekly value-weighted portfolio returns are then computed for the subsequent week *t+1*, and the portfolios are rebalanced on the following Sunday of week *t+1*. Subsequently, the Network/ME factor (*TNTM*) return is calculated as the average of the returns of the two high *NTM* ratio portfolios (*SH*, *BH*) minus the average of the returns of the two low *NTM* ratio portfolios (*SL*, *BL*):

$$TNTM = \frac{SH + BH}{2} - \frac{SL + BL}{2} \tag{10}$$

Finally, the size factor (*TSMB*) is the average return of six small portfolios minus the average return of the six big portfolios:

$$TSMB = \frac{SL + SM + SH + SL + SM + SW}{6} - \frac{BL + BM + BH + BL + BM + BW}{6} \tag{11}$$

Table 17 presents the summary statistics of the time-series factor returns. It is evident that all three factors—*TSMB*, *TNTM*, and *TMOM*—exhibit statistically significant results at conventional levels, further affirming their significance in our analysis.

– Table 17 about here –

3.3.9. Testing Long-Short Strategy Premiums

In this sub-section, we assess the efficacy of the four crypto-specific factors in pricing seven cross-sectional zero-investment strategies. Our analysis underscores the pivotal role of the size factor (*TSMB*) in mitigating pricing errors across multiple long-short strategies (see Table 18). Specifically, the incorporation of the size factor leads to insignificant alphas for strategies involving Volume, Illiquidity, and three on-chain variables (*TxUSD*, *TVU*, and *TVC*).

The positive and significant coefficients associated with the size factor (*TSMB*) and the "value" factor (*TNTM*) indicate that tokens with low trading volume and liquidity issues tend to exhibit smaller size and distress, as indicated by the *NTM* ratio. However, the coefficients of *TNTM* are found to be insignificant for both volume and illiquidity premiums (see Table 18).

While most coefficients of the crypto-market factor $(R_{CM} - R_f)$ in Table 18 are either insignificant or only marginally significant, this outcome can be attributed to the zero-investment strategy's effectiveness in eliminating the common component related to the entire market through the long fifth quintile portfolio and short first quintile portfolio.

Despite the inclusion of the four-factor model, it falls short of fully explaining the return premiums of the other five strategies. Particularly noteworthy is the momentum factor (*TMOM*), which demonstrates no pricing power for the size strategy. Despite highly significant coefficients in the regressions of all momentum strategies, it fails to eliminate pricing errors and render the alphas insignificant. This disparity in results may potentially be attributed to extreme values, particularly in the early sample period when the limited number of tokens in each quintile portfolio led to less diversified portfolios.

– Table 18 about here –

3.3.10. Testing 25 Size-NTM Portfolios

In this sub-section, we investigate whether the three factors established in the previous section adequately price all the excess returns of the 25 *Size-NTM* portfolios. Following the approach outlined by Fama and French (1996), we conduct regressions of the time-series portfolios' excess returns on the returns of factor mimicking portfolios. If the factors effectively capture the expected returns of portfolios, the time-series regression intercepts should approximate 0.

Our regression analysis aims to ascertain whether the risk factors formulated in the previous section encapsulate the cross-sectional variation of the ERC-20 utility tokens' average excess returns. In Table 19, we present the results of the regression model (12) for the 25 *Size – NTM* portfolios on the broad cryptocurrency market excess return.

$$R(t) - R_f(t) = a + b\left[R_M(t) - R_f(t)\right] + e(t) \tag{12}$$

The highly significant coefficient values of b underscore a robust explanatory power of the cryptocurrency market factor on the LHS portfolios. However, despite this, the market factor leaves certain variations in portfolio excess returns unexplained, as evidenced by the significant values of most intercepts. For instance, the portfolio with the smallest size and highest NTM ratio exhibits a notably significant intercept of 11.6% with a *t*-statistic of 8.13.

– Table 19 about here –

By incorporating the size factor (*TSMB*), "value" factor (*TNTM*), and momentum factor (*TMOM*), we employ the four-factor regression model (13) for all 25 portfolios and present the results in Table 20.

$$R(t) - R_f(t) = a + b\left[R_M(t) - R_f(t)\right] + sTSMB(t) + nTNTM(t) + mTMOM(t) + e(t) \tag{13}$$

Most portfolios exhibit significant size factor coefficients, denoted as s, and "value" factor coefficients, denoted as n. As anticipated, portfolios in the smaller size groups (S_1, S_2 and S_3) tend to display higher and positive size coefficients compared to those in the larger size groups (S_4 and S_5), reflecting the greater exposure of the smaller size portfolios to the size factor. Similarly, given that high *NTM* ratio portfolios exhibit higher exposure to the "value" factor than low *NTM* ratio portfolios, we observe a growth pattern of "value" factor coefficients from the low *NTM* quintile to the high quintile.

Upon comparing the intercepts in Table 20 with those in Table 19, it becomes evident that the majority of intercepts in Table 20 are insignificant. Moreover, with higher average R^2 values and lower Root MSEs, the four-factor model demonstrates superior pricing power on the 25 Size-NTM portfolios compared to the one-factor model. However, some portfolios in the small size and high NTM ratio groups still exhibit significant intercepts.

– Table 20 about here –

3.4. Conclusion

This research paper delves into the intricate landscape of cryptocurrencies, specifically focusing on the distinctions between crypto-coins and crypto-tokens, with a primary emphasis on ERC-20 utility tokens within the Ethereum blockchain. By examining a comprehensive set of 19 return predictors — encompassing market-related variables, on-chain activity metrics, and quasi-value proxies — this study sheds light on the cross-sectional return patterns in cryptocurrency markets.

The paper introduces a novel pricing-factor model inspired by Fama and French (1996), tailored to the unique characteristics of cryptocurrencies. Notably, the quasi-value factors, *VTM* and *NTM*, stand out as innovative approaches to capture the intrinsic value of tokens, shedding light on the economic activity facilitated by blockchain technology. Furthermore, the research provides a robust methodology, employing a zero-investment strategy and evaluating the performance of crypto-specific factors through cross-sectional zero-investment premiums and double-sorting portfolios.

