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The impact of Environmental, Social and Governance principles on digital assets performance

Author: Andrej Danailov
Student number: 556070
Thesis supervisor: Dr. Ruben de Bliek
Second reader: Dr. Marshall Ma
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ABSTRACT

Since their inception, ICOs have raised over $50 billion. However, during the 2018 boom, more than 80% of ICOs turned out to be scams, with a survival rate of just 10%. These statistics highlight the dynamic and sometimes risky nature of the ICO landscape (ICOBench, 2023). This study investigates whether digital assets that engage in specific ESG practices, such as community engagement, transparency, or electricity consumption, can significantly impact post-coin offerings (PCOs) and other performance metrics. The goal is to determine if these ESG practices are primary drivers of abnormal returns, including cumulative abnormal returns (CAR) for investors and their indirect effect on cryptocurrency prices. The study examines the cumulative average abnormal return (CAAR) in relation to the ESG activity levels of 40 of the largest and most liquid digital assets. It involves gathering and analyzing data on ESG practices and their effects on digital asset performance, with a particular focus on post-ICO periods. The methodology employs regression analysis to identify correlations and potential causations between ESG scores and abnormal returns while addressing selection bias where necessary. The findings reveal that digital assets typically show negative cumulative abnormal returns (CARs) across event windows when assessing ESG performance. However, Top-Tier assets tend to fare better with higher ESG scores, whereas Lower-Tier assets perform worse. This overall negative correlation implies that higher ESG scores are generally associated with lower abnormal returns across all assets. These results differ from much of the existing literature, which often finds positive correlations between ESG performance and financial returns. However, it is relevant for researchers, as it emphasizes the importance of considering the unique traits of digital assets, like their volatility and market dynamics, when examining ESG impacts.

Keywords: Digital Assets, Abnormal return, ESG Score, Event Window, Estimation window

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CHAPTER 1 Introduction

Entrepreneurs use cryptocurrencies or digital currencies through initial coin offerings (ICOs) to raise capital online. Benedetti & Kostovetsky (2021) reported that since January 2017, over 1,000 startups have collectively raised around $12 billion via ICOs. The success of an ICO or digital assets offerings for investors can be measured by the cryptocurrency token's return on investment (ROI), considering its purchase price during the sale (Campino, Brochado & Rosa, 2022). In their article, Benedetti and Kostovetsky (2021) noted that the average return on the ICO price to the first day's opening market price is 179%, achieved over an average holding period of just 16 days. The underlying cause of this phenomenon remains unknown to both the public and the scientific community. This thesis explores whether digital assets engaging in specific environmental, social and governance (ESG) practices, such as community engagement, transparency, or electricity consumption, can significantly influence PCO/post-coin offerings (digital asset performance metrics). We further explored whether they can be considered the main causes for abnormal returns (including ROI for investors and the impact on cryptocurrency prices). In summary, this study combines finance, ESG, and technology to clarify the dynamics of PCOs of digital assets.

The study by Benedetti & Kostovetsky (2021) provides insights into the dynamics of ICOs and their interaction with social media platforms like Twitter. They analyzed the determinants of Initial Coin Offerings (ICOs) underpricing and related cryptocurrency prices to Twitter activity. Their study aimed to investigate if engagement on Twitter can significantly influence investor sentiment and impact the prices of cryptocurrencies. Recently, investor sentiment and its impact on cryptocurrency prices have become a popular method for seed and early-stage funding, surpassing traditional sources. Meyer & Ante's (2020) study explores how the characteristics of initial coin offerings (ICOs) influence cross-listing returns. Using event study methodology, they analyzed various tokens issued through ICOs, calculated abnormal returns for specific samples, and considered how whitepaper characteristics affect perceived project quality and cross-listing returns. Nagel & Kranz (2022) further examined technological, organizational, and environmental factors influencing the trajectory of token sales, providing insights into the current state of crypto company fundraising. These studies attribute the abnormal returns of ICOs to entrepreneurs' lack of expertise in assessing market demand for their tokens, the absence of experienced underwriters (referencing Benveniste and Spindt, 1989), or the high uncertainty about the value of startups (Rock, 1986).

Although these papers have garnered significant attention due to the impressive performance of cryptocurrencies, the core issue of how the Cumulative Average Abnormal Return (CAAR) correlates with the level of environmental, social, and governance (ESG) activity of specific digital assets is not tackled. Utilizing the first institutional-grade ESG benchmark for digital assets, launched in February 2024 by CCData in collaboration with the Crypto Carbon Ratings Institute (CCRI) (ESG Benchmark, 2024), we investigated the relationship between ESG activity levels and CAAR. This benchmark includes a set of 40 digital assets. I aimed to prove that previous results are generalizable to a different but similar context. There is an investigation into whether there are abnormal price fluctuations in ESG active versus less active companies. So, by using a constructive replication and adding new variables and conditions, such as ESG benchmarking score, I explored: "How do 40 of the largest and most liquid digital assets perform on returns?". It will also change the context by adding another variable, such as the institutional ESG Benchmark, from a dataset of the first digital assets issued in February 2024 to examine the possible abnormal returns.

The authors of the study of Benedetti & Kostovetsky (2021) used different data sets, such as icodata.io, icobench.com, corating.com, icodrops.com, and ico-check.com, to explore the most available characteristics of ICOs. They also merge the datasets using four identifiers: token/platform name, ticker symbol, website URL, and Twitter handle. Finally, they used coinmarketcap.com (CMC) for cryptocurrency market data, widely considered the best available data source for cryptocurrency volume and prices, and Twitter.com for each Twitter account. I gathered data on ESG practices from the latest report- February 2024 for digital asset third-party ESG ratings; I also used the ccdata.io dataset and will collect data on ICO performance/digital asset performance from cryptocurrency exchanges, financial reports that provide information on a wide range of financial topics, including blockchain and cryptocurrencies such as the Investopedia.com. In addition, I used some control variables as factors that might influence ICO performance, such as market conditions or industry trends. For the statistical analysis, I used regression and correlation analysis to assess the relationship between ESG practices and CAAR where the dependent variable is the CAAR and ESG activity indicators (e.g., community engagement scores, transparency, electricity consumption) are the independent variables plus, e.g., market volatility and token characteristics as control variables. To calculate the CAAR for all 40 digital assets ranked with ESG score, an event window was considered: with an event date such as 29th of February 2024 (+/- 16 days for the event window) when the ESG score is issued/announced, while the estimation window was 34 days before the event window. After calculating the abnormal returns (AR) for each digital asset, we then calculated the cumulative abnormal returns (CAR) for all digital assets and performed regression analysis.

I believe that socially, environmentally and governance-active companies positively influence investor sentiment and token prices, leading to higher Cumulative Average Abnormal Returns (CAAR). This suggests that digital assets' efforts towards ESG (Environmental, Social, and Governance) practices result in abnormal returns. My research seeks to understand how ESG backing affects abnormal volume fluctuations in ESG-active or so-called Top-Tier and less-active or so-called Lower-Tier digital assets (Hayes, 2022). This study aims to enhance the knowledge of abnormal returns associated with Initial Coin Offerings (ICOs) or, more precisely, post-ICOs or digital asset offerings. I intend to contribute to the existing knowledge of digital asset offerings by analyzing newer data sets and addressing selection bias where necessary. I hypothesize that High ESG-backed digital assets experience higher positive abnormal returns than their less ESG-backed counterparts due to their trustworthy, ethical, and sustainable practices, which can boost demand for tokens during ICOs and drive up prices. The broader market trend favours ESG investments, as growing awareness leads investors to seek companies aligned with sustainable practices. Prior research indicates that ICOs are younger and riskier, requiring a high expected rate of return to attract investor demand (Benedetti & Kostovetsky, 2021). Therefore, I aim to expand on this topic by connecting it with ESG variables. I also expect to confirm a positive relationship between market cap and the number of ESG activities. Their sustainable practices may result in higher CAAR for digital assets.

CHAPTER 2 Theoretical Framework

2.1 Post -ICO performance

In this chapter, we provide an overview of topics related to post-ICO performance, its background, and the empirical studies that are connected to this topic. Additionally, we explained the differences between post-ICOs and IPOs, their similarities with crowdfunding initiatives, and the accounting-based performance of post-ICOs and their financial perspectives have introduced the first industrial ESG benchmark for digital assets issued on 29th of February 2024 and the two groups of digital assets.

2.1.1 Background

Post-ICO performance pertains to an investment's operational and financial results following its initial coin offering (ICO), which enables investors to raise capital by issuing secure tokens. These tokens are the exclusive payment method for the venture's future products or services (Lyandres, Palazzo, & Rabetti, 2022). According to Aslan, Şensoy, and Akdeniz's (2023) research, ventures with liquid tokens experience enhanced operational flexibility and instiled confidence among investors. Hence, the liquidity of tokens significantly impacts post-ICO performance. Also, a substantial fundraising amount typically signifies successful post-coin offerings based on token sales (Reif, 2024).
Post-ICOs differ from traditional IPOs in several ways: they, like ICOs, operate with less regulatory oversight and cater to a global audience. Additionally, post-ICOs utilize decentralized platforms, while IPOs rely on centralized exchanges and adhere to stricter regulatory requirements. They are similar to Crowdfunding as ICOs exhibit raising capital from a large pool of contributors (Lyandres, Palazzo, & Rabetti, 2022).

The chapter titled "Initial Coin Offerings (ICOs): Risks, Regulation, and Accountability" by Usman W, explains that back in 2013, software engineer J.R. Willet pioneered the concept of initial coin offerings (ICOs) by launching Mastercoin (later rebranded as Omni Layer). Since then, ICOs have evolved into a prominent fundraising method, enabling entrepreneurs and start-ups to issue tokens to investors and secure capital. These tokens are vital to the project's ecosystem, functioning like securities. The entire process operates through self-executing smart contracts embedded in blockchain technology, eliminating intermediaries and minimizing transaction costs (Kher, Terjesen, & Liu, 2021).

Since their inception, ICOs have raised over $50 billion. However, during the 2018 boom, more than 80% of ICOs turned out to be scams. The survival rate for ICOs is just 10%. The largest ICO ever was EOS, which raised a staggering $4.2 billion in 2018. On the flip side, the infamous Bitconnect scam defrauded investors of $2.6 billion. These statistics highlight the dynamic and sometimes risky nature of the ICO landscape (ICOBench, 2023). The systematic review of 152 articles related to blockchain technology highlights blockchain applications, including ICOs, as emerging phenomena that have received limited attention from management and entrepreneurship scholars. It sheds light on the intersection of technology and finance. It emphasizes that blockchain operates as a decentralized system where no single entity has exclusive control over the validation process or information flow (Kher et al., 2021).

The regulation of digital assets is still developing and varies widely across regions. In the US, agencies like the SEC and CFTC have applied existing securities and commodities laws to digital assets, often through enforcement actions. However, a comprehensive, unified regulatory framework specifically for digital assets is still missing. The article by Reitman, Caires, Mapp, Forni, and North (2023) discusses the evolving regulatory landscape for digital assets in 2023. It underscores the ongoing challenges and discussions about the most effective regulatory strategies, stressing the importance of clear guidelines to promote efficient development and stability in the crypto sector (Reitman, Caires, Mapp, Forni, & North, 2023).

Conversely, the EU has advanced towards a more defined regulatory framework. For example, the Markets in Crypto-Assets (MiCA) regulation seeks to create a clear structure for issuing and trading digital assets. However, a universally accepted ranking system for digital assets is still lacking.

The Investopedia article titled "MSCI ESG Ratings Definition, Methodology, Example" offers valuable insights into MSCI ESG ratings. These ratings evaluate how well a company, or in our case, digital asset, manages risks associated with environmental, social, and governance issues in its daily operations. Scores and grades are comparable across all assets, revealing that Proof-of-Work coins and centralized assets generally perform poorly against ESG standards. 'Top-tier' assets are those with a grade of BB or higher, while those with a grade of B or lower are classified as 'Lower-Tier' (Hayes, 2022).

2.1.2 Empirical studies

This section reviews the relevant research literature and introduces Hypotheses 1 and 2.

2.1.2.1 Accounting-based and Market-based performance:

Analysts evaluate a firm's performance using Return on Assets (ROA). This metric assesses how effectively a company utilizes its economic resources in relation to the investments made. Importantly, ROA doesn't differentiate between debt and equity financing; it measures overall efficiency. The Corporate Governance Institute (2023) emphasizes that assessing an asset's financial performance involves using various business-related algorithms. These algorithms help determine precise information about the potential effectiveness of financing decisions. Masa'deh, Tayeh, Al-Jarrah, and Tarhini (2015, 135) discuss accounting-based performance, which applies profitability ratios to provide insights into the expected return for investors holding equity in a company. This concept extends to digital assets as well, as according to Campino, Brochado and Rosa (2022), the success of initial coin offerings (ICOs) or digital asset offerings can be measured by the cryptocurrency token's return on investment (ROI). So, investors evaluate the ROI to assess the profitability of their investment.

Market-based performance, on the other side, relies on valuation ratios, which compare the market value or asset price of a business with its core competencies related to growth and profitability (Nguyen Xuan Tho, Le Thuy Dung, & Ngo Thi Thuong Huyen, 2021). These approaches collectively help investors make informed decisions about various assets, including digital ones. Our study uses ratios that measure a firm's performance based on its accounting and market results.

2.1.2.2 A Financial Perspective - Analyzing Blockchain ROI and Event Studies :

Over the years, financial performance evaluation systems have undergone two distinct stages: One between 1880 and 1980, when traditional financial indicators such as profit, return on investment, and productivity were used, and the other afterwards due to changes in the global market. In the second one, the focus has shifted towards a modern financial performance assessment with a comprehensive framework that provides essential support for both short-term and long-term management of assets (Tudose & Avasilcai, 2020). According to the same article, in recent years, investors have shown interest in alternative forms of return on investment (ROI), such as social return on investment (SROI), which was developed in the late 1990s and goes beyond traditional financial metrics by considering broader impacts of projects, including social and environmental factors not typically reflected in conventional financial accounts.

Blockchain platforms act as transparent digital ledgers, improving accountability by documenting transactions and tracking assets within business networks (Davidson et al., 2018). When assessing digital assets, unique metrics like Return on Investment (ROI) for evaluating investment profitability, token prices for blockchain and daily prices for cryptocurrencies are considered alongside traditional financial indicators. To calculate ROI for digital assets, we can divide the benefit (or return) generated by the investment by the initial cost of the investment. The result is typically expressed as a percentage or a ratio (Fernando, 2024). Our performance analysis is based on the traditional system with some elements incorporated from the second financial performance evaluation system, considering the short-term and long-term management of digital assets. So, in the short term, we calculated return on investment (ROI) or actual return (R), abnormal return (AR) and cumulative abnormal return (CAR) based on the daily price fluctuations for each digital asset and calculated the cumulative average abnormal return (CAAR), which is a valid approach to reflect overall performance. The CAAR quantifies abnormal returns over time for digital assets. It is based on the Abnormal Asset Return (AAR), which evaluates abnormal returns across individual assets to understand how digital asset prices react during event windows. Positive CAAR may signal favourable market reactions, influencing investment choices. (Kolari & Pynnönen, 2023, Oler, Harrison, & Allen, 2008).

The field of event studies, particularly concerning abnormal returns associated with announcements, has been widely explored in existing literature. Brown & Warner (1980) and Fama (1991) explained that market efficiencies can be discovered through event studies carried out across longer time horizons.

However, as digital asset decisions account for high price volatility, the concept of using shorter event windows aligns with the theory of Very Short-Time Price Change (VSTPC) proposed by Virgilio (2022). The VSTPC theory also suggests that traditional factors affecting price changes become less relevant in highly volatile markets.

The objective of this study is to examine abnormal returns for digital assets during event periods linked to the ESG Report publication date.

Our goal is to investigate the relationship between ESG factors and financial performance within the cryptocurrency ecosystem.

We plan to base our analysis on a significant event: the release of the first institutional-grade ESG benchmark for digital assets on the 29th of February, 2024. This benchmark, developed by CCData in partnership with the Crypto Carbon Ratings Institute (CCRI), assesses ESG risks and opportunities associated with 40 major digital assets across 11 core evaluation categories.

Hypothesis 1. Top-Tier assets have higher CAR compared to Lower-Tier assets over an event window.

Hypothesis 2. The assets outperformed what would be predicted based on market trends.

2.2 Background ESG history, ESG for digital assets, Different ESG scores

This chapter provides an overview of topics related to environmental, social, and governance (ESG). We delve into the ESG History, framework and discuss ESG ratings for digital assets.

The notion of ESG (Environmental, Social, and Governance) originated from a 2006 report by the United Nations Principles for Responsible Investment (UNPRI), as highlighted by Hoepner et al. (2021). UNPRI advocate that conscientious investors should carefully evaluate the effects of ESG (Environmental, Social, and Governance) factors; since then, this perspective has gained prominence in investment decisions worldwide. ESG matters were initially addressed in 2006 with the United Nations Principles for Responsible Investment (PRI) report, which included the Freshfield Report and "Who Cares Wins". Notably, this marked the first instance of incorporating ESG criteria into the financial assessment of companies (Ademi & Klungseth, 2022).