Our findings reveal several return predictors that exhibit statistically significant long-short premiums. Notably, size, volume, and liquidity predictors display consistent and significant premiums across quintile portfolios, underscoring their importance in explaining cryptocurrency returns. Among the eight momentum predictors analyzed, only the past two-week, three-week, and four-week returns demonstrate significant long-short strategies, highlighting the short-term nature of momentum effects in cryptocurrency markets

For the quasi-value predictors serving as proxies for intrinsic value, while the VTM-based portfolios yield insignificant differences between high and low quintiles, the NTM ratio emerges as a robust predictor, producing significant positive returns in zero-investment strategies and maintaining consistency across double-sorting portfolios based on size and NTM. These findings suggest that network activity, as captured by on-chain metrics, plays a critical role in cryptocurrency valuation.

Building on these predictors, we develop crypto-specific factors, including the crypto-market factor, size factor (TSMB), quasi-value factor (TNTM), and momentum factor (TMOM), to explain the cross-sectional variation in token returns. The four-factor model demonstrates significant explanatory power, particularly for the size and NTM factors, as evidenced by the regression tests on long-short strategy premiums and 25 size-NTM portfolios. The inclusion of size and quasi-value factors significantly reduces pricing errors for strategies involving volume, illiquidity, and on-chain metrics, while the momentum factor exhibits limited pricing power, particularly for the size-based strategies.

Empirical results from the 25 size-NTM portfolios further validate the model, with most intercepts becoming insignificant upon incorporating the size, NTM, and momentum factors, thereby enhancing the model's pricing accuracy. However, some portfolios, particularly those in the small size and high NTM ratio groups, continue to display significant intercepts, indicating potential areas for future refinement.

In summary, this chapter provides empirical evidence that market-related predictors, on-chain activity metrics, and quasi-value proxies are critical in deciphering cryptocurrency returns. The developed crypto-specific factors, particularly size and NTM, offer substantial explanatory power for cross-sectional return variations, contributing to the broader asset pricing literature in digital finance. These findings not only enhance our understanding of cryptocurrency pricing mechanisms but also offer a robust framework for future research exploring the dynamic interplay between market fundamentals and blockchain-based economic activities.

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Table 3. 1: Summary Statistics for Ethereum-based tokens (ERC-20) Utility Tokens

This table provides a comprehensive overview of summary statistics for a sample comprising 1,020 ERC-20 utility tokens. Encompassing data from 2016 to 2022, inclusive, the sample includes ERC-20 tokens with market values exceeding 1 million. Panel A presents the annual mean, standard deviation (Std) and median for the market-related variables: $MktCap$ (market capitalization in millions) and $Volume$ (trading volume in millions); Panel B presents the annual summary statistics including mean, standard deviation (Std) and median for the three on-chain variables: $TxUSD$ (dollar value of transactions in millions), $TxCnt$ (transaction counts) and DUA (unique active addresses). Panel C presents a more complete summary statistics for both market-related and on-chain variables for the entire sample period. The summary statistics includes the mean (mean), standard deviation (Std), skewness (skew), kurtosis (kurt), minimum (min), 5^{th} percentile (5%), 25^{th} percentile (25%), median (median), 75^{th} percentile (75%), 95^{th} percentile (95%), and maximum (max) values. The variables also include r^D (daily returns in percentage) and r^W (weekly returns in percentage).

Panel A

Year	Number of Tokens	MktCap (Millions)			Volume (Millions)		
		Mean	Std	Median	Mean	Std	Median
2016	7	10.61	7.82	8.56	0.07	0.07	0.06
2017	77	105.65	123.44	69.62	4.90	8.86	1.86
2018	184	79.04	152.09	22.65	4.76	11.64	0.88
2019	233	46.66	221.50	6.97	5.39	19.32	0.69
2020	423	60.96	255.51	8.07	12.35	57.25	0.92
2021	831	291.86	2233.99	33.46	28.12	137.12	1.73
2022	1015	181.36	1776.54	14.80	12.10	63.20	0.56
2023	1015	127.12	1465.22	7.90	5.73	32.15	0.21

Panel B

Year	Number of Tokens	$TxUSD$ (Millions)			$TxCnt$			DUA		
		Mean	Std	Median	Mean	Std	Median	Mean	Std	Median
2017	72	3.47	4.82	0.91	551	704	391	447	537	309
2018	180	1.15	2.21	2.30	220	394	103	155	251	84
2019	260	0.66	2.30	0.36	183	557	52	93	215	37
2020	474	22.41	398.94	0.08	428	1149	94	194	498	61
2021	891	16.22	157.23	0.28	350	1231	95	197	753	63
2022	1,014	3.73	26.99	1.18	222	2056	35	111	1030	25
2023	971	0.91	5.65	0.22	204	3086	21	110	1558	16

Panel C

	Number of Tokens	Mean	Std	Skew	Kurt	Min	Q5	Q25	Median	Q75	Q95	Max
r^D	1020	0.13	0.74	8.63	153.75	-2.53	-0.62	-0.16	0.10	0.32	0.94	14.69
r^W	1020	0.62	3.65	1.47	10.53	-16.85	-4.43	-1.30	0.52	2.05	6.43	31.12
MktCap (Millions)	1020	139.96	849.73	20.33	516.64	0.06	1.37	6.38	18.51	62.54	430.05	23058.52
Volume (Millions)	1020	13.63	58.39	9.13	103.15	0.00	0.03	0.26	1.02	5.15	47.70	891.07
TxUSD (Millions)	1020	7.87	98.65	29.80	929.67	0.00	0.02	0.15	0.54	1.79	18.12	3099.41
TxCnt	1020	286	2023	28	833	0	4	24	68	180	831	61991
DAU	1020	149	1028	28	841	0	3	17	43	108	425	31553

Table 3. 2: Size Quintile Portfolios

This table presents the time-series averages of weekly value-weighted and equal-weighted excess returns for all size (log value of Market Capitalization) quintile portfolios throughout the entire sample period from 2016 to 2022, along with the return differences obtained by longing the small size portfolio and shorting the large size portfolio. Every Sunday, tokens are reallocated to five size groups (from small to big), with each group being held for one week. Statistical significance levels are denoted by ***, **, and *, indicating significance at the 1%, 5%, and 10% levels, respectively.

		Small	**2**	**3**	**4**	**Large**	**Small - Large**
Size Portfolios							
Value Weighted	**Mean**	0.057^{***}	0.012	0.012	0.007	-0.004	0.061^{***}
	t-value	(5.66)	(1.44)	(1.40)	(0.84)	(-0.56)	(8.15)
Equally Weighted	**Mean**	0.022^{**}	-0.015^{*}	-0.012	-0.013	-0.018^{**}	0.040^{***}
	t-value	(2.55)	(-1.93)	(-1.48)	(-1.58)	(-2.31)	(6.24)

Table 3. 3: Volume Quintile Portfolios

This table presents the time-series averages of weekly value-weighted and equal-weighted excess returns for all volume (log value of trading volume) quintile portfolios throughout the entire sample period from 2016 to 2022. The results show the time-series averages of weekly value-weighted and equal-weighted returns and the return difference by long low volume portfolio and short high-volume portfolio. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

		Low	**2**	**3**	**4**	**High**	**Low - High**
Volume Portfolios							
Value Weighted	**Mean**	0.020^{**}	0.010	0.008	0.003	-0.009	0.029^{***}
	t-value	(2.11)	(1.18)	(0.94)	(0.42)	(-1.22)	(3.93)
Equally Weighted	**Mean**	0.014^{*}	-0.004	-0.007	-0.013^{*}	-0.025^{***}	0.039^{***}
	t-value	(1.69)	(-0.45)	(-0.89)	(-1.72)	(-3.20)	(6.09)

Table 3. 4: Momentum Quintile Portfolios

This table reports the univariate portfolio analysis results based on multiple momentum strategies including past one-week r_{-1}, two-week r_{-2}, three-week r_{-3}, four-week r_{-4}, eight-week r_{-8}, half-year (26 weeks r_{-26}), one-year (52 weeks r_{-52}) and two-year (104 weeks r_{-104}) returns. The time-series of weekly value-weighted and equal weighted returns are presented from Panel A to Panel H, respectively. The return differences by long winner portfolio and short loser portfolio are reported in the last column. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Momentum Portfolios		**Loser**	**2**	**3**	**4**	**Winner**	**Winner - Loser**
Panel A: One Week							
Value-Weighted	**Mean**	-0.005	-0.003	0.003	0.007	0.006	0.011
	t-value	(-0.60)	(-0.41)	(0.39)	(0.80)	(0.74)	(1.46)
Panel B: Two Weeks							
Value Weighted	**Mean**	-0.001	0.001	-0.001	0.003	0.016*	0.017**
	t-value	(-0.16)	(0.07)	(-0.08)	(0.32)	(1.76)	(2.15)
Panel C: Three Weeks							
Value Weighted	**Mean**	-0.004	-0.002	0.006	0.001	0.012	0.016**
	t-value	(-0.48)	(-0.22)	(0.68)	(0.16)	(1.36)	(2.18)
Panel D: One Month							
Value Weighted	**Mean**	-0.002	-0.005	0.002	0.001	0.013	0.016**
	t-value	(-0.30)	(-0.65)	(0.29)	(0.11)	(1.49)	(2.16)
Panel E: Two Months							
Value Weighted	**Mean**	0.005	0.000	0.009	-0.001	0.003	-0.003
	t-value	(0.65)	(0.01)	(1.06)	(-0.15)	(0.31)	(-0.34)
Panel F: Half-Year							
Value Weighted	**Mean**	0.000	0.000	-0.012	-0.001	0.000	0.000
	t-value	(-0.02)	(0.03)	(-1.52)	(-0.10)	(-0.01)	(0.02)
Panel G: One Year							
Value Weighted	**Mean**	-0.006	-0.008	-0.006	0.003	-0.007	-0.002
	t-value	(-0.77)	(-0.92)	(-0.63)	(0.25)	(-0.81)	(-0.19)
Panel H: Two Years							
Value Weighted	**Mean**	-0.011	-0.003	-0.006	−0.017**	-0.011	0.000
	t-value	(-1.33)	(-0.31)	(-0.68)	(-2.11)	(-1.33)	(-0.05)

Table 3. 5: Illiquidity Quintiles Portfolios

This table reports the mean of time-series weekly returns of illiquidity quintiles. The value of illiquidity equals to the results of the equation: $Illiquidity_t = \frac{1}{D}\sum_{d=1}^{D}\frac{|R_{i,d}|}{Volume_{i,d}}$. The results include the time-series averages of weekly value-weighted and equal-weighted excess returns for all illiquidity quintile portfolios over the entire sample period from 2016 to 2022 and the return differences by long low illiquidity portfolio (I5) and short high illiquidity (or liquidity) portfolio (I1). On every Sunday, all ERC-20 tokens are re-allocated to five illiquidity groups (Low to High). Each group is held for one week. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

		Liquidity(I1)	I2	I3	I4	Illiquidity(I5)	I5 – I1
Illiquidity Portfolios							
Value Weighted	**Mean**	0.004	0.004	0.011	0.014	0.027***	0.022***
	t-value	(0.55)	(0.51)	(1.32)	(1.58)	(2.80)	(3.27)
Equally Weighted	**Mean**	0.013*	0.010	0.013*	0.018**	0.044***	0.031***
	t-value	(1.76)	(1.31)	(1.75)	(2.34)	(4.89)	(4.72)

Table 3. 6: Dollar Value Transactions (*TxUSD*)