GreenCryptoResearch (GCR) has pioneered the world's first ESG rating specifically tailored for cryptocurrencies. Their thorough evaluation allows investors to assess the environmental, social, and governance (ESG) risks linked to different coins and tokens. Ethereum (ETH) earned an impressive "AA" grade in its first ESG Benchmark, highlighting Ethereum's strong adherence to ESG standards (GreenCryptoResearch, n.d.).

The article on Investopedia titled "MSCI ESG Ratings Definition, Methodology, Example" provides valuable insights into MSCI ESG ratings. A high ESG rating indicates that the company successfully controls these risks compared to its peers. Conversely, a low ESG rating suggests higher uncontrolled risks in these areas. By integrating ESG evaluations and scores with financial analysis, investors gain insights into a company's long-term, sustainable growth potential.

2.2.1 Empirical studies

First Institutional ESG benchmark, rating, score and groups

These weightings are determined by CCData and the Crypto Carbon Ratings Institute (CCRI) and are subject to potential adjustments in future benchmark editions. Within each category, various metrics assess an asset's ESG compliance quantitatively or qualitatively. These metrics are assigned points based on their relative significance within the category, a determination made at the discretion of CCData and the Crypto Carbon Ratings Institute (CCRI). Points are aggregated within each category and are then scaled to the category weighting. Each category score is summed up to reach a total score. Each asset receives a grade based on its final score, spanning from AA to E. These scores and grades are consistent across all assets, revealing that Proof-of-Work coins and centralized assets exhibit relatively poor alignment with ESG standards. Two main categories are formed for the set of 40 digital assets: 'Top-Tier' if they achieve a grade of BB or higher and 'Lower-Tier' category if they have a grade of B or lower (ESG Benchmark, 2024).

2.3 Relationship between CAAP and ESG benchmarks

In their extensive review of over 2,000 ESG-related studies, Friede et al. (2015) discovered that approximately 90% of these studies showed a positive correlation between Environmental, Social, and Governance (ESG) factors and financial performance. This finding highlights the growing recognition of ESG considerations as drivers of sustainable business success. According to stakeholder theory, successful companies skillfully manage relationships with shareholders and creditors, employees, suppliers, customers, government, community, and the environment (Freeman, 2015).

Key findings of the study of Rabbani et al. (2021) reveal that a request was issued by financial institutions towards their clients for a direct link between ESG performance and financial success, prompting them to conduct due diligence on these matters regardless of regulatory frameworks. Their main recommendation is that corporate treasuries considering bitcoin hedging on their balance sheets should carefully plan and execute to meet internal ESG requirements. However, it's important to note that cryptocurrency remains an experimental financial innovation and does not align with the goals of ESG investing. Additionally, the growing production of cryptocurrencies poses environmental risks, which can impact ESG investment objectives.

A study by Ciaian et al. (2022) discovered a significant link between investors' ESG (environmental, social, and governance) preferences and their exposure to crypto-assets. They reveal that ESG-conscious investors exhibit greater interest in crypto-assets compared to traditional asset classes like bonds and stocks. The paper titled "Blockchain for Sustainability: A Systematic Literature The paper titled 'Blockchain for Sustainability: A Systematic Literature Review for Policy Impact' rigorously investigates how blockchain technology contributes to sustainability. Researchers analyze existing literature to uncover trends, gaps, and potential policy implications related to blockchain platforms in large-scale industries. The study underscores the importance of practical traceability solutions that account for feasibility and cost considerations. Furthermore, it suggests that integrating blockchain technology into traditional markets could lead to positive outcomes for global sustainability (Mulligan, Morsfield, & Cheikosman, 2024).

Many researchers have widely assessed the correlation between cumulative average abnormal return CAAP and ESG score. The results of the study of Momparler, Carmona and Climent (2024) show that the relationship between ESG ratings and mutual fund performance exhibits a positive correlation, where the ESG score emerges as a significant predictor of fund performance. The study of Yang, Zhang and Ye (2024) reveals that there is a strong negative correlation between corporate ESG performance and the pledge ratio of major shareholders. This implies that equity pledges by major shareholders have an adverse effect on ESG performance. Specifically, the pressure from controlling shareholders' equity pledges primarily reduces companies' performance in social responsibility and governance areas, while it does not significantly impact environmental construction. In Fu and Li's (2023) study, regression analysis results show that ESG factors positively and significantly impact corporate financial performance. Additionally, digital transformation enhances this positive effect even further.

Recent research examining the connection between ESG (Environmental, Social, and Governance) factors and financial performance consistently found positive correlations. For instance, a study by Whelan, Atz, Van Holt, and Clark (2021) analyzed over 1,000 research papers published between 2015 and 2020. Notably, the study revealed that ESG investing returns were comparable to conventional investments. Nasdaq's research on the 2019 Morgan Stanley Capital International (MSCI) ESG rankings for the S&P 500 found that sustainability leaders, as per MSCI ESG rankings, experienced higher returns and lower risks over five years. In contrast, companies with weaker sustainability performance showed the opposite outcomes (Ademi & Klungseth, 2022). The academic literature widely agrees that there is a strong link between Environmental, Social, and Governance (ESG) factors and corporate performance. Researchers generally concur that negative ESG events harm a company's overall performance (Krüger, 2015).

The impact of ESG on financial performance is multifaceted. Regression analysis reveals that ESG positively and significantly influences corporate financial performance. Moreover, digital transformation (DT) further enhances this positive effect. Notably, the positive impact of current ESG on financial performance gradually diminishes over time. These findings highlight the intricate interplay between ESG factors and digital assets (Sang, Loganathan, & Lin, 2024; Wu, Li, Liu, & Li, 2024; Hou, Liu, Zahid, & Maqsood, 2024; Jin & Wu, 2023; Fu & Li, 2023).

From another perspective, the connection between ESG (environmental, social, and governance) factors and the performance of digital assets is complex. Although consensus is lacking, certain studies propose that adverse ESG events can influence digital asset performance. These events may involve environmental disputes, social concerns, or governance lapses tied to a particular digital asset or its issuing entity (Ahmad, Yaqub, & Lee, 2024). The study by Clark and Lalit (2020) also sheds light on the relationship between ESG practices and financial performance. It distinguishes between two types of companies: those excelling in ESG practices (the "Leaders") and those actively improving their ESG practices (the "Improvers"). Companies that already reflect ESG practices in their stock prices may not necessarily generate additional excess returns due to ESG integration, while companies actively enhancing their ESG practices exhibit uncorrelated alpha-enhancing potential over the long term. He confirms that material ESG issue improvement can lead to positive returns only beyond what is already priced into the market (Clark & Lalit, 2020).

Hypothesis 3. Digital Assets which belong to group one- Top-Tier Assets have a positive correlation with the ESG score over an event window.

Hypothesis 3. 1. Digital Assets, which belong to group one- Top-Tier Assets positively correlate with the Environmental score over the event window.

Hypothesis 3. 2. Digital Assets which belong to group one- Top-Tier Assets have a positive correlation with the Social score over the event window.

Hypothesis 3. 3. Digital Assets which belong to group one- Top-Tier Assets have a positive correlation with the Governance score over the event window.

Hypothesis 4. Digital Assets which belong to group two - Lower -Tier Assets have a negative correlation with the ESG score over an event window

Hypothesis 4. 1. Digital Assets, which belong to group two - Lower-Tier Assets, negatively correlate with the Environmental score over the event window.

Hypothesis 4. 2. Digital Assets which belong to group two - Lower -Tier Assets have a negative correlation with the Social score over the event window.

Hypothesis 4.3. Digital Assets which belong to group two- Lower -Tier Assets have a negative correlation with the Governance score over the event window.

CHAPTER 3 Data Sample

We collected panel data on price fluctuations on a set of 40 digital assets for the period January 2024 to April 2024. We also have checked the price fluctuation from the 1st of October 2023 till the 20th of April 2024 to see if the Very Short-Time Price Change (VSTPC) theory applies to the time window definition (Virgilio, 2022). Our starting point was chosen as February 29, 2024, which coincided with the launch of the first ESG benchmarking study, an institutional grade ESG benchmark for digital assets issued by CCData in collaboration with the Crypto Carbon Ratings Institute (CCRI) (ESG Benchmark, 2024). This event had the potential to significantly impact digital asset prices as investors increasingly rely on ESG ratings to identify assets better suited to withstand economic downturns and other risks (D'Amato, D'Ecclesia, and Levante, 2021).

Our study examined digital assets with ESG benchmark/activity indicators, including community engagement scores, transparency, and electricity consumption. Our primary focus was on a comprehensive scenario where all ESG characteristics are simultaneously considered, resulting in an overall score for each digital asset. However, we also separately explored their individual characteristics related to environmental, social, and governance aspects (ESG ranking report, 2024).

We also considered the categorization of digital assets ranked as Top Tier (with a score of more than 60) and Lower Tier (with a score of less than 60). These categorized assets served as dummy variables, allowing us to compare ESG-active and non-active digital assets. Additionally, the Methodology for defining the ESG score is an indicator for assessing ESG performance and defining the ESG rating for digital assets. The first institutional ESG Benchmark for digital assets emerged through a collaboration between CCData and the Crypto Carbon Ratings Institute (CCRI). This benchmark offers a holistic framework for evaluating the ESG implications of 40 major, highly liquid digital assets. It assesses these assets across 11 essential categories, encompassing aspects like decentralization, security, and climate impact. Ethereum secured an AA grade, while Solana and Cardano received an A. This report signifies a crucial step toward embedding robust ESG criteria within the digital asset industry (ESG Benchmark, 2024). Their innovative methodology incorporates diverse qualitative and quantitative metrics spanning all ESG dimensions. Each asset receives a grade (AA to E) indicating its ESG compliance with the digital asset industry.

The selected assets represent the most liquid digital assets listed in the ESG benchmarking report for February 2024. These assets include well-known cryptocurrencies such as Ethereum, Solana, Polygon, Cardano, and Bitcoin, among others. On average, some digital assets had proven the following data: overall, Ethereum's price increased by approximately 48.5%, Solana's price increased by approximately 63.8%, Polygon's price increased by approximately 57.3%, and Aptos and Polkadot increased by 116.7% and 77.8% respectively for the period 01/10/2023 till 16/03/2024 (yahoofinance.com).

Variables

ROI, as highlighted by Pandey and Kumar (2022), is a powerful financial performance metric. It uniquely reflects how efficiently resources are utilized, directly connecting investment results to resource effectiveness. Reiff (2024) suggests that evaluating the success of an ICO or digital asset offering involves assessing the cryptocurrency token's return on investment (ROI), considering its purchase price during the sale.

Consequently, we computed *actual returns* by analyzing daily price fluctuations of digital assets within the specified time window. Given the ongoing debate about the interplay between ESG (Environmental, Social, and Governance) factors and *Cumulative Average Abnormal Return* on digital assets, we examined price differences over a 100-day time window to explore the impact of ESG.

ESG: To measure ESG performance, we adopted the ESG rating system developed by CCData in collaboration with the Crypto Carbon Ratings Institute (CCRI) (ESG Benchmark, 2024), which provides semi-annual ESG ratings categorized into seven grades (methodological updates are introduced at a 6-month frequency, with quarterly reviews taking place), as follows from high to low: AA, A, BB, B, C, D, and E. We assigned ESG grades ranging from 1-7 based on the total score obtained for the three main principals (environment, social and governance on equal bases; each category counts for 33,33% and is aggregated to form a total cumulative score of a maximum of 100) so that ratings were formed from the one with the best score for all three categories to the one with the smallest score. For instance, an ESG rating of 1 corresponds to the highest score (AA), and subsequent ratings decrease as scores diminish till the 40th one, taking into consideration the following grading: >70 AA, 65-70 A, 60-65 BB, 55-60 B, 50-55 C, 45-50 D, <45 E. Top-Tier Assets must maintain a minimum score of 60 (equivalent to a BB rating). At the same time, Lower-Tier Assets fall below this threshold. Higher scores represent higher ESG performance, whereas lower scores represent lower ESG performance. We used the semi-annual average ESG scores to measure a digital asset's ESG performance. We also calculated the standard deviation for each score of the digital asset. Subsequently, we calculated each digital asset's cumulative average return on investment (CAR) and its standard deviation. Next, we created our grouping dummy by assigning 1 to (1) Top-Tier Assets and 2 to (2) Lower-Tier Assets.

Using the *S&P Cryptocurrency Broad Digital Market (BDM) Index* as an intercept for market returns and considering the sensitivity of digital asset returns to market fluctuations (the slope), we estimated both estimated and abnormal returns on investment. The index represents a broad investable universe designed to measure the performance of digital assets that meet minimum liquidity and market capitalization (S&P Dow Jones Indices LLC, 2021).

Table 1 presents definitions and descriptions of all variables:

Table 1: Definition and description of variables

Type	Variable	Symbol	Variable definition
Dependent	Financial performance	R	Actual return - a digital asset's price relative to its previous value (daily returns for each digital asset).
	Financial performance	ERR	Estimated/expected rate of return based on the market.
	Financial performance	AR	Abnormal Return for the digital assets (difference between the actual and estimated return).
	Financial performance	CAR	Cumulative abnormal return
	Financial performance	CAAR	The sum of the average abnormal return
Independent	ESG	ESG	According to ESG rating "E-AA", 7-grade ratings are assigned 1–7
	ESG Group 1-dummy	Top-Tier Assets	Must maintain a minimum score of 60 (equivalent to a BB rating)
	ESG Group 2-dummy	Lower-Tier Assets	Digital Assets that fall below this threshold of 60
	S&P Cryptocurrency Broad Digital Market (BDM) Index	(BDM) Index	S&P Cryptocurrency Broad Digital Market (BDM) Index (S&P Dow Jones Indices LLC, 2021)

Researchers have investigated different estimation windows for this purpose. Field and Hanka (2001) explored various event windows, while Krivin et al. (2003) highlighted the trade-off between longer windows (which yield a larger data sample) and shorter windows (closer to the event). Typically, an event window covers a short period around the event, with common lengths being ±1 day, ±3 days, or ±5 days. So, in our analysis of digital assets, as is given in Figure 1, we chose a 16-day event window and a 24-day estimation period, resulting in a total time window of 66 days, with a 10-day difference between the estimation and event window. In our case, the event day is the 29th of February 2024 as a day of issue of the first Institutional Benchmark report for digital asset third-party ESG ratings.

The event study also incorporates the right index, which serves as a standard for expected returns (Miller, 2023). Choosing the right index is typically straightforward, especially when dealing with a limited set of indices, as is the case for digital assets. However, Glas's book (2022) states that constructing a digital asset index involves careful methodological consideration and rigorous back-testing. For his analysis, he favours an equally weighted index encompassing all available digital assets instead of a market-cap-weighted index. Trimborn and Härdle (2018) developed an index specifically for cryptocurrencies. This index includes 30 different digital assets and is known as the "CRypto IndeX". However, in situations where event studies involve a large number of digital assets, opting for a broad market index might be more cost-effective than testing individual indices for each case (Marks, Musumeci, & Smith, 2018).

So, in our analysis, the S&P Cryptocurrency Broad Digital Market (BDM) Index serves as a key indicator for estimating expected returns. Issued by S&P Dow Jones Indices LLC, which invests in Lukka and occasionally provides consultative services to the S&P Digital Assets Index Committee, this index monitors the performance of digital assets listed on recognized open digital exchanges. It includes more than 240 coins and is designed to reflect a broad investable universe in the cryptocurrency market (Education, 2022).

Table 2: Descriptive statistics

Statistics	**return**	**expected return**	**abnormal return**	**CAR**	**ESG**	**top tier ESG**	**low tier ESG**	**market index**
Mean	0.57156	0.78554	-0.21921	0.57156	60.08250	66.61667	50.28125	-0.00645
Median	0.53476	0.69408	-0.16335	0.55620	61.95000	66.60000	51.05000	0.00000
Standard Deviation	1.06764	0.82419	0.90787	0.38690	9.74487	4.57133	6.63920	0.10451
Sample Variance	1.13985	0.67928	0.82424	0.14969	94.96251	20.89710	44.07896	0.01092
Kurtosis	56.19224	54.73732	51.23053	-0.17489	-0.44672	-0.02970	-1.15691	83.69601
Skewness	-1.33563	-0.04400	2.16870	0.54857	-0.52147	0.69982	-0.23424	-8.72875
Minimum	-14.93193	-8.28174	-10.07219	0.00011	38.80000	60.80000	38.80000	-1.00000
Maximum	12.57876	9.38681	9.60541	1.49874	77.90000	77.90000	59.50000	0.10673
Count	4040	1320	1320	40	40	24	16	101

Note: return, expected return and abnormal return are shown as percentages; real values are multiplied by 100.