This table reports the univariate portfolio analysis results of log value of on-chain dollar-value transactions (*TxUSD*). The results show the time-series averages of weekly value-weighted and equal-weighted returns and the return difference by long the low transaction quintile portfolio (the 1st quintile) and short the high transaction quintile portfolio (the 5th quintile). ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

		Low	2	3	4	High	Low - High
Ln (TxUSD)							
Value Weighted	**Mean**	0.009	0.004	0.007	0.006	-0.004	0.012**
	t-value	(1.07)	(0.44)	(0.73)	(0.66)	(-0.45)	(2.11)
Equally Weighted	**Mean**	0.030***	0.019**	0.019**	0.013	0.003	0.027***
	t-value	(3.80)	(2.38)	(2.12)	(1.54)	(0.40)	(5.72)

Table 3. 7: Counts of Transactions (*TxCnt*)

This table reports the univariate portfolio analysis results based on log value of the counts of on-chain transactions (*TxCnt*). The results show the time-series averages of weekly value-weighted and equal-weighted returns and the return difference by long the low transaction quintile portfolio (the 1st quintile) and short the high transaction quintile portfolio (the 5th quintile). ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

		Low	2	3	4	High	Low - High
Ln (TxCnt)							
Value Weighted	**Mean**	0.003	0.008	0.003	-0.001	-0.002	0.005
	t-value	(0.33)	(0.90)	(0.38)	(-0.12)	(-0.26)	(0.85)
Equally Weighted	**Mean**	0.022***	0.024***	0.020**	0.012	0.007	0.015***
	t-value	(2.93)	(2.95)	(2.21)	(1.40)	(0.85)	(3.31)

Table 3. 8: Daily Active Unique Address (*DAU*)

This table reports the univariate portfolio analysis results based on log value of the number of daily active unique address (*DAU*). The results show the time-series averages of weekly value-weighted and equal-weighted returns and the return difference by long the low transaction quintile portfolio (the 1st quintile) and short the high transaction quintile portfolio (the 5th quintile). ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

		Low	2	3	4	High	Low - High
ln *DAU*							
Value Weighted	**Mean**	0.007	-0.001	0.005	-0.003	-0.001	0.001
	t-value	(0.86)	(-0.12)	(0.60)	(-0.36)	(-0.18)	(1.50)
Equally Weighted	**Mean**	0.022***	0.019**	0.021**	0.010	0.010	0.012**
	t-value	(3.02)	(2.32)	(2.30)	(1.16)	(1.25)	(2.46)

Table 3. 9: *TVU* Quintile Portfolios

This table reports the univariate portfolio analysis results of *TVU* (Dollar Amount of Transactions/Number of Active Unique Addresses). The results show the time-series averages of weekly value-weighted and equal-weighted returns and the return difference by long the low *TVU* quintile portfolio (the 1st quintile) and short the high *TVU* quintile portfolio (the 5th quintile). ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

		Low	2	3	4	High	Low - High
TVU							
Value Weighted	**Mean**	0.008	0.006	0.012	-0.002	-0.004	0.012**
	t-value	(0.94)	(0.71)	(1.26)	(-0.19)	(-0.54)	(2.09)
Equally Weighted	**Mean**	0.031***	0.021***	0.018**	0.008	0.004	0.028***
	t-value	(3.84)	(2.69)	(2.02)	(1.00)	(0.47)	(5.55)

Table 3. 10: TCU Quintile Portfolios

This table reports the univariate portfolio analysis results of *TCU* (Transaction Counts/Number of Active Unique Addresses). The results show the time-series averages of weekly value-weighted and equal-weighted returns and the return difference by long the low *TCU* quintile portfolio (the 1st quintile) and short the high *TCU* quintile portfolio (the 5th quintile). ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

		Low	2	3	4	High	Low - High
TCU							
Value Weighted	**Mean**	0.003	0.006	0.000	-0.006	0.000	0.003
	t-value	(0.37)	(0.67)	(-0.02)	(-0.71)	(-0.01)	(0.48)
Equally Weighted	**Mean**	0.021***	0.025***	0.018**	0.011	0.008	0.013**
	t-value	(2.81)	(2.87)	(2.04)	(1.44)	(0.98)	(2.43)

Table 3. 11: TVC Quintile Portfolios

This table reports the univariate portfolio analysis results of *TVC* (Dollar Amount of Transactions/Transaction Counts). The results show the time-series averages of weekly value-weighted and equal-weighted returns and the return difference by long the low *TVC* quintile portfolio (the 1st quintile) and short the high *TVC* quintile portfolio (the 5th quintile). ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

		Low	2	3	4	High	Low - High
TVC							
Value Weighted	**Mean**	0.011	0.010	0.011	0.008	-0.007	0.017***
	t-value	(1.20)	(1.08)	(1.26)	(0.73)	(-0.84)	(3.11)
Equally Weighted	**Mean**	0.033***	0.021**	0.015*	0.012	0.004	0.029***
	t-value	(3.97)	(2.55)	(1.85)	(1.25)	(0.53)	(6.29)

Table 3. 12: *VTM* Quintile Portfolios

This table reports the univariate portfolio analysis results of *VTM* variable, which is defined as the z-score of the ratio of the trailing 7-day average of dollar-valued on-chain transactions current market capitalization. The results include the time-series averages of weekly value-weighted and equal-weighted excess returns for all the *VTM* quintile portfolios over the entire sample period from 2016 to 2022 and the return differences by long low *VTM* portfolio and short high *VTM* portfolio. Every Sunday, all ERC-20 tokens are re-allocated to five *VTM* groups (Low to High). Each group is held for one week. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

		Low	2	3	4	High	High - Low
VTM							
Value Weighted	**Mean**	0.002	0.001	-0.002	0.003	-0.005	-0.007
	t-value	(0.19)	(0.09)	(-0.30)	(0.41)	(-0.64)	(-1.23)
Equally Weighted	**Mean**	-0.007	-0.004	-0.001	-0.003	-0.010	-0.003
	t-value	(-0.91)	(-0.46)	(-0.10)	(-0.32)	(-1.23)	(-0.77)

Table 3. 13: *NTM* Quintile Portfolios

This table reports the univariate portfolio analysis results of the *z*-score of *NTM* variable (Network to Market Cap). The network equals the previous 7-days average number of unique active addresses. The results include the time-series averages of weekly value-weighted and equal-weighted excess returns for all the *NTM* quintile portfolios over the entire sample period from 2016 to 2022 and the return differences by long low *NTM* portfolio and short high *NTM* portfolio. Every Sunday, all ERC-20 tokens are re-allocated to five *NTM* groups (Low to High). Each group is held for one week. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

		Low	2	3	4	High	Low - High
NTM							
Value Weighted	**Mean**	-0.003	-0.006	-0.003	0.014	0.031***	0.030***
	t-value	(-0.36)	(-0.80)	(-0.38)	(1.39)	(2.73)	(3.73)
Equally Weighted	**Mean**	0.010	0.006	0.012	0.022***	0.051***	0.043***
	t-value	(1.49)	(0.83)	(1.49)	(2.66)	(4.91)	(5.89)

Table 3. 14: Average Weekly Returns for Portfolios Formed on Size and NTM: ERC-20 Tokens Sorted on Market Capitalization (Vertical) then NTM (Horizontal)

Portfolios are formed weekly. The breakpoints for the size (the value of market capitalization) quintiles are determined on Sunday of week *t* by using all available ERC-20 tokens on Ethereum blockchain. And then, the breakpoints for the z-score of NTM (the ratio of the amount of active unique addresses to market capitalization) quintiles are further determined for the same token sample on the same Sunday. After that, the 5 by 5 value-weighted two-dimensional portfolios at the intersections of the rankings can be constructed. The value-weighted returns on the resulting 25 Size-NTM portfolios are then calculated for week *t+1*. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

	NTM Quintiles					
Size Quintile	**Low**	**2**	**3**	**4**	**High**	**High - Low**
Small	0.029**	0.022*	0.040***	0.061***	0.102***	0.086***
	(2.31)	(1.92)	(3.22)	(4.64)	(6.47)	(5.81)
2	-0.005	0.000	0.012	0.020**	0.040***	0.052***
	(-0.52)	(-0.04)	(1.14)	(2.04)	(3.33)	(4.86)
3	0.000	0.006	0.015	0.012	0.026**	0.030***
	(-0.04)	(0.62)	(1.47)	(1.18)	(2.23)	(3.48)
4	-0.008	0.016	-0.002	0.002	0.030***	0.034***
	(-0.87)	(1.56)	(-0.16)	(0.22)	(2.70)	(4.25)
Big	-0.012	-0.006	−0.015*	0.003	0.000	0.019**
	(-1.43)	(-0.62)	(-1.72)	(0.30)	(-0.02)	(2.51)
Small - Big	0.044***	0.028***	0.052***	0.060***	0.095***	
	(3.68)	(3.03)	(5.39)	(5.25)	(6.63)	

Table 3. 15: TFIR Quintile Portfolios (Short-term)

This table reports the univariate portfolio analysis results based on short-term token's fundamental implied return (*TFIR*) including past 1 week, 2 weeks and 4 weeks moving average. The token fundamentals include Dollar Value Transactions (*TxUSD*), Counts of Transactions (*TxCnt*), Daily Active Unique Address (*DAU*), ratio between Dollar Amount of Transactions and Number of Active Unique Addresses (*TVU*), ratio between Transaction Counts and Number of Active Unique Addresses (*TCU*) and ratio between Dollar Amount of Transactions and Transaction Counts (*TVC*). The return differences by long high TFIR portfolio and short low TFIR portfolio are reported in the last column. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

TFIR Portfolios		**Low**	**2**	**3**	**4**	**High**	**High - Low**
Panel A: TxUSD							
Value-Weighted	**Mean**	0.004	0.011	0.009	0.005	0.000	-0.004
	t-value	(0.44)	(1.02)	(0.72)	(0.49)	(0.01)	(-0.56)
Panel B: TxCnt							
Value Weighted	**Mean**	0.002	-0.005	0.003	0.004	-0.002	-0.002
	t-value	(0.20)	(-0.54)	(0.30)	(0.36)	(-0.18)	(-0.35)
Panel C: DAU							
Value Weighted	**Mean**	0.003	-0.005	0.002	0.001	-0.002	-0.006
	t-value	(0.31)	(-0.47)	(0.14)	(0.12)	(-0.14)	(-0.90)
Panel D: TVU							
Value Weighted	**Mean**	0.000	-0.001	0.014	0.008	0.012	0.011
	t-value	(0.04)	(-0.04)	(1.03)	(0.72)	(1.00)	(1.35)
Panel E: TCU							
Value Weighted	**Mean**	0.004	0.006	0.002	0.003	0.005	-0.005
	t-value	(0.35)	(0.61)	(0.14)	(0.24)	(0.46)	(-0.67)
Panel F: TVC							
Value Weighted	**Mean**	-0.006	0.000	0.005	0.014	0.025**	0.026***
	t-value	(-0.58)	(0.03)	(0.44)	(1.11)	(1.99)	(3.16)

Table 3. 16: TFIR Quintile Portfolios (Long-term)

This table reports the univariate portfolio analysis results based on long-term token's fundamental implied return (*TFIR*) including past 26 weeks, 52 weeks and 104 weeks moving average. The token fundamentals include Dollar Value Transactions (*TxUSD*), Counts of Transactions (*TxCnt*), Daily Active Unique Address (*DAU*), ratio between Dollar Amount of Transactions and Number of Active Unique Addresses (*TVU*), ratio between Transaction Counts and Number of Active Unique Addresses (*TCU*) and ratio between Dollar Amount of Transactions and Transaction Counts (*TVC*). The return differences by long high *TFIR* portfolio and short low *TFIR* portfolio are reported in the last column. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