To analyze the data for this study, the price information for each digital asset was sourced from Yahoo Finance. A dataset was compiled for each estimation period and event window per digital asset, and based on the announcement on the 29th of February, 40 unique events for each digital asset were covered separately. Each event had 16-day and 5-day event windows on either side of the announcement date, resulting in 33 or 11 event windows, respectively. Following the methodology in Chapter 4, market returns (based on the S&P Cryptocurrency Broad Digital Market (BDM) Index data), intercept, slope, r-squared, and standard error for each estimation period were calculated (as given in supplementary material, see worksheet "return" from "Digital asset Prices 10 01 till 20 04 2024 v12.xlsx"). In addition, based on the first institutional-grade ESG benchmark for digital assets, launched in February 2024 by CCData in collaboration with the Crypto Carbon Ratings Institute (CCRI) (ESG Benchmark, 2024), the Environmental, Social, and Governance (ESG) categories were subdivided into specific metrics. Each metric was given a weight according to its relative importance. Subsequently, the estimated normal returns, abnormal returns, cumulative abnormal returns, and abnormal return t-tests were computed for each event window (33-day and 11-day). Additional variables, including the digital asset's grouping variables and market expectations of the announcement, the BDM Index value within the event window, and the announcement date, were all coded into the dataset. This information was sourced from various references mentioned earlier in section 3. The datasets were then imported into the Excel table and R version 4.2.2. to verify calculations, assess significance, and perform correlation analyses. Appendix 1 includes some of the tables produced in Excel, Appendix 2 includes the R compile report used, and supplementary material is also given.

CHAPTER 4 Method

In their study, Kim, Ryu, and Yang (2021) demonstrated that information sharing can lead to immediate and significant stock price reactions. The study highlighted that stocks with high levels of information coverage often experience rapid price adjustments, reflecting the market's quick response to new information. Busse and Green (2002) noted that stocks react swiftly to CNBC Morning and Midday Call reports. They found that while price adjustments often stabilize within fifteen minutes, significant price movements can continue for up to ten days.

February 29, 2024, was selected to signify the release of the year's first industrial ESG report, offering new and comprehensive ESG data anticipated to impact market behaviour. Selecting this date enables me to examine the immediate market responses to new ESG data, consistent with the Very Short-Time Price Change (VSTPC) theory, which posits that markets quickly adjust prices following new information releases (Kim, Ryu, & Yang, 2021). This event is important because ESG scores have become vital in investment decisions. Announcing ESG scores can lead to significant market reactions as investors reassess asset value and risk profile based on environmental, social, and governance performance. Studying the impact of these announcements helps us understand how ESG information influences market behaviour and asset prices (Busse & Green, 2002).

The universal applicability of ESG principles makes them relevant for all digital assets, as these, like traditional securities, are scrutinized by investors for their sustainability and ethical impact. With ESG considerations increasingly integrated into investment strategies, the announcement of ESG scores can influence the perceived value of all digital assets (Gavrilakis & Floros, 2023). Examining the impact of the ESG score announcement on all digital assets at once offers a thorough perspective on the market's response to ESG information. This method reduces bias and ensures that the results are not confined to specific assets, providing a broader understanding of how ESG factors affect the entire digital asset market, highlighting the interconnected nature of these assets and the overall significance of ESG considerations (Gavrilakis & Floros, 2023). So, considering all of that together with the above-mentioned theory of Very Short-Time Price Change (VSTPC), we considered an event window based on the use of a standard event study technique which minimizes the analyst's discretion, resulting in fewer subjective decisions and reduced bias: 29th of February 2024 (+/- 16 days) when the ESG score is issued/announced, and the estimation window starts 34 days before the event window, using a fixed length of time of 24 days (Krivin, Patton, Rose, & Tabak, 2003).

Consequently, we collected price data for each digital asset out of 40 in total during the entire event window from invesopedia.com, yahoofinance.com, coinmarketcap.com, coindesk.com, for 2024 as well as its ESG activity level from the ESG report since February 2024. Finally, we obtained a total of 4080 unbalanced panel data points from 40 listed digital assets in the ESG February 2024 report. I used Excel for data processing and model estimation, as well as R statistics software version 4.2.2. for additional analysis of the model performed.

Kothari and Warner (2007) provide evidence that the properties of event study methods can vary depending on the characteristics of the event, such as volatility. This reinforces the importance of carefully selecting the event period. Wells (2004) offers a beginner's guide to event studies, highlighting the two key periods of interest when conducting such studies. He emphasizes that identifying the event period for evaluating the return on investment is the most challenging aspect. The event window is presented in Figure 1:

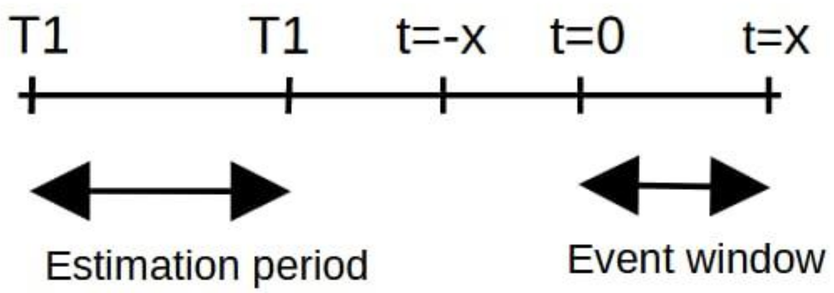

Figure 1: Time window with estimation period given between T1 and T2 as well as Event date t=0 and event window between -x and x

In our study, we use a methodology that is consistent with the methods outlined in that guide and is based on the methodology of both Kothari and Warner (2007), Wells (2004), plus MacKinlay (1997). So, prior to the date of the announcement, as already specified 29th of February 2024, of the issue of the first Industrial report on ESG ranking, an Estimation Period (EP) commencing at Time1 and concluding at Time 2 is used, with the intention of measuring the normal performance of both the market and the digital assets without any impact or influence from the announcement of interest. Surrounding the event date of 29th of February is our Event Window (EW), designated by the announcement date at t=0 and with 16 days on either side.

The time between Time 1 and Time 2 in my study is 24 (10/01-03/02/2024) days, allowing for a sufficient measurement of normal returns without impact from the Report announcement. The estimation period in event studies generally ranges from 60 to 120 days. However, shorter periods may be more suitable for digital assets with high price volatility. MacKinlay (1997) indicates that shorter event windows can be effective in specific situations. A 33-day event window, for example, can effectively capture the necessary data while considering short-term price fluctuations. The event window and estimation period do not overlap; there is a ten-day gap between Time 2 and the start of the event window (t=-16), consistent with MacKinlay (1997).

Although there are important distinctions between ICO, IPO and post-ICOs, the ICO process is somewhat similar to an IPO and even closer to post-ICOs and hence, it is helpful to explore the underpricing phenomenon surrounding post-ICOs by consulting the ICO and IPO literature (Aslan et al., 2023).
In order to measure abnormal returns due to the ESG rating announcing the digital asset score[1], the actual return is calculated together with the estimated return within the event window. Then, the estimated/expected returns are subtracted from the actual returns. The relevant formulas used for this analysis are given below.

Considering our data's panel structure, we employed regression and correlation analyses to investigate how Environmental, Social, and Governance (ESG) levels impact the financial performance of investors in digital assets (Chen et al., 2020), Eq. 4, 5 and 6 is established to test H1, H2, H3 and H4 with their sub-hypothesis.
First, to calculate the Actual Returns (R), we computed the daily returns for each digital asset using the formula:

$$R_i = \frac{P_{i,t} - P_{i,t-1}}{P_{i,t-1}} \tag{1}$$

Where (R_i) is the daily return for the digital asset (i), (P {I,t}) is the digital asset price at time (t)-day I, and (P {I,t-1}) is the digital asset price at the previous time.-day 2.
In parallel, we calculated the expected return for each digital asset (Eq.2) based on a market model, which helped us to test H2 together with Eq4 and Eq5.:

$$\mathrm{E}R\mathrm{it} = \alpha \mathrm{i} + \beta \mathrm{i}\ R\mathrm{mt} \tag{2}$$

Where ERit and Rmt represent the returns of the digital asset I and the market m at the period of interest t. αi represents the intercept, β represents the slope. For the market return of this analysis, the S&P Cryptocurrency Broad Digital Market (BDM) Index has been used, as has been previously mentioned, due to its popularity as a market index in representing a wide-ranging number of digital assets across multiple sectors in addition to its position as one of the leading indices for digital assets. Then, we calculated the abnormal return for each day:

$$AR_i = R_i - E(R_i) \tag{3}$$

And the cumulative abnormal return for each digital asset based on Eq3.:

$$\mathrm{C}AR_i = \sum_{t=1}^{N} AR_i \tag{4}$$

[1] As one example of an ESG rating announcement for Etherium, on 29th of February 2024 highlighting improvements in its governmental practices (with a score of 24.1) and social responsibility initiatives (with score of 28.5), while for environmental practices is less than Solana (25.3 versus 26.5 respectively) (ESG Benchmark, 2024).

Where (N) is the number of time window days, 33.
And have summed up the abnormal returns over the entire event window (e.g., pre and post-earnings announcement period of 33 days in total):

$$CAAR = \frac{1}{N}\sum_{t=1}^{N} AR_i \quad (5)$$

Then, based on the ESG activity metrics for each digital asset during the event window, we calculated the Correlation between CAAR and ESG activity metrics (De Leeuw, 1983). We used the Pearson correlation coefficient[2] for the two groups separately (groups 1 and 2) and for each ESG score:

$$\rho = \frac{Cov(CAAR, ESG)}{\sigma_{CAAR} \cdot \sigma_{ESG}} \quad (6)$$

We opted for the Pearson correlation coefficient over the two-sample t-test, which primarily compares the means of two groups because it allowed us to determine if there is a connection between higher ESG scores and the performance of digital assets. This approach is more suitable for our research, as we are examining the relationship between ESG scores and asset performance to understand the impact of ESG principles on digital assets.
In addition, we have measured the influence of each activity level independently (for Environment, Governance and Social) on the CAAR for the two groups.
To assess the model's robustness, websites that we utilized an event window, starting 16 trading days before the announcement and ending 16 trading days after. In addition, we used another event window starting five days before the announcement and ending five days after. The first window aims to capture a broader effect of the digital asset-related announcement, giving the market time to absorb the information, while the second window focuses on capturing the immediate market reaction to the announcement.

Significance test results and model regression

T-tests are statistical methods used to determine if there is a significant difference between the means of two groups, and in this context, they assess the significance of various types of returns for digital assets. These returns include actual returns, estimated returns (ER), abnormal returns (AR), cumulative abnormal returns (CAR), and cumulative average abnormal returns (CAAR). The null hypotheses tested are whether the actual return (H01), estimated return (H02), abnormal return (H03), and cumulative abnormal return (H04) are different from zero. If these null hypotheses are rejected, it indicates that the returns are significantly different from zero, suggesting that specific events, such as the announcement of an ESG report, significantly impact the returns. This analysis helps understand the short-term and overall trend which impacts such events on digital asset returns, providing valuable insights for financial studies to gauge market reactions to new information (Brown & Warner, 1985).

Therefore, we performed T-tests on all returns (R, ER, AR, CAR, CAAR) to assess their significance on daily, average, and cumulative levels. The null hypotheses outlined below will aid in drawing conclusions from the results presented in this section, highlighting the impact of the related announcement on abnormal returns. Using this method, we searched for evidence to suggest that the abnormal returns of digital assets are affected by announcing the ESG report to the market if their values differ from zero.

The findings from the T-statistics are presented in section 5.3, which covers the overall cumulative abnormal returns for both event windows, evaluated based on ESG scoring and the significance test conducted.

CHAPTER 5 Results & Discussion

The results of both event windows are presented in this chapter, beginning with the longer, 33-day event study results to determine how the market priced all included digital assets in response to the event-related announcement. This was followed by the results from the shorter, 11-day event study, seeing if there was more of an immediate reaction from the market. Following this, additional regressions and abnormal return comparisons have been presented. Any references to significance within the results were conducted using the methodology outlined in Section 4. If abnormal returns, average abnormal returns, cumulative abnormal returns, or cumulative average abnormal returns deviate from zero, the ESG score announcement will impact the results, as seen in our analysis of some digital assets (Brown & Warner, 1985). The detailed results for each of the 40 digital assets are listed in the same order as ranked in the first industrial report since February 29, 2024, and are provided in the supplementary material. For some digital assets such as Stellar.Lumens, Dai. Dai, Algorant, CircleusdCoin, LiteCoin, and BUSD, H01 equals zero. For H02, Algorant, Tether, CircleusdCoin, and BUSD are equal to zero. H03 and H04, the results confirm that also abnormal returns do not exist for some of these assets. Further analysis is necessary because the event window's small sample size prevented us from verifying the data set's normal distribution and checking for homoscedasticity of variance (constant variance). The expanded results of these analyses are discussed in the following section.

5.1 33 Day event window

Figure 2 shows the 33-day cumulative abnormal return (CAR) for the Top-Tier group based on the data in Tables 2 and 3 below. At the same time, Figure 3 also shows the 33-day cumulative abnormal return (CAR) for the Lower-Tier group based on the data in Table 3. The figures illustrate the daily cumulative abnormal returns (CARs) for each digital asset, categorized by their ESG score benchmark, with a significance test conducted over 33 days from (t = -16) to (t = 16).

For the Top-Tier group, prior to Day 0 (the event date), the CAR for all digital assets ranges from -4.3% to 6.8%, indicating some variability but generally within a moderate range. This suggests a mixed market reaction to the upcoming event, with some assets experiencing slight gains and others slight losses. After the event date (from t = 0 to t = 16), noticeable differences in CAR are observed for Algorand (ALGO). Specifically, nine of these post-event days for Algorand have positive CARs, while the other seven are statistically significant with negative returns. The changes in CAR for the remaining assets range from -1.5% to 0.2%, indicating a narrow spectrum of market reactions without any significant influence of ESG scores on digital asset returns. However, the event's varied impact on different digital assets underscores diverse market perceptions and reactions. The T-test results indicate that the CAR values for each digital asset are significant at the 95% level, meaning the observed changes are statistically meaningful and not due to random chance. Nonetheless, this does not necessarily highlight the event's influence on the market performance of these digital assets.

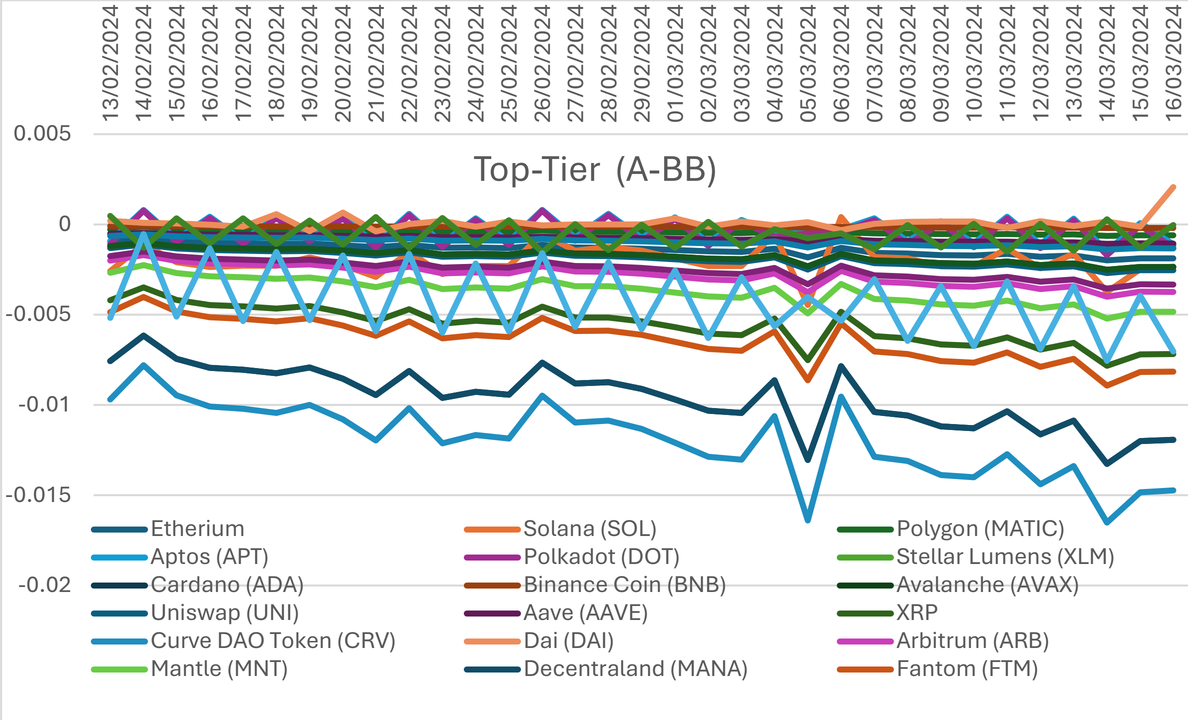

Figure 2: 33-Day Cumulative Abnormal Return (CAR) for Top-Tier Group

Figure legend: Shows CAR change during the event window for all the digital assets in the Top-tier group (given in different colours). Some assets are omitted.