TFIR Portfolios		**Low**	**2**	**3**	**4**	**High**	**High - Low**
Panel A: TxUSD							
Value-Weighted	Mean	0.012	0.031^{**}	0.005	0.033^{***}	0.026^{**}	0.008
	t-value	(1.02)	(2.45)	(0.47)	(2.75)	(2.05)	(0.83)
Panel B: TxCnt							
Value Weighted	Mean	0.027^{*}	0.010	0.010	0.002	0.008	-0.018
	t-value	(1.98)	(0.77)	(0.69)	(0.21)	(0.62)	(-1.60)
Panel C: DAU							
Value Weighted	Mean	0.024^{*}	0.012	0.011	0.000	0.004	-0.020^{*}
	t-value	(1.80)	(1.05)	(0.83)	(0.01)	(0.29)	(-1.97)
Panel D: TVU							
Value Weighted	Mean	0.018	0.021	0.021	0.030^{**}	0.023^{*}	0.004
	t-value	(1.54)	(1.60)	(1.62)	(2.37)	(1.79)	(0.30)
Panel E: TCU							
Value Weighted	Mean	0.025^{*}	0.010	0.019	0.000	0.003	-0.017^{*}
	t-value	(1.94)	(0.87)	(1.39)	(-0.04)	(0.27)	(-1.75)
Panel F: TVC							
Value Weighted	Mean	0.019	0.025^{*}	0.024^{*}	0.026^{*}	0.019	-0.002
	t-value	(1.49)	(1.95)	(1.83)	(1.94)	(1.57)	(-0.14)

Table 3. 17: Time-series Factor Return Summary Statistics

	$\boldsymbol{R_{CM}}$ - $\boldsymbol{R_f}$	**TSMB**	**TNTM**	**TMOM**
Mean	-0.010	0.041^{***}	0.023^{***}	0.010^{**}
Std. dev.	0.113	0.086	0.123	0.103
t(Mean)	(-1.48)	(6.22)	(4.31)	(2.22)

***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Table 3. 18: Cryptocurrency Specific Factor Regressions for Simple Weekly Excess Returns on 10 Long-Short Strategies

This table reports the regressions of long-short strategy return premiums on the four crypto-specific factors, including the crypto-market factor $R_{CM} - R_f$, crypto-size factor $TSMB$, crypto - "value" factor $TNTM$, and crypto-momentum factor $TMOM$. The alpha is the intercept of the regression and represents the pricing error. The LHS of each regression is the time-series weekly return premium of each zero-investment (long-short) strategy including Size, Volume (trading volume), Illiquidity, Past Two-week (r_{-2}), Three-week (r_{-3}), Four-week (r_{-4}) returns and three on-chain variables including Dollar Value Transactions (*TxUSD*), Dollar Amount of Transactions/Number of Active Unique Addresses (*TVU*), and Dollar Amount of Transactions/Transaction Counts (*TVC*). The RHS are the time-series mimicking portfolios returns based on each crypto-specific factor. The values of alpha, coefficients, R-squares and the root of mean squared error (Root MSE) are reported for each strategy, and the t-statistics for coefficients and F-value for R-squares are presented in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Long-Short Strategies	Alpha	$R_{CM} - R_f$	TSMB	TNTM	TMOM	R2	Root MSE
Size Premium	0.026^{***}	0.077^{**}	0.946^{***}	0.135^{***}		0.601	0.065
	(5.69)	(2.17)	(18.35)	(4.04)		(137.23)	
	0.028^{***}	0.104^{***}	0.968^{***}		0.010	0.578	0.067
	(6.14)	(2.89)	(18.32)		(0.25)	(124.39)	
	0.026^{***}	0.078^{**}	0.947^{***}	0.139^{***}	-0.025	0.602	0.065
	(5.71)	(2.19)	(18.34)	(4.07)	(-0.59)	(102.76)	
Volume Premium	0.001	-0.102^{**}	0.419^{***}	0.003		0.171	0.072
	(0.15)	(-2.59)	(7.31)	(0.08)		(18.75)	
	0.003	-0.092^{**}	0.430^{***}		-0.154^{***}	0.185	0.070
	(0.52)	(-2.42)	(7.69)		(-3.43)	(21.21)	
	0.002	-0.098^{**}	0.425^{***}	0.030	-0.162^{***}	0.207	0.071
	(0.40)	(-2.52)	(7.57)	(0.81)	(-3.52)	(17.74)	
Illiquidity Premium	0.003	-0.045	0.435^{***}	0.005		0.165	0.075
	(0.50)	(-1.08)	(7.29)	(0.12)		(18.02)	
	0.004	-0.034	0.446^{***}		-0.152^{***}	0.196	0.074
	(0.86)	(-0.86)	(7.66)		(-3.24)	(22.21)	
	0.004	-0.040	0.442^{***}	0.031	-0.160^{***}	0.198	0.074
	(0.75)	(-0.99)	(7.54)	(0.81)	(-3.34)	(16.80)	
r_{-2} Premium	0.026^{***}	-0.041	-0.180^{**}	0.088		0.024	0.108
	(3.51)	(-0.69)	(-2.1)	(1.57)		(2.24)	
	0.021^{***}	-0.061	-0.207^{***}		0.607^{***}	0.293	0.092
	(3.37)	(-1.22)	(-2.84)		(10.35)	(37.65)	
	0.022^{***}	-0.058	-0.205^{***}	-0.014	0.611^{***}	0.293	0.092
	(3.37)	(-1.14)	(-2.79)	(-0.30)	(10.17)	(28.17)	
r_{-3} Premium	0.024^{***}	-0.006	-0.132	-0.058		0.017	0.102
	(3.40)	(-0.11)	(-1.63)	(-1.11)		(1.57)	
	0.018^{***}	-0.045	-0.172^{**}		0.431^{***}	0.170	0.094
	(2.79)	(-0.88)	(-2.31)		(7.21)	(18.68)	

	0.020^{***}	-0.019	-0.151^{**}	-0.136^{***}	0.465^{***}	0.193	0.093
	(3.18)	(-0.37)	(-2.05)	(-2.79)	(7.71)	(16.30)	
	0.027^{***}	0.021	-0.200^{**}	-0.074		0.032	0.102
	(3.86)	(0.38)	(-2.47)	(-1.41)		(3.02)	
r_{-4} Premium	0.022^{***}	-0.016	-0.236^{***}		0.351^{***}	0.129	0.096
	(3.28)	(-0.30)	(-3.09)		(5.71)	(13.48)	
	0.024^{***}	0.010	-0.215^{***}	-0.138^{***}	0.386^{***}	0.153	0.095
	(3.66)	(0.20)	(-2.84)	(-2.76)	(6.22)	(12.26)	
	-0.001	-0.042	0.399^{***}	-0.093^{**}		0.117	0.086
	(-0.12)	(-0.89)	(5.82)	(-2.1)		(12.05)	
***TxUSD* Premium**	-0.003	-0.064	0.381^{***}		0.038	0.104	0.087
	(-0.52)	(-1.36)	(5.53)		(0.69)	(10.60)	
	-0.001	-0.044	0.397^{***}	-0.104^{**}	0.065	0.121	0.086
	(-0.21)	(-0.93)	(5.78)	(-2.29)	(1.16)	(9.38)	
	0.001	0.001	0.313^{***}	-0.028		0.088	0.085
	(0.12)	(0.02)	(5.04)	(-0.64)		(8.89)	
***TVU* Premium**	-0.002	-0.012	0.330^{***}		0.131^{**}	0.112	0.084
	(-0.36)	(-0.27)	(5.38)		(2.47)	(11.49)	
	-0.001	-0.001	0.325^{***}	-0.054	0.146^{**}	0.117	0.084
	(-0.09)	(-0.02)	(5.29)	(-1.23)	(2.68)	(9.01)	
	0.006	0.025	0.272^{***}	0.008		0.069	0.085
	(1.01)	(0.53)	(4.35)	(0.19)		(6.74)	
***TVC* Premium**	0.004	0.019	0.286^{***}		0.153^{***}	0.100	0.084
	(0.71)	(0.42)	(4.65)		(2.88)	(10.16)	
	0.005	0.023	0.284^{***}	-0.020	0.158^{***}	0.101	0.084
	(0.79)	(0.50)	(4.61)	(-0.45)	(2.90)	(7.65)	

Table 3. 19: Portfolio Excess Return Regressions

This table presents the results of 25 regressions based on the following regression: $R(t) - R_f(t) = a + b[R_M(t) - R_f(t)] + e(t)$. The LHS variables in each set of the 25 regressions are the weekly excess returns on the 25 Size-NTM portfolios. The RHS variable is the cryptocurrency market factor defined as the excess market return, $R_{CM} - R_f$. The results include intercepts, slopes for the market factor, R-squares and the root of mean squared error (Root MSE). All the t-statistics for these coefficients are also reported. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

	NTM Quintiles									
Size Quintile	**Low**	**2**	**3**	**4**	**High**	**Low**	**2**	**3**	**4**	**High**
			a					***t*-value**		
Small	0.039^{***}	0.032^{***}	0.051^{***}	0.075^{***}	0.116^{***}	3.34	3.14	5.07	6.59	8.13
2	0.001	0.010	0.018^{**}	0.026^{***}	0.054^{***}	0.21	1.36	2.46	3.54	4.94
3	0.002	0.018^{**}	0.026^{***}	0.025^{***}	0.036^{***}	0.27	2.12	3.34	2.71	3.63
4	0.001	0.023^{***}	0.012^{*}	0.010	0.041^{***}	0.14	3.08	1.66	1.34	4.12
Big	-0.003	0.003	-0.001	0.009	0.013	-0.47	0.35	-0.20	1.23	1.56
			b					***t*-value**		
Small	1.039	0.940	1.032	0.990	1.073	10.10	10.47	11.62	9.84	8.65
2	0.766	0.863	0.823	0.942	0.929	12.63	13.07	12.57	14.47	9.66
3	0.859	0.898	0.977	0.879	0.927	13.73	12.38	14.22	10.98	10.67
4	0.843	0.934	0.985	0.800	0.912	13.58	14.29	15.74	12.43	10.43
Big	0.799	0.805	0.866	0.706	0.796	13.95	12.01	14.85	11.29	11.05
			R2					**Root MSE**		
Small	0.259	0.282	0.324	0.262	0.209	0.200	0.170	0.169	0.186	0.239
2	0.359	0.382	0.360	0.430	0.251	0.118	0.124	0.124	0.124	0.181
3	0.405	0.356	0.417	0.300	0.290	0.118	0.137	0.132	0.152	0.164
4	0.396	0.420	0.470	0.351	0.284	0.118	0.126	0.119	0.123	0.164
Big	0.414	0.334	0.448	0.312	0.318	0.109	0.129	0.108	0.119	0.129

Table 3. 20: Portfolio Excess Return Regressions Including Additional Factors

This table presents the results of 25 regressions based on the following regression: $R(t) - R_f(t) = a + b[R_M(t) - R_f(t)] + sTSMB(t) + nTNTM(t) + mTMOM(t) + e(t)$. The LHS variables in each set of the 25 regressions are the weekly excess returns on the 25 Size-NTM portfolios. The RHS variables are the cryptocurrency market factor defined as the market excess return, $R_{CM} - R_f$, size factor $TSMB$, "value" factor $TNTM$, and momentum factor $TMOM$. The results include intercepts, slopes for the market factor, size factor, NTM factor and momentum factor coupled with R-squares and root of mean squared error (Root MSE). All the t-statistics for these coefficients are also reported. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