For the Lower-Tier group, prior to Day 0 (the 'event date'), the Cumulative Abnormal Returns (CAR) for almost all digital assets range from -2.8% to 5.9%, with statistically significant days spanning from (t = -16) to (t = 0). After the event date (t = 0 to t = 16), the CAR ranges from -7.9% to 3.5%. The CARs before the event date indicate moderate variability, suggesting a mixed market reaction to the upcoming event, with some assets experiencing slight gains and others slight losses. This also implies an absence of significant events impacting these assets during that time. While after the event, the market reaction to the upcoming event was mixed, indicating a broad spectrum of market reactions, highlighting the diverse impact of the event on different digital assets, and showcasing varying market perceptions and reactions.
For the Lower-Tier group, prior to Day 0 (the 'event date'), the Cumulative Abnormal Returns (CAR) for almost all digital assets range from -2.8% to 5.9%, with statistically significant days spanning from (t = -16) to (t = 0). After the event date (t = 0 to t = 16), the CAR ranges from -7.9% to 3.5%. The CARs before the event date indicate moderate variability, suggesting a mixed market reaction to the upcoming event, with some assets experiencing slight gains and others slight losses. This also implies an absence of significant events impacting these assets during that time. While after the event, the market reaction to the upcoming event was mixed, indicating a broad spectrum of market reactions, highlighting the diverse impact of the event on different digital assets, and showcasing varying market perceptions and reactions.

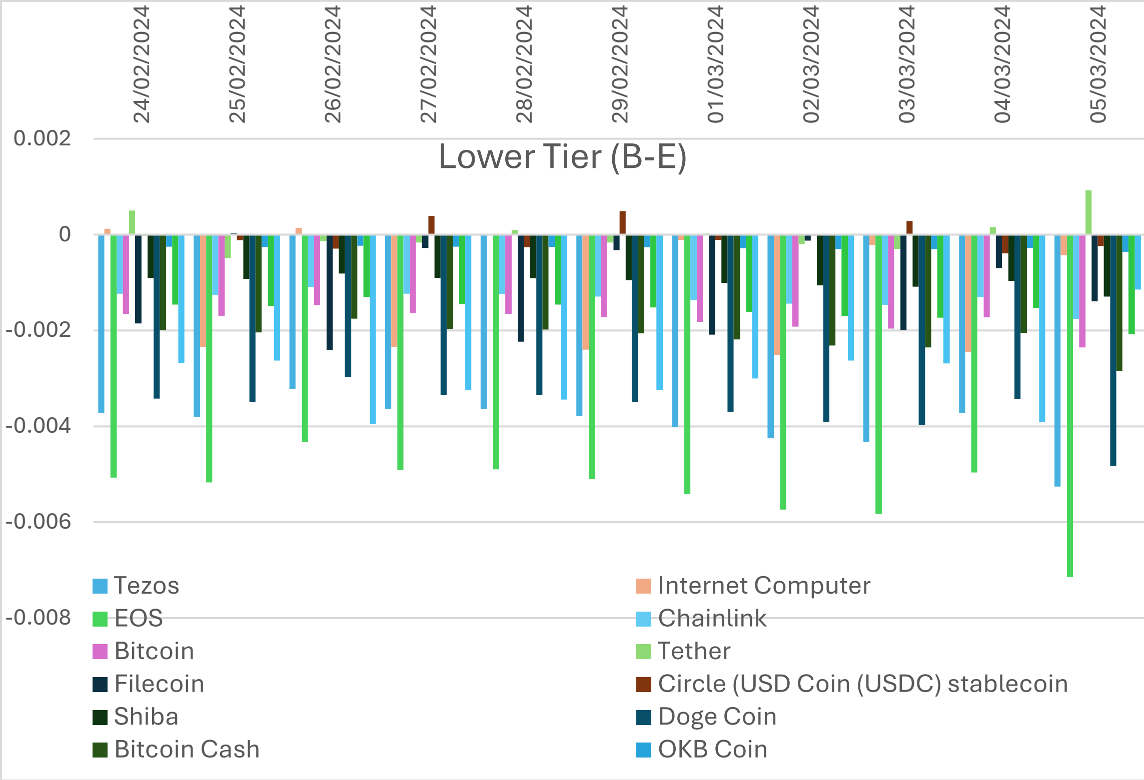

Figure 3: 33-Day Cumulative Abnormal Return (CAR) for Lower-Tier Group

Figure legend: Shows CAR change during the event window for all the digital assets in the Low-tier group (given in different colours). Some assets are omitted.

This underscores the significance of events like the ESG report's announcement in shaping these digital assets' market performance. After the event date (from (t = 0) to (t = 16)), noticeable differences in CAR are observed for LiteCoin and BUSD, reinforcing the importance of the event, such as the announcement of the ESG report in influencing the market performance of these digital assets. Overall, Figures 4 and 5 and their respective tables illustrate a fluctuating post-event period for CARs, averaging around 19.7% for the Top-Tier group and 11.4% for the Lower-Tier group from days t = 0 to t = 16. Most negative returns occur within the event window after the event date for both groups. This suggests that the event had a limited impact on the digital assets in both groups, as investors likely reacted negatively, leading to a decrease in asset prices. This indicates a more neutral impact on the assets in both groups.

However, considering the range of CARs in both groups (for the Top-Tier group, changes in CAR range from -1.5% to 0.2%, while for the Lower-Tier group, they range from -7.9% to 3.5%), it is evident that the ESG report had no specific impact on the Top-Tier group in the post-event period. In contrast, the Lower-Tier group shows a moderate to more decisive influence. This could imply that the market was generally neutral in its reaction to the Top-Tier group or that the event’s influence was not strong enough to sway overall sentiment significantly. However, for the Lower-Tier group, the event had some impact and could shape future market perceptions and reactions.

5.2 11-day event window

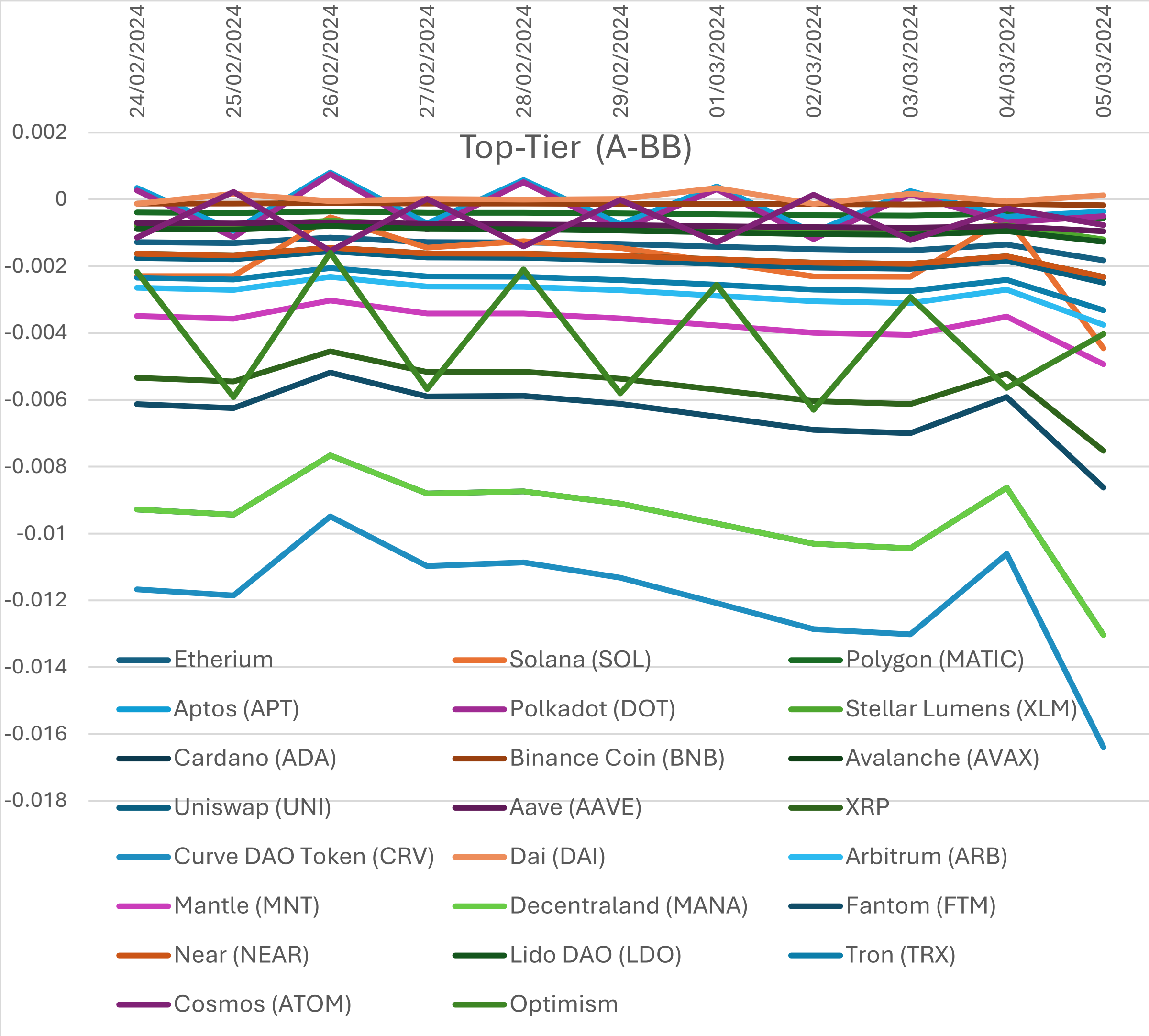

Figure 4: 11-Day Cumulative Abnormal Return (CAR) for Top -Tier Group

Figure legend: Shows CAR change during the event window for all the digital assets in the Top-tier group (given in different colours). Some assets are omitted.

Figure 4 illustrates the 11-day cumulative abnormal return (CAR) for the Top-Tier group, based on the data in Table 1 in the supplementary material from Excel and provided in Appendix 1. Similarly, Figure 5 depicts the 11-day CAR for the Lower-Tier group based on the data provided in the same Table in Appendix 1. These figures present the daily CARs for each digital asset, categorized by their ESG score benchmark, with a significance test conducted over the entire 11-day period from (t = -5) to (t = 5).
For the Top-Tier group, before Day 0 (the event date), the CAR for nearly all digital assets ranges from -4.3% to 6.8% over the period from (t = -5) to (t = 0), indicating some variability but generally within a moderate range. This suggests a mixed market reaction to the upcoming event, with some assets experiencing slight gains and others slight losses.

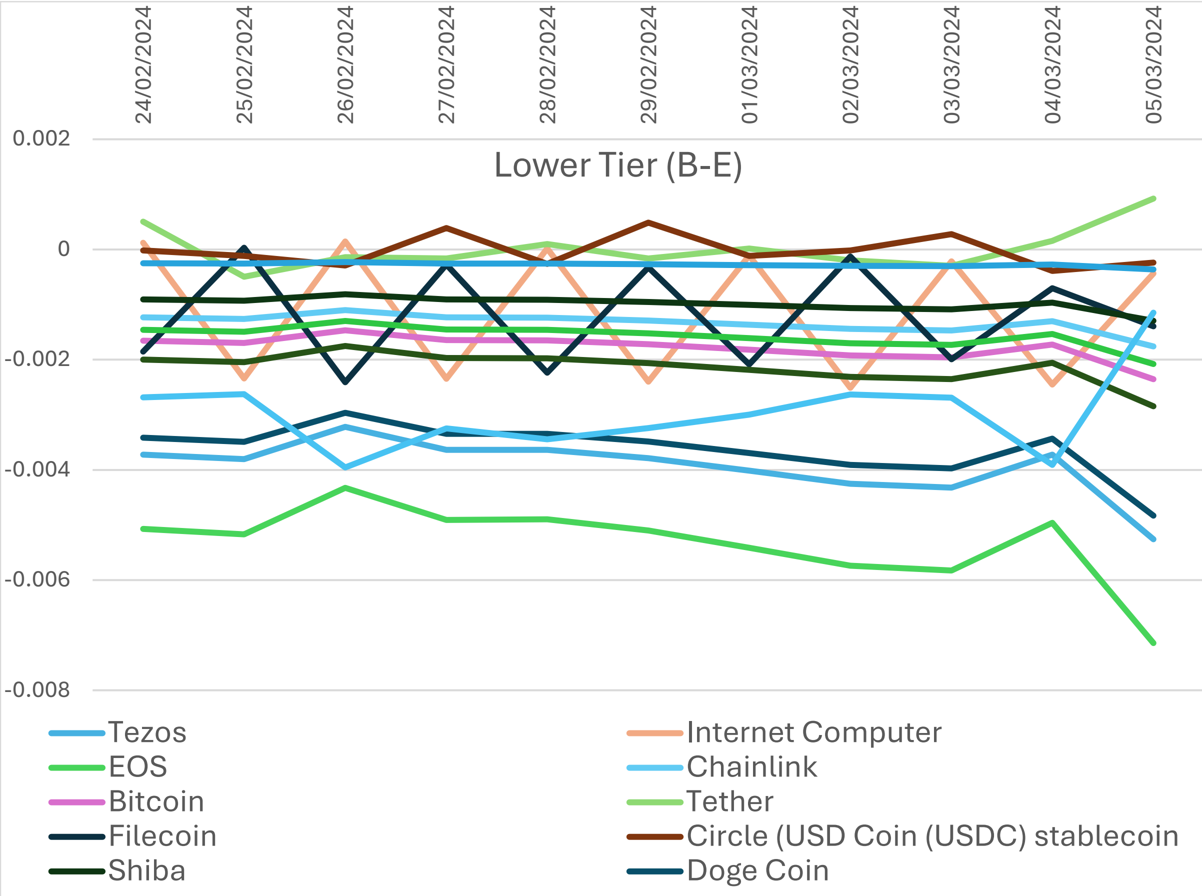

Figure 5: 11-Day Cumulative Abnormal Return (CAR) for Lower-Tier Group

Figure legend: Shows CAR change during the event window for all the digital assets in the Low-tier group (given in different colours)

After the event date (from t = 0 to t = 5), noticeable differences in CAR are observed for Algorand (ALGO) during the three days from (t = 0 to t = 3) (February 29 to March 3, 2024). Notably, three of these post-event days for Algorand have positive CARs, while the other two are statistically significant with negative returns. The changes in CAR for the remaining assets varied from -6.3% to 9.1%, indicating a broad spectrum of market reactions. Some assets experienced substantial positive abnormal returns, while others faced notable negative returns. This wide range highlights the diverse impact of the event on different digital assets, showcasing varying market perceptions and reactions.

The T-test results indicate that the CAR values for each digital asset are significant at the 95% level. This significance implies that the observed changes are statistically meaningful and not due to random variation, highlighting the moderate importance of the event in affecting the market performance of these digital assets.

For the Lower-Tier group, before Day 0 (the ‘event date’), the CAR for almost all digital assets ranges from -2.2% to 2.1%, with statistically significant days spanning from (t = -5) to (t = 0). After the event date (from t = 0 to t = 5), the CAR ranges from -7.9% to 2.1%. The CARs before the event date indicate very small variability, suggesting that the market maintained stable expectations for the digital assets in this group. This stability suggests an absence of significant events impacting these assets during that time.

After the event, the market reaction was mixed, with some assets experiencing slight gains and others slight losses. This indicates a broad spectrum of market reactions, with some assets experiencing substantial positive abnormal returns and others facing notable negative returns. This wide range highlights the diverse impact of the event on different digital assets, showcasing varying market perceptions and reactions. This underscores the event's importance in influencing these digital assets' market performance. Noticeable differences in CAR are observed for LiteCoin and BUSD during the two to three-day period from (t = 0 to t = 3) (February 29 to March 3, 2024), indicating varied market reactions to the event.

Overall, Figures 2 and 3 and their respective tables show a fluctuating post-event period for CARs, averaging around 15.4% for the Top-Tier group and 10% for the Lower-Tier group from days t = 0 to t = 5. Most positive returns within the event window occur after the event date for the Lower-Tier group, while the Top-Tier group sees an almost equal number of positive and negative returns throughout the event window. For the Lower-Tier group, the fact that most positive returns occur after the event date indicates that the event had a favourable impact on the digital assets in this group. Investors likely reacted positively to the event, leading to an increase in asset prices.

For the Top-Tier group, the nearly equal number of positive and negative returns throughout the event window suggests that the event had a more neutral or mixed impact on these assets. This could imply that the market was divided in its reaction or that the event’s influence was not strong enough to sway overall sentiment significantly.

5.3 Overall cumulative abnormal returns for both event windows based on ESG scoring and significance test performed

Tables 3 and 4 compare the CAARs of each digital asset over both the 33-day and 11-day event windows, with test statistics showing significantly different returns from zero (this analysis is derived from the CAR calculations for each digital asset, as detailed in Appendix 1, Table 1, and supplemented by the additional material provided in the Excel file). The event windows show significant influence for only three out of forty digital assets, indicating that the event generally has no impact, especially for the Top-Tier group. In contrast, it has a moderate influence on the Lower-Tier group. This can be attributed to the relatively small betas and the lack of increased expected returns during the estimation periods for most digital assets. The betas for digital assets are detailed in the supplementary material (see worksheet “return” from “Digital assets Prices 10 01 till 20 04 2024 v12.xlsx”), while all daily expected returns, abnormal returns (AR), cumulative abnormal returns (CAR), Average cumulative abnormal returns (CAAR) and test statistics for each day and event in the 33-day window are also in Appendix 1 and 2, as well as for the 11-day window.

Table 3: The Impact of ESG Practices on Top-Tier Asset Performance: Analyzing Cumulative Abnormal Returns in Post-Coin Offerings (Overall Cumulative Abnormal Returns for Top-Tier group based on CAAR calculation and T-test (significance test) performed for the influence of ESG score announcement on digital asset prices)

ASSET	CAAR (33 days)	test statistics	CAAR (11 days)	test statistics
TOP-TIER ASSETS				
Ethereum	-0,001386966	-23,638***	-0,001385466	-25,387***
Solana (SOL)	-0,002019306	-22,234***	-0,001888099	-5,775***
Polygon (MATIC)	-0,000435323	-21,907***	-0,000433811	-25,476***
Aptos (APT)	-0,000283268	-8,886***	-0,000173361	-0,872
Polkadot (DOT)	-0,000420672	-12,234***	-0,000302516	-1,404
Stellar Lumens (XLM)	-0,000843616	-21,815***	-0,000837336	-19,058***
Cardano (ADA)	-0,009561613	-30,282***	-0,00955792	-22,706***
Binance Coin (BNB)	-0,000134714	-20,959***	-0,000133983	-25,368***
Avalanche (AVAX)	-0,001759184	-24,146***	-0,001758102	-25,298***
Uniswap (UNI)	-0,001889491	-24,312***	-0,001888579	-25,263***
Aave (AAVE)	-0,000779625	-23,346***	-0,000781203	-33,619***
XRP	-0,005598335	-27,772***	-0,005601078	-24,024***
Curve DAO Token (CRV)	-0,011936647	-31,491***	-0,011922814	-22,002***
Dai (DAI)	0,000106671	2,335*	3,97732E-05	0,911
Algorand (ALGO)	0,007410554	1,486	0,011228968	0,700
Arbitrum (ARB)	-0,002827457	-25,375***	-0,002827893	-24,979***
Mantle (MNT)	-0,003700511	-26,221***	-0,0037021	-24,687***
Decentraland (MANA)	-0,009561613	-30,282***	-0,00955792	-22,706***
Fantom (FTM)	-0,006397918	-28,343***	-0,006400394	-23,746***
Near (NEAR)	-0,001759184	-24,146***	-0,001758102	-25,298***
Lido DAO (LDO)	-0,000965762	-22,979***	-0,00096399	-25,462***
Tron (TRX)	-0,002503757	-25,030***	-0,00250372	-25,082***
Cosmos (ATOM)	-0,000546851	-15,441***	-0,000661065	-3,183**
Optimism	-0,004279278	-29,401***	-0,004062047	-7,335***

Note Significance codes are to be interpreted as:
*** 0<= p-value <=0,001; ** 0,001< p-value <=0,01; * 0,01< p-value <=0,05; · 0,05< p-value <=0,1; (blank) 0,1< p-value <=1;

So, despite the overall adverse market reaction, Top-Tier assets demonstrated more resilience or were less adversely affected than Lower-Tier assets. This indicates higher investor confidence or perceived stability in Top-Tier assets despite the adverse event, thereby supporting Hypothesis One. The T-test, or significance test, revealed that all null hypotheses showed returns significantly different from zero, indicating that the ESG score has a notable impact on the CAAR.

Table 4: The Impact of ESG Practices on Lower-Tier Asset Performance: Analyzing Cumulative Abnormal Returns of lower-tier assets in Post-Coin Offerings and significance test performed for the influence of ESG score announcement on digital asset prices

ASSET	CAAR (33 days)	test statistics	CAAR (11 days)	test statistics
LOWER-TIER ASSETS				
Tezos	-0,003941024	-26,436***	-0,003942877	-24,604***
Internet Computer	-0,00127428	-21,560***	-0,001138884	-3,077*
EOS	-0,005321025	-27,564***	-0,005323749	-24,131***
Chainlink	-0,001336931	-23,565***	-0,001335385	-25,398***
Bitcoin	-0,001784135	-24,178***	-0,001783084	-25,291***
Tether	-8,45163E-05	-1,387	2,30555E-05	0,192
Filecoin	-0,001054161	-18,040***	-0,001214411	-4,260**
Circle (USD Coin (USDC) stablecoin	8,70465E-05	1,423	-2,67231E-05	-0,304
Shiba	-0,000986043	-23,013***	-0,000984278	-25,459***
DogeCoin	-0,003625302	-26,152***	-0,003626802	-24,712***
Litecoin	-0,002069566	-0,717	-0,00261717	-0,298
Bitcoin Cash	-0,002141912	-24,594***	-0,002140638	-24,735***
OKB Coin	-0,000277264	-21,473***	-0,000276071	-25,442***
BUSD	0,002639479	1,993·	0,00405643	0,995
Ethereum Classic	-0,001577276	-23,905***	-0,001575975	-25,343***
Monero	-0,002862218	-35,151***	-0,002960352	-12,725***

Note Significance codes are to be interpreted as:
*** 0<= p-value <=0,001; ** 0,001< p-value <=0,01; * 0,01< p-value <=0,05; · 0,05< p-value <=0,1; (blank) 0,1< p-value <=1;

5.4 Pearson correlation analysis

Tables 5, 6, and 7 present the results of the Pearson correlation analysis, investigating the link between the cumulative average abnormal return and the ESG score announcement from the first industrial report since February 29, 2024. This analysis follows the model outlined in Section 3 and the conceptual framework, addressing the research question, hypotheses 2-4, and their sub-hypotheses.
The CAAR for both groups is shown in Tables 4 and 5 over the 33-day and 11-day event windows, respectively.

The correlation coefficients for each group, along with the overall coefficient, are provided in Table 6 against explanatory variables such as changes in ESG scores based on the ranking report since February 29, 2024, examining whether the announcement of the ESG score was anticipated by investors in digital assets.

The relationship between CAAR and ESG scores for both groups and the overall correlation coefficient is insignificant. Additionally, the overall coefficient is negative (-0.09 and -0.11), as well as for the lower-tier group, suggesting that higher ESG scores are associated with lower CAARs. This indicates that better ESG performance might lead to worse market performance or that ESG performance adversely influences CAAR. This also implies that CAAR was higher when an announcement surprised the market and was unexpected compared to those included in expected market updates. Both effects are significant at the 5% level. However, for the Top-Tier group, the correlation is positive, meaning that better ESG scores lead to higher CAARs or that better ESG performance might lead to better market performance.

Table 5: CAAR for Top-Tier Group for 33-days event window

	Asset	CAAR 33 days	CAAR 11 days
Top-Tier	Etherium	-0,001386966	-0,001385466
	Solana (SOL)	-0,002019306	-0,001888099
	Polygon (MATIC)	-0,000435323	-0,000433811
	Aptos (APT)	-0,000283268	-0,000173361
	Polkadot (DOT)	-0,000420672	-0,000302516
	Stellar Lumens (XLM)	-0,000843616	-0,000837336
	Cardano (ADA)	-0,009561613	-0,00955792
	Binance Coin (BNB)	-0,000134714	-0,000133983
	Avalanche (AVAX)	-0,001759184	-0,001758102
	Uniswap (UNI)	-0,001889491	-0,001888579
	Aave (AAVE)	-0,000779625	-0,000781203
	XRP	-0,005598335	-0,005601078
	Curve DAO Token (CRV)	-0,011936647	-0,011922814
	Dai (DAI)	0,000106671	3,97732E-05
	Algorand (ALGO)	0,007410554	0,011228968
	Arbitrum (ARB)	-0,002827457	-0,002827893
	Mantle (MNT)	-0,003700511	-0,0037021
	Decentraland (MANA)	-0,009561613	-0,00955792
	Fantom (FTM)	-0,006397918	-0,006400394
	Near (NEAR)	-0,001759184	-0,001758102
	Lido DAO (LDO)	-0,000965762	-0,00096399
	Tron (TRX)	-0,002503757	-0,00250372
	Cosmos (ATOM)	-0,000546851	-0,000661065
	Optimism	-0,004279278	-0,004062047

The results are mixed: one contradicts Hypothesis 2 (Essentially, the market's reaction to the event or announcement was negative, resulting in a decline in the value of the assets. In other words, the returns for these assets were below the market average during the event window.

This suggests that, on average, the assets performed worse than anticipated based on market trends.). While the other confirms Hypothesis 3 and 4 (Digital Assets which belong to group one- Top-Tier Assets have a positive correlation with the ESG score over an event window and Digital Assets which belong to group two- Lower -Tier Assets have a negative correlation with the ESG score over an event window).

Table 6: CAAR for Lower-Tier Group for 33-days event window

	Asset	CAAR 33 days	CAAR 11 days
Lower-Tier	Tezos	-0,003941024	-0,003942877
	Internet Computer	-0,00127428	-0,001138884
	EOS	-0,005321025	-0,005323749
	Chainlink	-0,001336931	-0,001335385
	Bitcoin	-0,001784135	-0,001783084
	Tether	-8,45163E-05	2,30555E-05
	Filecoin	-0,001054161	-0,001214411
	Circle (USD Coin (USDC) stablecoin	8,70465E-05	-2,67231E-05
	Shiba	-0,000986043	-0,000984278
	DogeCoin	-0,003625302	-0,003626802
	Litecoin	-0,002069566	-0,00261717
	Bitcoin Cash	-0,002141912	-0,002140638
	OKB Coin	-0,000277264	-0,000276071
	BUSD	0,002639479	0,00405643
	Ethereum Classic	-0,001577276	-0,001575975
	Monero	-0,002862218	-0,002960352

Further discussion of the results related to these hypotheses is provided in Sections 6 and 7.

Table 7: Pearson correlation coefficients for Top-Tier and Lower-Tier Groups for 33 event window

CAAR-ESG	overall	top tier	lower tier
Corr. coef 33days	-0,110777165	0,169904	-0,290835659
Corr. coef 11 days	-0,092562466	0,140509	-0,283636336

5.5 *Addressing hypotheses*

Hypothesis 1. Top-Tier assets have higher CAR compared to Lower-Tier assets over an event window.

Overall, the findings from both the 33-day and 11-day event windows generally show negative CARs for digital assets following the announcement of the first industrial ESG Benchmark score. Hypothesis 1 aligns closely with the main research question regarding the impact of such announcements on the financial performance of digital assets. Although statistical significance cannot be definitively established due to the small sample size, it is clear that announcements related to ESG performance for digital assets at or near their all-time prices significantly lowered the average result. Therefore, while this study does not confirm the hypothesis significantly, it anecdotally suggests that, on average, digital assets experience negative CARs over both event windows. This indicates lower investor confidence or perceived stability in investing in digital assets based on their ESG performance. However, since Top-Tier assets have higher (less negative) CAR than Lower-Tier assets, they are more favourable, even in an overall negative environment, thereby supporting Hypothesis One.

Future larger-scale studies over extended periods may provide more definitive conclusions.

Hypothesis 2. The assets outperformed what would be predicted based on market trends.

Based on the correlation results and significance test, insufficient evidence supports Hypothesis 2. The market's reaction to the event or announcement was predominantly negative, leading to a decline in the value of the assets. This means that the returns for these assets were below the market average during the event window, indicating that, on average, the assets performed worse than expected based on market trends.

However, this metric might be more effective in measuring abnormal performance in future studies with larger sample sizes. Expanding the sample size could enhance the robustness of the findings and contribute to the project's open-source nature, encouraging more researchers to incorporate such data into their studies.

Although the results of this study do not support the hypothesis, it may still be valuable to pursue a similar approach in future research. Incorporating models that utilize daily sentiment of the digital assets market could provide deeper insights and potentially yield more conclusive results. This approach could help understand the nuanced market reactions to ESG announcements and improve the overall analysis of digital asset performance.

Hypothesis 3. Hypothesis 3. Digital Assets which belong to group one- Top-Tier Assets have a positive correlation with the ESG score over an event window.

> *Hypothesis 3. 1. Digital Assets, which belong to group one- Top-Tier Assets positively correlate with the Environmental score over the event window.*
> *Hypothesis 3. 2. Digital Assets which belong to group one- Top-Tier Assets have a positive correlation with the Social score over the event window.*
> *Hypothesis 3. 3. Digital Assets which belong to group one- Top-Tier Assets have a positive correlation with the Governance score over the event window.*

Hypothesis 4. Digital Assets which belong to group two - Lower -Tier Assets have a negative correlation with the ESG score over an event window

Hypothesis 4. 1. Digital Assets, which belong to group two - Lower-Tier Assets, negatively correlate with the Environmental score over the event window.

Hypothesis 4. 2. Digital Assets which belong to group two - Lower -Tier Assets have a negative correlation with the Social score over the event window.

Hypothesis 4.3. Digital Assets which belong to group two- Lower -Tier Assets have a negative correlation with the Governance score over the event window.

Based on the Pearson correlation coefficients for both groups, Hypotheses 3 and 4, together with their sub-hypotheses, suggest the following:

Top-Tier Assets: These assets positively correlate with the ESG score over the event window, indicating that higher ESG scores are associated with better performance. Specifically, the correlation coefficients are 0.169904 for the 33-day window and 0.140509 for the 11-day window.
Lower-Tier Assets: These assets correlate negatively with the ESG score over the event window, suggesting that higher ESG scores are associated with poorer performance. The correlation coefficients are -0.290835659 for the 33-day window and -0.283636336 for the 11-day window.
Overall Correlation: The overall correlation between CAAR and ESG scores is negative, with coefficients of -0.110777165 for the 33-day window and -0.092562466 for the 11-day window.

This analysis indicates that while Top-Tier assets tend to perform better with higher ESG scores, Lower-Tier assets tend to perform worse. The overall negative correlation suggests that, on average, higher ESG scores are associated with lower abnormal returns across all assets. This could imply that the market perceives ESG scores differently depending on the tier of the asset, with Top-Tier assets benefiting from higher ESG scores and Lower-Tier assets being negatively impacted. This confirms Hypotheses 3 and 4 together with their sub-hypotheses.

5.6 Results and the Literature Reviewed

Although the results do not provide strong evidence for Hypotheses One and Two, they indicate that digital assets tend to show negative cumulative abnormal returns (CARs) in both event windows when ESG performance is considered. This finding contrasts with much of the existing literature, which often reports positive correlations between ESG performance and financial returns. For example, Momparler, Carmona, and Climent (2024) observed a positive relationship between ESG ratings and mutual fund performance, which may differ from my findings due to the distinct characteristics of digital assets. Similarly, Fu and Li (2023) reported a positive impact of ESG on corporate financial performance, which contrasts with my results as well. However, my findings align with those of Yang, Zhang, and Ye (2024), who identified a negative correlation between corporate ESG performance and the pledge ratio of major shareholders, suggesting broader investor concerns.

Furthermore, Whelan, Atz, Van Holt, and Clark (2021) discovered that ESG investing yields returns similar to those of conventional investments. Additionally, Nasdaq's 2019 research highlighted that sustainability leaders often achieve higher returns. These findings contrast with my results, which could be attributed to the distinctive traits of digital assets, such as their volatility and market behaviour. Additionally, the analysis indicates that Top-Tier assets tend to perform better with higher ESG scores, while Lower-Tier assets perform worse. The overall negative correlation suggests higher ESG scores are generally linked to lower abnormal returns across all assets. This aligns with the literature, highlighting the universal applicability of ESG principles to digital assets, similar to traditional securities, as investors scrutinize them for sustainability and ethical impact (Gavrilakis & Floros, 2023). Companies already reflecting ESG practices in their stock prices may not generate additional excess returns from ESG integration, while those actively enhancing their ESG practices show potential for uncorrelated alpha-enhancing returns over the long term (Clark & Lalit, 2020). Nasdaq's research on MSCI ESG rankings found that sustainability leaders experienced higher returns and lower risks, whereas companies with weaker sustainability performance showed opposite outcomes (Ademi & Klungseth, 2022). The scholarly consensus is that adverse ESG events negatively affect overall corporate performance (Krüger, 2015).

CHAPTER 6 Conclusion

6.1 Main conclusion

This study investigated whether digital assets that engage in specific ESG practices, like community engagement, transparency, or electricity consumption, can significantly impact post-coin offerings (PCOs) and other performance metrics. This research provided an initial exploration of the impact of an ESG score announcement by the first industrial report issued by CCData in collaboration with the Crypto Carbon Ratings Institute (CCRI) on the financial performance of digital assets, focusing on the cumulative average abnormal returns (CAAR) over different event windows. The goal was to determine if these ESG practices are primary drivers of abnormal returns, including CAR for investors and their indirect effect on cryptocurrency prices. This research is crucial as it merges finance, ESG, and technology to shed light on the dynamics of PCOs of digital assets, a relatively unexplored area.

The study examined the cumulative average abnormal return (CAAR) in relation to the ESG activity levels of 40 of the largest and most liquid digital assets. It involved gathering and analyzing data on ESG practices and their effects on digital asset performance, with a particular focus on post-ICO periods. The methodology employed regression analysis to identify correlations and potential causations between ESG scores and abnormal returns while addressing selection bias where necessary.

The findings revealed that digital assets typically show negative cumulative abnormal returns (CARs) across both event windows when assessing ESG performance. However, Top-Tier assets tend to fare better with higher ESG scores, whereas Lower-Tier assets perform worse. This overall negative correlation implies that higher ESG scores are generally associated with lower abnormal returns across all assets. These results differ from much of the existing literature, which often finds positive correlations between ESG performance and financial returns. The results suggest lower investor confidence or perceived stability in investing in digital assets based on their ESG performance. Based on market trends, the market's reaction to the ESG announcements indicates that the assets performed worse than expected.