	NTM quintiles									
Size quintile	**Low**	**2**	**3**	**4**	**High**	**Low**	**2**	**3**	**4**	**High**
			a					***t*-value**		
Small	0.024**	0.020*	0.038***	0.036***	0.041***	2.23	1.79	3.37	3.03	2.99
2	-0.007	0.008	0.003	0.013	0.010	-0.93	0.94	0.32	1.57	0.90
3	-0.004	0.000	0.011	0.013	0.029***	-0.49	0.03	1.33	1.37	2.63
4	-0.002	0.010	0.000	0.007	0.028**	-0.20	1.25	0.05	0.85	2.55
Big	0.006	-0.001	0.005	0.008	0.011	0.88	-0.09	0.65	1.06	1.27
			b					***t*-value**		
Small	0.940	0.907	1.027	0.819	0.874	11.47	10.29	11.71	8.74	8.14
2	0.727	0.844	0.780	0.930	0.853	11.87	12.63	12.26	14.48	10.03
3	0.854	0.866	0.905	0.854	0.948	13.81	12.37	13.80	12.00	11.05
4	0.852	0.866	0.911	0.787	0.870	14.54	14.07	14.77	12.44	10.32
Big	0.813	0.738	0.903	0.721	0.828	14.24	15.14	15.61	12.11	11.47
			s					***t*-value**		
Small	0.430	0.563	0.442	0.687	1.029	3.43	4.29	3.21	4.86	6.25
2	0.339	0.087	0.416	0.277	0.510	3.63	0.85	4.27	2.81	3.94
3	0.045	0.210	0.288	0.142	-0.031	0.47	1.96	2.85	1.28	-0.24
4	0.080	-0.098	-0.027	-0.023	0.042	0.89	-1.03	-0.28	-0.24	0.32
Big	-0.169	-0.134	-0.292	-0.391	-0.389	-1.95	-1.80	-3.32	-4.13	-3.54
			n					***t*-value**		
Small	-0.277	-0.310	-0.111	0.194	0.845	-2.88	-2.96	-1.08	1.71	6.73
2	-0.134	0.0497	-0.003	0.043	0.680	-1.87	0.64	-0.04	0.57	6.71
3	0.052	0.150	0.107	0.057	0.183	0.71	1.82	1.38	0.68	1.82
4	-0.021	0.227	0.182	0.084	0.259	-0.31	3.16	2.50	1.13	2.58
Big	-0.151	-0.017	0.237	0.411	0.405	-2.24	-0.29	3.46	5.83	4.66
			m					***t*-value**		
Small	0.024	0.019	0.022	-0.211	-0.261	0.27	0.19	0.23	-1.98	-2.23
2	-0.079	-0.089	-0.081	-0.016	0.173	-1.19	-1.22	-1.16	-0.22	1.86
3	0.066	-0.016	-0.136	0.036	0.012	0.98	-0.21	-1.87	0.46	0.13
4	0.009	-0.029	0.028	0.013	-0.132	0.14	-0.43	0.42	0.19	-1.41
Big	0.204	0.024	0.024	-0.065	0.040	3.30	0.46	0.38	-0.97	0.50
			R2					**Root MSE**		
Small	0.378	0.354	0.388	0.340	0.466	0.151	0.157	0.160	0.167	0.197
2	0.393	0.393	0.425	0.487	0.485	0.112	0.123	0.116	0.116	0.153
3	0.438	0.411	0.465	0.379	0.334	0.113	0.128	0.120	0.013	0.130
4	0.456	0.454	0.475	0.381	0.318	0.108	0.112	0.113	0.116	0.153
Big	0.447	0.461	0.495	0.417	0.383	0.104	0.090	0.104	0.109	0.124

Table 3A. 1: Literature Overview of Cryptocurrency Factors

Title/Authors	Sample/Sample Period	Factors/Predictors	Findings
"Risks and Returns of Cryptocurrency" Liu and Tsyvinski (2018)	3 coins: (1) Bitcoin (January 1, 2011 - May 31, 2018); (2) Ripple (August 4, 2013 - May 31, 2018); (3) Ethereum (August 7, 2015 - to May 31, 2018).	1. Momentum; 2. Investor Attention Proxies; 3. Negative Investor Attention Proxy; 4. Price-to-"Dividend" Ratio; ("Dividend" – active addresses) 5. Realized Volatility; 6. Supply Conditions Proxies.	Momentum and both investor attention proxies appear to have significant predictive power.
"Do Fundamentals Drive Cryptocurrency Prices?" Bhambhwani et al., (2019)	5 coins: (1) Bitcoin (BTC) (2) Ethereum (ETH) (3) Litecoin (LTC) (4) Monero (XMR) (5) Dash (DSH) Sample Period: Start Date: August 7, 2015 End Date: January 31, 2019	1. Computing Power (Miners' Activity); 2. Network Adoption (Active Addresses).	Both factors explain return variation across the sample cryptocurrencies.
"Know When to Hodl 'Em, Know When to Fodl 'Em': An Investigation of Factor Based Investing in the Cryptocurrency Space" Hubrich (2017)	11 coins including BTC, DASH, DCR, DOGE, ETC, ETH, LTC, PIVX, XEM, XMR, and ZEC. Sample Period: From each coin's respective first observation date to the most current date.	1. Momentum; 2. Value; 3. Carry.	Short-term momentum and valuation factors play a significant role in explaining returns, while longer-term factors and carry have weaker impacts.

"Common Risk Factors in Cryptocurrency" Liu, Tsyvinski and Wu (2022)	1,827 coins and tokens; Sample Period: From the beginning of 2014 to July of 2020.	1. Size-Related Characteristics; 2. Momentum-Related Characteristics; 3. Volume-Related Characteristics; 4. Volatility-Related Characteristics.	A three-factor model with cryptocurrency market factor (CMKT), cryptocurrency size factor (CSMB), and cryptocurrency momentum factor (CMOM) successfully accounts for the excess returns of all ten identified successful zero-investment strategies based on the four types of characteristics.