These findings imply that the market views ESG scores differently based on the asset tier. Top-tier assets gain advantages from higher ESG scores, and lower-tier assets are adversely affected. For researchers, this emphasizes the importance of considering the unique traits of digital assets, like their volatility and market dynamics, when examining ESG impacts. For society and investors, it highlights the critical need to evaluate ESG practices in digital assets, as these can greatly affect investment results and perceived stability.

Future research should explore the relationship between ESG factors and financial performance within the cryptocurrency ecosystem, particularly emphasising the long-term effects of ESG practices on digital asset returns. Researchers could improve their analyses by utilizing larger and more diverse datasets and considering additional variables such as market conditions and investor sentiment. Examining how ESG practices influence digital asset performance could provide valuable insights and help develop more effective investment strategies.

6.2 Implications of findings

Based on the analysis of the hypotheses, this paper provides evidence of a nuanced market reaction of digital assets to ESG practices. While Top-Tier assets showed a positive correlation with ESG scores, indicating a favourable market perception, Lower-Tier assets exhibited a negative correlation. Given this study's initial and small-scale nature, there will be ample opportunities in the future to observe how digital assets perform relative to both the market and ESG practices. This will allow for measuring various other metrics and open up many more research topics in the coming years.

Regulators must carefully consider the levels at which investors can invest in digital assets. With no central authority and computer code governing the network, oversight and volatility are primary concerns. In the long term, if digital asset network adoption continues as predicted, it will pose challenges for central banks and governments as traditional currencies like dollars, euros, yen, and francs exit the current monetary system. The market's growth trajectory (US$2.02 trillion) suggests that cryptocurrencies are becoming more integral to the global financial system. It would be naive to assume there will be no further growth or disruption to the established financial system (CoinCodex, 2024).

6.3 Limitations

The first major limitation of this study is the small sample size, with only 40 digital assets and a 33-day event window. While this is a constraint, future studies will benefit from additional data and more firms. The inability to construct longer-term post-announcement windows also limits the forward-looking nature typically associated with event studies. Furthermore, with Microstrategy (MSTR) contributing to just one announcement, the lack of diversity in the current data will be less of a limitation in the future.

Secondly, using only the S&P Cryptocurrency Broad Digital Market (BDM) Index as the model benchmark for all digital assets, instead of multiple indices, may not add much value given the small dataset and recent nature of the events. These initial findings are intended to identify immediate trends that warrant further investigation.

Finally, this study did not control for digital assets' performance due to the small sample size and short event windows. However, this would be a valuable metric in future research, allowing for the construction of normal and abnormal return estimations weighted by digital assets holdings in conjunction with market returns. This could also form the basis for longer-term post-announcement event windows in future studies.

REFERENCES

Ademi, B., & Klungseth, N. J. (2022). Does it pay to deliver superior ESG performance? Evidence from US S&P 500 companies. *Journal of Global Responsibility, 13*(4), 421-449.

Ahmad, H., Yaqub, M., & Lee, S. H. (2024). Environmental-, social-, and governance-related factors for business investment and sustainability: A scientometric review of global trends. *Environment, Development and Sustainability*, *26*(2), 2965-2987.

Ante, L. (2019). Market reaction to exchange listings of cryptocurrencies. *Journal of Corporate Finance, 66*, 101786.

Aslan, A., Şensoy, A., & Akdeniz, L. (2023). Determinants of ICO success and post-ICO performance. *Borsa Istanbul Review*, *23*(1), 217-239.

Benedetti, H., & Kostovetsky, L. (2021). Digital tulips? Returns to investors in initial coin offerings. *Journal of Corporate Finance*, *66*, 101786.

Benveniste, L. M., & Spindt, P. A. (1989). How investment bankers determine the offer price and allocation of new issues. *Journal of Financial Economics*, *24*(2), 343-361. https://doi.org/10.1016/0304-405X(89)90051-2

Brown, S. J., & Warner, J. B. (1980). Measuring security price performance. *Journal of Financial Economics*, *8*(3), 205-258. https://doi.org/10.1016/0304-405X(80)90002-1

Brown, S. J., & Warner, J. B. (1985). Using daily stock returns: The case of event studies. *Journal of Financial Economics*, *14*(1), 3-31. https://doi.org/10.1016/0304-405X(85)90042-X

Busse, J. A., & Green, T. C. (2002). Market efficiency in real-time. *Journal of Financial Economics*, *65*(3), 415-437. https://doi.org/10.1016/S0304-405X(02)00147-5

Campino, J., Brochado, A., & Rosa, M. (2022). Initial coin offerings (ICOs): Why do they succeed? *Financial Innovation*, *8*(1), Article 17. https://doi.org/10.1186/s40854-021-00317-2

Clark, G. L., & Lalit, R. (2020). ESG practices and financial performance: Leaders vs. Improvers. *Journal of Sustainable Finance & Investment*, *10*(4), 345-367. https://doi.org/10.1080/20430795.2020.1863398

Chen, W. M., Bukhari, M., Cockshull, F., & Galloway, J. (2020). The relationship between citations, downloads and alternative metrics in rheumatology publications: a bibliometric study. *Rheumatology (Oxford, England), 59*(2), 277-280.

Chohan, U. W. (2020). Initial Coin Offerings (ICOs): Risks, Regulation, and Accountability. In S. Goutte, K. Guesmi, & S. Saadi (Eds.), *Cryptofinance and Mechanisms of Exchange* (pp. 165-177). Springer. https://doi.org/10.1007/978-3-030-30738-7_10

Ciaian, P., Cupak, A., Fessler, P., & Kancs, D. A. (2022). Environmental-social-governance preferences and investments in crypto-assets. *arXiv preprint arXiv:2206.14548*.

CoinCodex. (2024, August 8). Crypto historical data, price & market cap history. Retrieved from https://coincodex.com/historical-data/crypto/

Corporate Governance Institute. (2023). Assessing Financial Performance Using Business-Related Algorithms.

D'Amato, V., D'Ecclesia, R., & Levantesi, S. (2021). Fundamental ratios as predictors of ESG scores: A machine learning approach. *Decisions in Economics and Finance*, *44*(2), 1087-1110.

Davidson, S., De Filippi, P., & Potts, J. (2018). Blockchains and the economic institutions of capitalism. *Journal of Institutional Economics, 14*(4), 639-658.

De Leeuw, J. (1983). Models and methods for the analysis of correlation coefficients. *Journal of Econometrics, 22*(1-2), 113-137.

EDUCATION. (2022, February 11). FAQ: S&P Cryptocurrency Index Series.

ESG Benchmark. (2024). The first institutional ESG benchmark for digital assets.

Fama, E. F. (1991). Efficient capital markets: II. *The Journal of Finance*, *46*(5), 1575-1617. https://doi.org/10.1111/j.1540-6261.1991.tb04636.x

Fernando, J. (2024, May 16). Return on Investment (ROI): How to Calculate It and What It Means. *Investopedia*. Retrieved from https://www.investopedia.com/terms/r/returnoninvestment.asp

Friede, G., Busch, T., & Bassen, A. (2015). ESG and financial performance: Aggregated evidence from more than 2000 empirical studies. *Journal of Sustainable Finance & Investment, 5*(4), 210-233.

Freeman, R. E. (2015). *Stakeholder theory: The state of the art.* Cambridge University Press.

Freeman, R. E. (2010). *Strategic management: A stakeholder approach*. Cambridge University Press.

Fu, T., & Li, J. (2023). An empirical analysis of the impact of ESG on financial performance: The moderating role of digital transformation. *Frontiers in Environmental Science, 11*, 1256052.

Gavrilakis, N., & Floros, C. (2023). ESG performance, herding behaviour and stock market returns Evidence from Europe. *Operational Research, 23*(1), Article 3. https://doi.org/10.1007/s12351-023-00745-1

Glas, T. (2022). Asset pricing and investment styles in digital assets. *Advanced Studies in Diginomics and Digitalization*. https://doi.org/10.1007/978-3-030-95695-0

GreenCryptoResearch. (2024). TokensList ESG-Ratings Tokens. Retrieved from https://www.greencryptoresearch.com/tokens

GreenCryptoResearch. (2024). TokensList ESG-Ratings Tokens. Retrieved from https://www.greencryptoresearch.com/ratings

Hayes, A. (2022, October 5). *MSCI ESG ratings definition, methodology, example.* Investopedia.

Hoepner, A. G. F., Rezec, M., & Siegl, K. (2021). The notion of ESG (Environmental, Social, and Governance) originated from a 2006 report by the United Nations Principles for Responsible Investment (UNPRI). *In Sustainable Investing: Revolutions in Theory and Practice* (pp. 45-67). Springer. https://doi.org/10.1007/978-3-030-70539-8_3

Hou, D., Liu, Z., Zahid, R. A., & Maqsood, U. S. (2024). ESG dynamics in modern digital world: Empirical evidence from firm life-cycle stages. *Environment, Development and Sustainability*, 1-26.

ICOBench. (2023, March 20). 70+ ICO statistics updated for July 2024. Retrieved from https://icobench.com/stats/ico-statistics/

Investopedia. (2022, October 5). MSCI ESG ratings definition, methodology, example. Retrieved from https://www.investopedia.com/msci-esg-ratings-5111990

Jin, X., & Wu, Y. (2023). The impact of digital investment on corporate ESG performance–The regulatory effect based on the market environment. In Digitalization and Management Innovation II (pp. 400-407). IOS Press.

Kim, K., Ryu, D., & Yang, H. (2021). Information uncertainty, investor sentiment, and analyst reports. *International Review of Financial Analysis, 77*, 101835.

Kher, R., Terjesen, S., & Liu, C. (2021). Blockchain, Bitcoin, and ICOs: A review and research agenda. *Small Business Economics, 56*, 1699-1720.

Kolari, J. W., & Pynnönen, S. (2023). Event studies. In *Investment Valuation and Asset Pricing: Models and Methods* (pp. 201-225). Cham: Springer International Publishing.

Kothari, S. P., & Warner, J. B. (2007). Econometrics of event studies. In B. E. Eckbo (Ed.), Handbook of Corporate Finance: *Empirical Corporate Finance* (Vol. 1, pp. 3-36). Elsevier. https://doi.org/10.1016/B978-0-444-53265-7.50015-9

Krivin, D., Patton, R., Rose, E., & Tabak, D. (2003). Determination of the appropriate event window length in individual stock event studies. *Available at SSRN 466161*.

Krüger, F. (2015). *Corporate storytelling: Theorie und empirie narrativer public relations in der unternehmenskommunikation*. Springer-Verlag.

Lyandres, E., Palazzo, B., & Rabetti, D. (2022). Initial coin offering (ICO) success and post-ICO performance. *Management Science, 68*(12), 8658-8679.

MacKinlay, A. C. (1997). Event studies in economics and finance. *Journal of Economic Literature, 35*(1), 13-39. https://doi.org/10.3386/w0368

Masa'deh, R., Obeidat, B. Y., & Tarhini, A. (2016). A Jordanian empirical study of the associations among transformational leadership, transactional leadership, knowledge sharing, job performance, and firm performance: A structural equation modelling approach. *Journal of Management Development, 35*(5), 681–705.

Marks, J. M., Musumeci, J., & Smith, A. H. (2018). Industry indices in event studies. *Bentley University, Working Paper*.

Masa'deh, R., Tayeh, M., Al-Jarrah, I., & Tarhini, A. (2015). Accounting vs. market-based measures of firm performance related to information technology investments. *International Review of Social Sciences and Humanities, 9*(1), 129-145.

Meyer, A., & Ante, L. (2020). Effects of initial coin offering characteristics on cross-listing returns. *Digital Finance, 2*(3), 259-283.

Miller, D. L. (2023). An introductory guide to event study models. *Journal of Economic Perspectives, 37*(2), 203-230.

Momparler, A., Carmona, P., & Climent, F. (2024). Catalyzing sustainable investment: Revealing ESG power in predicting fund performance with machine learning. *Computational Economics*, 1-26.

Mulligan, C., Morsfield, S., & Cheikosman, E. (2024). Blockchain for sustainability: A systematic literature review for policy impact. *Telecommunications Policy, 48*(2), 102676.

Nagel, E., & Kranz, J. (2022). Revisiting blockchain token sales: How crypto companies raise (D) money. In *Blockchains and the token economy: Theory and practice* (pp. 261-285). Cham: Springer International Publishing.

Nasdaq. (2019). MSCI ESG rankings for the S&P 500: Sustainability leaders experienced higher returns and lower risks over five years. Retrieved from Nasdaq website.

Nguyen Xuan Tho, Le Thuy Dung, & Ngo Thi Thuong Huyen. (2021). Firm financial performance: A review on accounting & market-based approach. *International Journal of Business and Management Invention (IJBMI), 10*(6), 08-11.

Oler, D. K., Harrison, J. S., & Allen, M. R. (2008). The danger of misinterpreting short-window event study findings in strategic management research: An empirical illustration using horizontal acquisitions. *Strategic Organization, 6*(2), 151-184.

Pandey, S., & Kumar, P. (2022). A theoretical framework on return on investment (ROI) in academic libraries. *Library Hi Tech News, 39*(3), 5-11.

Rabbani, M. R., Bashir, S., Nawaz, N., & Amin, A. (2021). The impact of ESG performance on financial success: Evidence from financial institutions. *Journal of Sustainable Finance & Investment, 11*(3), 245-262. https://doi.org/10.1080/20430795.2020.1863398

Rock, K. (1986). Why new issues are underpriced. *Journal of Financial Economics, 15*(1-2), 187-212. https://doi.org/10.1016/0304-405X(86)90054-1

Reitman, D., Caires, E. S. M. (Liz), Mapp, M., Forni, E., & North, E. (2023, February 2). *Digital assets regulation in 2023: Is a new regulatory framework finally emerging?* DLA Piper.

Reiff, N. (2024, March 21). The most successful ICOs of all time. Reviewed by E. Rasure, Fact-checked by K. Munichiello. Retrieved from Investopedia - Most Successful ICOs of All Time.

Sang, Y., Loganathan, K., & Lin, L. (2024). Digital transformation and firm ESG performance: The mediating role of corporate risk-taking and the moderating role of the top management team. *Sustainability, 16*(14), 5907.

Sarstedt, M., Mooi, E., Sarstedt, M., & Mooi, E. (2019). Regression analysis. In *A concise guide to market research: The process, data, and methods using IBM SPSS Statistics* (pp. 209-256).

S&P Dow Jones Indices LLC. (2021, June 30). USD 1.46 trillion, based on 950+ assets priced by Lukka Prime.

Tho, N. X., Dung, L. T., & Huyen, N. T. T. (2021). Firm financial performance: A review on accounting & market-based approach. *International Journal of Business and Management Invention, 431*, 8-11.

Trimborn, S., & Härdle, W. K. (2018). CRIX is an Index for cryptocurrencies. *Journal of Empirical Finance, 49,* 107-122. https://doi.org/10.1016/j.jempfin.2018.08.004

Tudose, M. B., & Avasilcai, S. (2020). A review of the research on financial performance and its determinants. In *Innovation in Sustainable Management and Entrepreneurship: 2019 International Symposium in Management (SIM2019)* (pp. 229-244). Springer International Publishing.

Virgilio, G. P. M. (2022). A theory of very short-time price change: Security price drivers in times of high-frequency trading. *Financial Innovation, 8*(1), 66. https://doi.org/10.1186/s40854-022-00371-4

Yahoo Finance. (2024). Yahoo Finance. Retrieved July 17, 2024, from https://finance.yahoo.com/

Yang, K., Zhang, T., & Ye, C. (2024). The sustainability of corporate ESG performance: An empirical study. *Sustainability, 16*(6), 2377.

Whelan, T., Atz, U., Van Holt, T., & Clark, C. (2021). ESG and financial performance. *Uncovering the Relationship by Aggregating Evidence from, 1,* 2015-2020.

Wells, W. H. (2004). A beginner’s guide to event studies. *Journal of Insurance Regulation, 22*(4).

Wu, X., Li, L., Liu, D., & Li, Q. (2024). Technology empowerment: Digital transformation and enterprise ESG performance—Evidence from China’s manufacturing sector. *PLOS ONE, 19*(4), e0302029.

APPENDIX 1 Some Excel data and results

Table 1: CAR for each digital asset based on the supplementary material given in Excel (see worksheet "CAR" from "Digital assets Prices 10 01 till 20 04 2024 v12.xlsx")

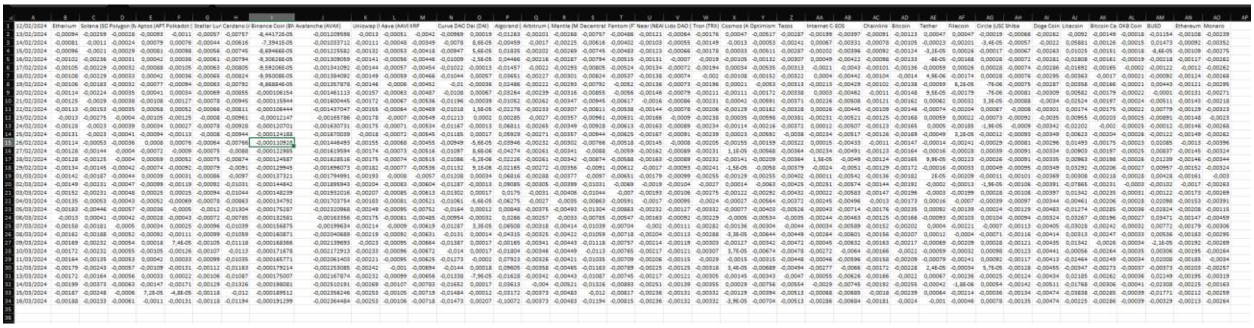

Table 2: Intercept and Slopes for digital assets based on the supplementary material given in Excel

Digital asset	intercept	slope
Etherium	0,006928802	-0,00297871
Solana (SOL)	0,003558211	-0,026173016
Polygon (MATIC)	0,003684785	-0,000847369
Aptos (APT)	0,003491435	-0,007167948
Polkadot (DOT)	0,003899543	-0,007656352
Stellar Lumens (XLM)	0,005345469	-0,00268636
Cardano (ADA)	0,021936413	-0,028567464
Binance Coin (BNB)	0,00198986	-0,00024774
Avalanche (AVAX)	0,007920039	-0,003883997
Uniswap (UNI)	0,008247682	-0,00420904
Aave (AAVE)	0,004979894	-0,000866656
XRP	0,015652174	-0,014866934
Curve DAO Token (CRV)	0,025366752	-0,037664821
Dai (DAI)	-6,93471E-05	0,001850006
Algorand (ALGO)	-0,004999094	0,950195717
Arbitrum (ARB)	0,010401255	-0,006661027
Mantle (MNT)	0,012186788	-0,009102812
Decentraland (MANA)	0,021936413	-0,028567464
Fantom (FTM)	0,016999888	-0,017462413
Near (NEAR)	0,007920039	-0,003883997
Lido DAO (LDO)	0,005669881	-0,001999452
Tron (TRX)	0,009692132	-0,005793538
Cosmos (ATOM)	0,003899671	0,005704207
Optimism	0,013193339	-0,0114207
Tezos	0,012652849	-0,009800094
Internet Computer	0,007161617	-0,001672226
EOS	0,01517173	-0,013988824
Chainlink	0,006788101	-0,002859764
Bitcoin	0,007983462	-0,003945919

Tether	-4,85507E-06	0,005116211
Filecoin	0,005660725	0,007729269
Circle (USD Coin (USDC) stablecoin	1,88793E-05	-0,006330046
Shiba	0,005735017	-0,002045409
DogeCoin	0,012039025	-0,008886884
Litecoin	0,006644673	-0,319433026
Bitcoin Cash	0,008860951	-0,004991713
OKB Coin	0,00290132	-0,000525979
BUSD	0,001015643	-0,325132565
Ethereum Classic	0,007446858	-0,003437167
Monero	0,003608879	0,01884079

APPENDIX 2 R calculations and report prepared

R-report-AD.R

Andrej

2024-08-17

```
############ cumulative abnormal return ################

CAR <- read.csv("C:/Users/andrej/BRISI/ab_ret_cum.csv",
                header=TRUE, sep =";", quote="", dec=",")

t.test( CAR$Etherium, mu=0)

##
##  One Sample t-test
##
## data:  CAR$Etherium
## t = -23.638, df = 32, p-value < 2.2e-16
## alternative hypothesis: true mean is not equal to 0
## 95 percent confidence interval:
##  -0.002951129 -0.002482874
## sample estimates:
##    mean of x
## -0.002717002

t.test( CAR$Solana..SOL.   , mu=0)

##
##  One Sample t-test
##
## data:  CAR$Solana..SOL.
## t = -22.234, df = 32, p-value < 2.2e-16
## alternative hypothesis: true mean is not equal to 0
## 95 percent confidence interval:
##  -0.004331492 -0.003604447
## sample estimates:
##   mean of x
## -0.00396797

t.test( CAR$Polygon..MATIC., mu=0)

##
##  One Sample t-test
##
## data:  CAR$Polygon..MATIC.
## t = -21.907, df = 32, p-value < 2.2e-16
## alternative hypothesis: true mean is not equal to 0
## 95 percent confidence interval:
##  -0.0009314930 -0.0007730049
## sample estimates:
```

```
##     mean of x
## -0.0008522489
```

```r
t.test( CAR$Aptos..APT., mu=0)
```

```
##
##  One Sample t-test
##
## data:  CAR$Aptos..APT.
## t = -8.886, df = 32, p-value = 3.753e-10
## alternative hypothesis: true mean is not equal to 0
## 95 percent confidence interval:
##  -0.0006555687 -0.0004110660
## sample estimates:
##     mean of x
## -0.0005333174
```

```r
t.test( CAR$Polkadot..DOT., mu=0)
```

```
##
##  One Sample t-test
##
## data:  CAR$Polkadot..DOT.
## t = -12.234, df = 32, p-value = 1.316e-13
## alternative hypothesis: true mean is not equal to 0
## 95 percent confidence interval:
##  -0.0009350435 -0.0006681162
## sample estimates:
##     mean of x
## -0.0008015798
```

```r
t.test( CAR$Stellar.Lumens..XLM., mu=0)
```

```
##
##  One Sample t-test
##
## data:  CAR$Stellar.Lumens..XLM.
## t = -21.815, df = 32, p-value < 2.2e-16
## alternative hypothesis: true mean is not equal to 0
## 95 percent confidence interval:
##  -0.001805715 -0.001497307
## sample estimates:
##    mean of x
## -0.001651511
```

```r
t.test( CAR$Cardano..ADA., mu=0)
```

```
##
##  One Sample t-test
##
## data:  CAR$Cardano..ADA.
## t = -30.282, df = 32, p-value < 2.2e-16
## alternative hypothesis: true mean is not equal to 0
## 95 percent confidence interval:
##  -0.02002353 -0.01749950
## sample estimates:
##   mean of x
## -0.01876152
```

```r
t.test( CAR$Binance.Coin..BNB., mu=0)

##
##  One Sample t-test
##
## data:  CAR$Binance.Coin..BNB.
## t = -20.959, df = 32, p-value < 2.2e-16
## alternative hypothesis: true mean is not equal to 0
## 95 percent confidence interval:
##  -0.0002892516 -0.0002380100
## sample estimates:
##     mean of x
## -0.0002636308

t.test( CAR$Avalanche..AVAX., mu=0)

##
##  One Sample t-test
##
## data:  CAR$Avalanche..AVAX.
## t = -24.146, df = 32, p-value < 2.2e-16
## alternative hypothesis: true mean is not equal to 0
## 95 percent confidence interval:
##  -0.003737477 -0.003155957
## sample estimates:
##    mean of x
## -0.003446717

t.test( CAR$Uniswap..UNI., mu=0)

##
##  One Sample t-test
##
## data:  CAR$Uniswap..UNI.
## t = -24.312, df = 32, p-value < 2.2e-16
## alternative hypothesis: true mean is not equal to 0
## 95 percent confidence interval:
##  -0.004012397 -0.003392030
## sample estimates:
##    mean of x
## -0.003702213

t.test( CAR$Aave..AAVE., mu=0)

##
##  One Sample t-test
##
## data:  CAR$Aave..AAVE.
## t = -23.346, df = 32, p-value < 2.2e-16
## alternative hypothesis: true mean is not equal to 0
## 95 percent confidence interval:
##  -0.001660424 -0.001393935
## sample estimates:
##    mean of x
## -0.001527179

t.test( CAR$XRP, mu=0)
```

```
##
##  One Sample t-test
##
## data:  CAR$XRP
## t = -27.772, df = 32, p-value < 2.2e-16
## alternative hypothesis: true mean is not equal to 0
## 95 percent confidence interval:
##  -0.01178443 -0.01017390
## sample estimates:
##   mean of x
## -0.01097917
```

```
t.test( CAR$Curve.DAO.Token..CRV., mu=0)
```

```
##
##  One Sample t-test
##
## data:  CAR$Curve.DAO.Token..CRV.
## t = -31.491, df = 32, p-value < 2.2e-16
## alternative hypothesis: true mean is not equal to 0
## 95 percent confidence interval:
##  -0.02494232 -0.02191164
## sample estimates:
##   mean of x
## -0.02342698
```

```
t.test( CAR$Dai..DAI., mu=0)
```

```
##
##  One Sample t-test
##
## data:  CAR$Dai..DAI.
## t = 2.335, df = 32, p-value = 0.02598
## alternative hypothesis: true mean is not equal to 0
## 95 percent confidence interval:
##  1.922637e-05 2.819928e-04
## sample estimates:
##    mean of x
## 0.0001506096
```

```
t.test( CAR$Algorand..ALGO., mu=0)
```

```
##
##  One Sample t-test
##
## data:  CAR$Algorand..ALGO.
## t = 1.4863, df = 32, p-value = 0.147
## alternative hypothesis: true mean is not equal to 0
## 95 percent confidence interval:
##  -0.006621079  0.042367651
## sample estimates:
##  mean of x
## 0.01787329
```

```
t.test( CAR$Arbitrum..ARB., mu=0)
```

```
##
##  One Sample t-test
##
```

```
## data:  CAR$Arbitrum..ARB.
## t = -25.375, df = 32, p-value < 2.2e-16
## alternative hypothesis: true mean is not equal to 0
## 95 percent confidence interval:
##  -0.005986604 -0.005096887
## sample estimates:
##    mean of x
## -0.005541746
```

```r
t.test( CAR$Mantle..MNT., mu=0)
```

```
##
##  One Sample t-test
##
## data:  CAR$Mantle..MNT.
## t = -26.221, df = 32, p-value < 2.2e-16
## alternative hypothesis: true mean is not equal to 0
## 95 percent confidence interval:
##  -0.007818102 -0.006690980
## sample estimates:
##    mean of x
## -0.007254541
```

```r
t.test( CAR$Decentraland..MANA., mu=0)
```

```
##
##  One Sample t-test
##
## data:  CAR$Decentraland..MANA.
## t = -30.282, df = 32, p-value < 2.2e-16
## alternative hypothesis: true mean is not equal to 0
## 95 percent confidence interval:
##  -0.02002353 -0.01749950
## sample estimates:
##   mean of x
## -0.01876152
```

```r
t.test( CAR$Fantom..FTM., mu=0)
```

```
##
##  One Sample t-test
##
## data:  CAR$Fantom..FTM.
## t = -28.343, df = 32, p-value < 2.2e-16
## alternative hypothesis: true mean is not equal to 0
## 95 percent confidence interval:
##  -0.01345071 -0.01164701
## sample estimates:
##   mean of x
## -0.01254886
```

```r
t.test( CAR$Near..NEAR., mu=0)
```

```
##
##  One Sample t-test
##
## data:  CAR$Near..NEAR.
## t = -24.146, df = 32, p-value < 2.2e-16
## alternative hypothesis: true mean is not equal to 0
```

```
## 95 percent confidence interval:
##  -0.003737477 -0.003155957
## sample estimates:
##    mean of x
## -0.003446717
```

```r
t.test( CAR$Lido.DAO..LDO., mu=0)
```

```
##
##  One Sample t-test
##
## data:  CAR$Lido.DAO..LDO.
## t = -22.979, df = 32, p-value < 2.2e-16
## alternative hypothesis: true mean is not equal to 0
## 95 percent confidence interval:
##  -0.002059128 -0.001723795
## sample estimates:
##    mean of x
## -0.001891461
```

```r
t.test( CAR$Tron..TRX., mu=0)
```

```
##
##  One Sample t-test
##
## data:  CAR$Tron..TRX.
## t = -25.03, df = 32, p-value < 2.2e-16
## alternative hypothesis: true mean is not equal to 0
## 95 percent confidence interval:
##  -0.005306144 -0.004507508
## sample estimates:
##    mean of x
## -0.004906826
```

```r
t.test( CAR$Cosmos..ATOM., mu=0)
```

```
##
##  One Sample t-test
##
## data:  CAR$Cosmos..ATOM.
## t = -15.441, df = 32, p-value < 2.2e-16
## alternative hypothesis: true mean is not equal to 0
## 95 percent confidence interval:
##  -0.0012366504 -0.0009484122
## sample estimates:
##    mean of x
## -0.001092531
```

```r
t.test( CAR$Optimism, mu=0)
```

```
##
##  One Sample t-test
##
## data:  CAR$Optimism
## t = -29.401, df = 32, p-value < 2.2e-16
## alternative hypothesis: true mean is not equal to 0
## 95 percent confidence interval:
##  -0.008923415 -0.007767062
## sample estimates:
```

```
##    mean of x
## -0.008345238
```

```r
t.test( CAR$Tezos, mu=0)
```

```
##
##  One Sample t-test
##
## data:  CAR$Tezos
## t = -26.436, df = 32, p-value < 2.2e-16
## alternative hypothesis: true mean is not equal to 0
## 95 percent confidence interval:
##  -0.008321798 -0.007131143
## sample estimates:
##   mean of x
## -0.00772647
```

```r
t.test( CAR$Internet.Computer, mu=0)
```

```
##
##  One Sample t-test
##
## data:  CAR$Internet.Computer
## t = -21.56, df = 32, p-value < 2.2e-16
## alternative hypothesis: true mean is not equal to 0
## 95 percent confidence interval:
##  -0.002694473 -0.002229282
## sample estimates:
##    mean of x
## -0.002461878
```

```r
t.test( CAR$EOS, mu=0)
```

```
##
##  One Sample t-test
##
## data:  CAR$EOS
## t = -27.564, df = 32, p-value < 2.2e-16
## alternative hypothesis: true mean is not equal to 0
## 95 percent confidence interval:
##  -0.011205940 -0.009663714
## sample estimates:
##   mean of x
## -0.01043483
```

```r
t.test( CAR$Chainlink, mu=0)
```

```
##
##  One Sample t-test
##
## data:  CAR$Chainlink
## t = -23.565, df = 32, p-value < 2.2e-16
## alternative hypothesis: true mean is not equal to 0
## 95 percent confidence interval:
##  -0.002845297 -0.002392548
## sample estimates:
##    mean of x
## -0.002618922
```

```
t.test( CAR$Bitcoin, mu=0)

##
##  One Sample t-test
##
## data:  CAR$Bitcoin
## t = -24.178, df = 32, p-value < 2.2e-16
## alternative hypothesis: true mean is not equal to 0
## 95 percent confidence interval:
##  -0.003790131 -0.003201143
## sample estimates:
##    mean of x
## -0.003495637

t.test( CAR$Tether, mu=0)

##
##  One Sample t-test
##
## data:  CAR$Tether
## t = -1.3871, df = 32, p-value = 0.175
## alternative hypothesis: true mean is not equal to 0
## 95 percent confidence interval:
##  -3.428248e-04  6.506514e-05
## sample estimates:
##     mean of x
## -0.0001388798

t.test( CAR$Filecoin, mu=0)

##
##  One Sample t-test
##
## data:  CAR$Filecoin
## t = -18.04, df = 32, p-value < 2.2e-16
## alternative hypothesis: true mean is not equal to 0
## 95 percent confidence interval:
##  -0.002330821 -0.001857858
## sample estimates:
##    mean of x
## -0.002094339

t.test( CAR$Circle..USD.Coin..USDC..stablecoin, mu=0)

##
##  One Sample t-test
##
## data:  CAR$Circle..USD.Coin..USDC..stablecoin
## t = 1.4233, df = 32, p-value = 0.1643
## alternative hypothesis: true mean is not equal to 0
## 95 percent confidence interval:
##  -6.485148e-05  3.656965e-04
## sample estimates:
##    mean of x
## 0.0001504225

t.test( CAR$Shiba, mu=0)
```

```
##
##  One Sample t-test
##
## data:  CAR$Shiba
## t = -23.013, df = 32, p-value < 2.2e-16
## alternative hypothesis: true mean is not equal to 0
## 95 percent confidence interval:
##  -0.002102140 -0.001760273
## sample estimates:
##    mean of x
## -0.001931207
```

```
t.test( CAR$Doge.Coin, mu=0)
```

```
##
##  One Sample t-test
##
## data:  CAR$Doge.Coin
## t = -26.152, df = 32, p-value < 2.2e-16
## alternative hypothesis: true mean is not equal to 0
## 95 percent confidence interval:
##  -0.007660525 -0.006553424
## sample estimates:
##    mean of x
## -0.007106974
```

```
t.test( CAR$Litecoin, mu=0)
```

```
##
##  One Sample t-test
##
## data:  CAR$Litecoin
## t = -0.71684, df = 32, p-value = 0.4787
## alternative hypothesis: true mean is not equal to 0
## 95 percent confidence interval:
##  -0.015639084  0.007496997
## sample estimates:
##    mean of x
## -0.004071044
```

```
t.test( CAR$Bitcoin.Cash, mu=0)
```

```
##
##  One Sample t-test
##
## data:  CAR$Bitcoin.Cash
## t = -24.594, df = 32, p-value < 2.2e-16
## alternative hypothesis: true mean is not equal to 0
## 95 percent confidence interval:
##  -0.004544761 -0.003849517
## sample estimates:
##    mean of x
## -0.004197139
```

```
t.test( CAR$OKB.Coin, mu=0)
```

```
##
##  One Sample t-test
##
```

```
## data:  CAR$OKB.Coin
## t = -21.473, df = 32, p-value < 2.2e-16
## alternative hypothesis: true mean is not equal to 0
## 95 percent confidence interval:
##  -0.0005941982 -0.0004912318
## sample estimates:
##    mean of x
## -0.000542715

t.test( CAR$BUSD, mu=0)

##
##  One Sample t-test
##
## data:  CAR$BUSD
## t = 1.9934, df = 32, p-value = 0.0548
## alternative hypothesis: true mean is not equal to 0
## 95 percent confidence interval:
##  -0.0001173595  0.0108744364
## sample estimates:
##   mean of x
## 0.005378538

t.test( CAR$Ethereum.Classic, mu=0)

##
##  One Sample t-test
##
## data:  CAR$Ethereum.Classic
## t = -23.905, df = 32, p-value < 2.2e-16
## alternative hypothesis: true mean is not equal to 0
## 95 percent confidence interval:
##  -0.00335338 -0.00282677
## sample estimates:
##    mean of x
## -0.003090075

t.test( CAR$Monero, mu=0)

##
##  One Sample t-test
##
## data:  CAR$Monero
## t = -35.151, df = 32, p-value < 2.2e-16
## alternative hypothesis: true mean is not equal to 0
## 95 percent confidence interval:
##  -0.005971448 -0.005317286
## sample estimates:
##    mean of x
## -0.005644367

########### cumulative abnormal return for 11 days frame ################

CAR11 <- read.csv("C:/Users/andrej/BRISI/ab_ret_cum11.csv",
                header=TRUE, sep =";", quote="", dec=",")

t.test( CAR11$Etherium, mu=0)
```

```
##
##  One Sample t-test
##
## data:  CAR11$Etherium
## t = -25.387, df = 10, p-value = 2.062e-10
## alternative hypothesis: true mean is not equal to 0
## 95 percent confidence interval:
##  -0.001507065 -0.001263868
## sample estimates:
##    mean of x
## -0.001385466
```

```
t.test( CAR11$Solana..SOL.   , mu=0)
```

```
##
##  One Sample t-test
##
## data:  CAR11$Solana..SOL.
## t = -5.775, df = 10, p-value = 0.0001789
## alternative hypothesis: true mean is not equal to 0
## 95 percent confidence interval:
##  -0.002616572 -0.001159627
## sample estimates:
##    mean of x
## -0.001888099
```

```
t.test( CAR11$Polygon..MATIC., mu=0)
```

```
##
##  One Sample t-test
##
## data:  CAR11$Polygon..MATIC.
## t = -25.476, df = 10, p-value = 1.992e-10
## alternative hypothesis: true mean is not equal to 0
## 95 percent confidence interval:
##  -0.0004717520 -0.0003958707
## sample estimates:
##     mean of x
## -0.0004338114
```

```
t.test( CAR11$Aptos..APT., mu=0)
```

```
##
##  One Sample t-test
##
## data:  CAR11$Aptos..APT.
## t = -0.87238, df = 10, p-value = 0.4035
## alternative hypothesis: true mean is not equal to 0
## 95 percent confidence interval:
##  -0.0006161389  0.0002694177
## sample estimates:
##     mean of x
## -0.0001733606
```

```
t.test( CAR11$Polkadot..DOT., mu=0)
```

```
##
##  One Sample t-test
##
```

```
## data:  CAR11$Polkadot..DOT.
## t = -1.404, df = 10, p-value = 0.1906
## alternative hypothesis: true mean is not equal to 0
## 95 percent confidence interval:
##  -0.0007826076  0.0001775761
## sample estimates:
##     mean of x
## -0.0003025157
```

```
t.test( CAR11$Stellar.Lumens..XLM., mu=0)
```

```
##
##  One Sample t-test
##
## data:  CAR11$Stellar.Lumens..XLM.
## t = -19.058, df = 10, p-value = 3.437e-09
## alternative hypothesis: true mean is not equal to 0
## 95 percent confidence interval:
##  -0.0009352317 -0.0007394405
## sample estimates:
##     mean of x
## -0.0008373361
```

```
t.test( CAR11$Cardano..ADA., mu=0)
```

```
##
##  One Sample t-test
##
## data:  CAR11$Cardano..ADA.
## t = -22.706, df = 10, p-value = 6.188e-10
## alternative hypothesis: true mean is not equal to 0
## 95 percent confidence interval:
##  -0.010495855 -0.008619985
## sample estimates:
##   mean of x
## -0.00955792
```

```
t.test( CAR11$Binance.Coin..BNB., mu=0)
```

```
##
##  One Sample t-test
##
## data:  CAR11$Binance.Coin..BNB.
## t = -25.368, df = 10, p-value = 2.077e-10
## alternative hypothesis: true mean is not equal to 0
## 95 percent confidence interval:
##  -0.0001457512 -0.0001222152
## sample estimates:
##     mean of x
## -0.0001339832
```

```
t.test( CAR11$Avalanche..AVAX., mu=0)
```

```
##
##  One Sample t-test
##
## data:  CAR11$Avalanche..AVAX.
## t = -25.298, df = 10, p-value = 2.135e-10
## alternative hypothesis: true mean is not equal to 0
```

```
## 95 percent confidence interval:
##  -0.001912951 -0.001603253
## sample estimates:
##    mean of x
## -0.001758102
```

```
t.test( CAR11$Uniswap..UNI., mu=0)
```

```
##
##  One Sample t-test
##
## data:  CAR11$Uniswap..UNI.
## t = -25.263, df = 10, p-value = 2.164e-10
## alternative hypothesis: true mean is not equal to 0
## 95 percent confidence interval:
##  -0.002055149 -0.001722008
## sample estimates:
##    mean of x
## -0.001888579
```

```
t.test( CAR11$Aave..AAVE., mu=0)
```

```
##
##  One Sample t-test
##
## data:  CAR11$Aave..AAVE.
## t = -33.619, df = 10, p-value = 1.281e-11
## alternative hypothesis: true mean is not equal to 0
## 95 percent confidence interval:
##  -0.0008329771 -0.0007294282
## sample estimates:
##     mean of x
## -0.0007812026
```

```
t.test( CAR11$XRP, mu=0)
```

```
##
##  One Sample t-test
##
## data:  CAR11$XRP
## t = -24.024, df = 10, p-value = 3.552e-10
## alternative hypothesis: true mean is not equal to 0
## 95 percent confidence interval:
##  -0.006120560 -0.005081597
## sample estimates:
##    mean of x
## -0.005601078
```

```
t.test( CAR11$Curve.DAO.Token..CRV., mu=0)
```

```
##
##  One Sample t-test
##
## data:  CAR11$Curve.DAO.Token..CRV.
## t = -22.002, df = 10, p-value = 8.428e-10
## alternative hypothesis: true mean is not equal to 0
## 95 percent confidence interval:
##  -0.01313022 -0.01071541
## sample estimates:
```

```
##   mean of x
## -0.01192281

t.test( CAR11$Dai..DAI., mu=0)

##
##  One Sample t-test
##
## data:  CAR11$Dai..DAI.
## t = 0.91051, df = 10, p-value = 0.384
## alternative hypothesis: true mean is not equal to 0
## 95 percent confidence interval:
##  -5.755725e-05  1.371033e-04
## sample estimates:
##    mean of x
## 3.977303e-05

t.test( CAR11$Algorand..ALGO., mu=0)

##
##  One Sample t-test
##
## data:  CAR11$Algorand..ALGO.
## t = 0.69971, df = 10, p-value = 0.5001
## alternative hypothesis: true mean is not equal to 0
## 95 percent confidence interval:
##  -0.02452818  0.04698612
## sample estimates:
##  mean of x
## 0.01122897

t.test( CAR11$Arbitrum..ARB., mu=0)

##
##  One Sample t-test
##
## data:  CAR11$Arbitrum..ARB.
## t = -24.979, df = 10, p-value = 2.419e-10
## alternative hypothesis: true mean is not equal to 0
## 95 percent confidence interval:
##  -0.003080139 -0.002575646
## sample estimates:
##    mean of x
## -0.002827892

t.test( CAR11$Mantle..MNT., mu=0)

##
##  One Sample t-test
##
## data:  CAR11$Mantle..MNT.
## t = -24.687, df = 10, p-value = 2.717e-10
## alternative hypothesis: true mean is not equal to 0
## 95 percent confidence interval:
##  -0.004036241 -0.003367958
## sample estimates:
##    mean of x
## -0.003702099
```

```r
t.test( CAR11$Decentraland..MANA., mu=0)

##
##  One Sample t-test
##
## data:  CAR11$Decentraland..MANA.
## t = -22.706, df = 10, p-value = 6.188e-10
## alternative hypothesis: true mean is not equal to 0
## 95 percent confidence interval:
##  -0.010495855 -0.008619985
## sample estimates:
##   mean of x
## -0.00955792

t.test( CAR11$Fantom..FTM., mu=0)

##
##  One Sample t-test
##
## data:  CAR11$Fantom..FTM.
## t = -23.746, df = 10, p-value = 3.982e-10
## alternative hypothesis: true mean is not equal to 0
## 95 percent confidence interval:
##  -0.007000947 -0.005799841
## sample estimates:
##    mean of x
## -0.006400394

t.test( CAR11$Near..NEAR., mu=0)

##
##  One Sample t-test
##
## data:  CAR11$Near..NEAR.
## t = -25.298, df = 10, p-value = 2.135e-10
## alternative hypothesis: true mean is not equal to 0
## 95 percent confidence interval:
##  -0.001912951 -0.001603253
## sample estimates:
##    mean of x
## -0.001758102

t.test( CAR11$Lido.DAO..LDO., mu=0)

##
##  One Sample t-test
##
## data:  CAR11$Lido.DAO..LDO.
## t = -25.462, df = 10, p-value = 2.003e-10
## alternative hypothesis: true mean is not equal to 0
## 95 percent confidence interval:
##  -0.001048347 -0.000879633
## sample estimates:
##   mean of x
## -0.00096399

t.test( CAR11$Tron..TRX., mu=0)
```

```
##
##  One Sample t-test
##
## data:  CAR11$Tron..TRX.
## t = -25.082, df = 10, p-value = 2.323e-10
## alternative hypothesis: true mean is not equal to 0
## 95 percent confidence interval:
##  -0.002726134 -0.002281305
## sample estimates:
##   mean of x
## -0.00250372
```

```
t.test( CAR11$Cosmos..ATOM., mu=0)
```

```
##
##  One Sample t-test
##
## data:  CAR11$Cosmos..ATOM.
## t = -3.1833, df = 10, p-value = 0.009765
## alternative hypothesis: true mean is not equal to 0
## 95 percent confidence interval:
##  -0.0011237781 -0.0001983523
## sample estimates:
##     mean of x
## -0.0006610652
```

```
t.test( CAR11$Optimism, mu=0)
```

```
##
##  One Sample t-test
##
## data:  CAR11$Optimism
## t = -7.335, df = 10, p-value = 2.497e-05
## alternative hypothesis: true mean is not equal to 0
## 95 percent confidence interval:
##  -0.005295972 -0.002828122
## sample estimates:
##    mean of x
## -0.004062047
```

```
t.test( CAR11$Tezos, mu=0)
```

```
##
##  One Sample t-test
##
## data:  CAR11$Tezos
## t = -24.604, df = 10, p-value = 2.809e-10
## alternative hypothesis: true mean is not equal to 0
## 95 percent confidence interval:
##  -0.004299951 -0.003585804
## sample estimates:
##    mean of x
## -0.003942878
```

```
t.test( CAR11$Internet.Computer, mu=0)
```

```
##
##  One Sample t-test
##
```

```
## data:  CAR11$Internet.Computer
## t = -3.0767, df = 10, p-value = 0.01171
## alternative hypothesis: true mean is not equal to 0
## 95 percent confidence interval:
##  -0.0019636555 -0.0003141124
## sample estimates:
##    mean of x
## -0.001138884
```

```r
t.test( CAR11$EOS, mu=0)
```

```
##
##  One Sample t-test
##
## data:  CAR11$EOS
## t = -24.121, df = 10, p-value = 3.414e-10
## alternative hypothesis: true mean is not equal to 0
## 95 percent confidence interval:
##  -0.005815523 -0.004831974
## sample estimates:
##    mean of x
## -0.005323748
```

```r
t.test( CAR11$Chainlink, mu=0)
```

```
##
##  One Sample t-test
##
## data:  CAR11$Chainlink
## t = -25.398, df = 10, p-value = 2.054e-10
## alternative hypothesis: true mean is not equal to 0
## 95 percent confidence interval:
##  -0.001452539 -0.001218231
## sample estimates:
##    mean of x
## -0.001335385
```

```r
t.test( CAR11$Bitcoin, mu=0)
```

```
##
##  One Sample t-test
##
## data:  CAR11$Bitcoin
## t = -25.291, df = 10, p-value = 2.141e-10
## alternative hypothesis: true mean is not equal to 0
## 95 percent confidence interval:
##  -0.001940174 -0.001625994
## sample estimates:
##    mean of x
## -0.001783084
```

```r
t.test( CAR11$Tether, mu=0)
```

```
##
##  One Sample t-test
##
## data:  CAR11$Tether
## t = 0.19239, df = 10, p-value = 0.8513
## alternative hypothesis: true mean is not equal to 0
```

```
## 95 percent confidence interval:
##  -0.0002439518  0.0002900626
## sample estimates:
##   mean of x
## 2.30554e-05
```

```r
t.test( CAR11$Filecoin, mu=0)
```

```
##
##  One Sample t-test
##
## data:  CAR11$Filecoin
## t = -4.2602, df = 10, p-value = 0.001662
## alternative hypothesis: true mean is not equal to 0
## 95 percent confidence interval:
##  -0.0018495606 -0.0005792623
## sample estimates:
##    mean of x
## -0.001214411
```

```r
t.test( CAR11$Circle..USD.Coin..USDC..stablecoin, mu=0)
```

```
##
##  One Sample t-test
##
## data:  CAR11$Circle..USD.Coin..USDC..stablecoin
## t = -0.30392, df = 10, p-value = 0.7674
## alternative hypothesis: true mean is not equal to 0
## 95 percent confidence interval:
##  -0.0002226347  0.0001691888
## sample estimates:
##     mean of x
## -2.672296e-05
```

```r
t.test( CAR11$Shiba, mu=0)
```

```
##
##  One Sample t-test
##
## data:  CAR11$Shiba
## t = -25.459, df = 10, p-value = 2.005e-10
## alternative hypothesis: true mean is not equal to 0
## 95 percent confidence interval:
##  -0.0010704193 -0.0008981361
## sample estimates:
##     mean of x
## -0.0009842777
```

```r
t.test( CAR11$Doge.Coin, mu=0)
```

```
##
##  One Sample t-test
##
## data:  CAR11$Doge.Coin
## t = -24.712, df = 10, p-value = 2.689e-10
## alternative hypothesis: true mean is not equal to 0
## 95 percent confidence interval:
##  -0.003953806 -0.003299799
## sample estimates:
```

```
##    mean of x
## -0.003626802

t.test( CAR11$Litecoin, mu=0)

##
##  One Sample t-test
##
## data:  CAR11$Litecoin
## t = -0.29793, df = 10, p-value = 0.7719
## alternative hypothesis: true mean is not equal to 0
## 95 percent confidence interval:
##  -0.02219056  0.01695622
## sample estimates:
##   mean of x
## -0.00261717

t.test( CAR11$Bitcoin.Cash, mu=0)

##
##  One Sample t-test
##
## data:  CAR11$Bitcoin.Cash
## t = -24.735, df = 10, p-value = 2.666e-10
## alternative hypothesis: true mean is not equal to 0
## 95 percent confidence interval:
##  -0.002333470 -0.001947805
## sample estimates:
##    mean of x
## -0.002140638

t.test( CAR11$OKB.Coin, mu=0)

##
##  One Sample t-test
##
## data:  CAR11$OKB.Coin
## t = -25.442, df = 10, p-value = 2.019e-10
## alternative hypothesis: true mean is not equal to 0
## 95 percent confidence interval:
##  -0.0003002485 -0.0002518926
## sample estimates:
##     mean of x
## -0.0002760705

t.test( CAR11$BUSD, mu=0)

##
##  One Sample t-test
##
## data:  CAR11$BUSD
## t = 0.9949, df = 10, p-value = 0.3432
## alternative hypothesis: true mean is not equal to 0
## 95 percent confidence interval:
##  -0.005028199  0.013141058
## sample estimates:
##  mean of x
## 0.00405643
```

```r
t.test( CAR11$Ethereum.Classic, mu=0)
```

```
##
##  One Sample t-test
##
## data:  CAR11$Ethereum.Classic
## t = -25.343, df = 10, p-value = 2.098e-10
## alternative hypothesis: true mean is not equal to 0
## 95 percent confidence interval:
##  -0.001714532 -0.001437418
## sample estimates:
##    mean of x
## -0.001575975
```

```r
t.test( CAR11$Monero, mu=0)
```

```
##
##  One Sample t-test
##
## data:  CAR11$Monero
## t = -12.725, df = 10, p-value = 1.68e-07
## alternative hypothesis: true mean is not equal to 0
## 95 percent confidence interval:
##  -0.003478729 -0.002441976
## sample estimates:
##    mean of x
## -0.002960352
```