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Exploring the Low Volatility Puzzle in Cryptocurrency Markets: A Pricing Dynamics Perspective

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Preface and Acknowledgements

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Abstract

This research paper investigates pricing factors and anomalies in the cryptocurrency market, focusing on the period from 2015-09-04 to 2024-04-19. A sample of 52 cryptocurrencies are chosen based on the quality of available data and on their significance in the overall market. This study leverages traditional equity markets methodologies to construct several sorted portfolio strategies and a 4-factor model to determine the determinant of cryptocurrency prices. By analysing the relationship between on one side cryptocurrency returns and on the other side market, size, momentum, and volatility factors, the paper aims to increase the comprehension of the cryptocurrency market dynamics. Further subsamples analysis displays the effect of the low volatility anomaly in different market settings. Overall, results indicate that cryptocurrencies with lower volatility outperform their riskier counterparts when considering risk adjusted returns in every market condition. This finding offers valuable implication for portfolio allocation, risk management, and regulatory policies.

Keywords: Low-volatility anomaly, Cryptocurrency, Factor investing, Halving

JEL Classification: G11

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Chapter 1 Introduction

On January 3rd 2009, Satoshi Nakamoto launched Bitcoin, a digital currency built on a new technology, Blockchain. What started as a utopian project led by a few believers soon became a unique and promising asset class known as Cryptocurrencies. As of March 2024, the aggregated cryptocurrency market is valued at an astonishing $2.5 trillion. Bitcoin presently holds a market capitalization close to the entire market value of silver, standing at approximately $1.35 trillion, with considerable potential for further expansion. From 2010 to 2021, Bitcoin's impressive average yearly returns of around 160% display a fast-paced adoption for the ecosystem and a global appeal for the asset as an investment alternative (Rose, 2022). Since its debut, the market has sparked significant interest from investors, researchers, and regulators. It is therefore essential to clearly describe its main characteristics.

As a novel asset class, digital currencies exhibit several unique features that differentiate them from traditional assets. A key factor in their success is the decentralization component, which allows secure peer-to-peer transactions without the need for intermediaries like banks or governments (Sarwar et al., 2019). Digital currencies rely on blockchain technology which is a distributed ledger that enables data storage and its distribution across a group of nodes. Transactions are recorded in immutable blocks, providing users with transaction trust, transparency, and lower costs due to the lack of third parties and a high degree of automation. In terms of supply dynamics, Bitcoin set solid foundations with a fixed supply cap and an algorithmic distribution pattern, differentiating itself from traditional assets. It is seen by some as a store of value due to its slow and somewhat steady inflationary tendency. The supply of Bitcoin and several other currencies can be highly influenced by events called "halvings", which occur every four years and reduce the rate at which new units are mined by half. Understanding the implications of halvings is crucial for investors and researchers which ultimately triggered researchers to study this phenomenon since its inception (Ramos et al., 2020). Another important concept is the hash rate, which refers to the speed of computer processing power in the Bitcoin network (Lopatin, 2019). A higher hash rate indicates an increased in the security of the network, as it becomes harder for miners to compete. However, digital currencies are usually volatile and speculative, and can be compared to technological stocks in the early 2000s. This volatility can be attributed to the lack of valuation methods and underlying cash flows or intrinsic value, relying heavily on supply and demand dynamics influenced by investor sentiment and media attention. Critics have questioned the suitability of cryptocurrencies as a store of value or medium of exchange due to these reasons (Baur & Dimpfl, 2021). Lastly, the cryptocurrency market operates 24/7, unlike the stock market with specific trading hours, which may have implications for the applicability of traditional investment strategies such as factor models or certain anomalies.

After discussing the main characteristics of cryptocurrencies, it is important to describe the state of academic and scientific literature. Filippou et al. (2021) point out that despite the popularity of return predictability studies for assets such as equities, there is limited research in the cryptocurrency environment. The lack of comprehensive models can be attributed to the nascent nature of cryptocurrencies and their industry-specific characteristics. Therefore, it is crucial to provide additional insights to improve overall comprehension. Conducting research on factor investing in the cryptocurrency market is important for several reasons. Firstly, cryptocurrencies have gained attention from many actors such as investors or regulators, making it a relevant asset class. Understanding the factors that are driving returns can provide valuable information for investors and portfolio managers seeking to diversify their investments and enjoy profitable strategies. Second, the unique characteristics of cryptocurrencies, such as their decentralization, technology, and supply dynamics, may lead to differences in return patterns compared to traditional asset classes. This also applies for regulators which may need to understand these unique characteristics before creating a regulatory framework. Investigating these factors can contribute to a better understanding of the cryptocurrency market's efficiency and potential anomalies. Third, the speculative nature of cryptocurrencies makes it interesting to investigate factors strategies that can mitigate risk and enhance risk-adjusted returns. Researching the low-volatility anomaly and the impact of halving events on volatility strategies can provide valuable insights for risk management and portfolio construction in this volatile market.

This paper aims to assess cryptocurrency market-specific pricing factors by drawing insights from comparable studies in traditional financial markets. The focus is on crypto-specific characteristics and the low-volatility anomaly, which has not been studied yet. This anomaly is highly relevant in an environment where the threshold for volatility is usually higher than in the equity market, potentially leading to different conclusions. The impact of halving events on volatility strategies is also analyzed using interaction effects. Through this analysis, the paper contributes to the literature on market efficiency and the similarities with other assets, such as the equity market.

The findings from this paper support the idea that low volatility anomalies are present in the cryptocurrency market and present periods in which such irregularities are more likely to appear. Moreover, small cryptocurrencies are found to yield higher returns than large cryptocurrencies. Lastly, the momentum factor is confirmed by displaying that past winners outperform past losers.

The remainder of this paper is organized as follows. Chapter 2 provides a literature review on the efficient market Hypothesis and the existing literature in a cryptocurrency market environment. Chapter 3 delves into the data collection process and the different modifications and adjustments applied. Chapter 4 describes the methodology used in this study to analyse a multitude of portfolios. Chapter 5 discusses results, robustness techniques and a discussion of implications brought by this study. Chapter 6 concludes this paper and mentions its limitations.

Chapter 2 Theoretical Framework

2.1 The Efficient Market Hypothesis (EMH)

The traditional financial view is reflected by the Efficient Market Hypothesis (EMH). EMH states that markets are efficient when the value of an asset fully reflects available information. This Hypothesis served as a starting point for early studies on the cryptocurrency market.

One of the early papers to analyze the weak efficiency of Bitcoin was Urquhart (2016). The author applied several metrics of linear and non-linear dependence to a sample from August 1, 2010, to July 31, 2016. Urquhart (2016) concluded that Bitcoin returns were significantly inefficient over the full sample, with evidence suggesting that efficiency tended to increase over time.

Subsequent studies revisited Urquhart's (2016) work. For instance, Nadarajah and Chu (2017) analyzed the same dataset but power-transformed Bitcoin's returns. They did not find evidence against market efficiency.

In more recent years, researchers have included altcoins with significant market capitalizations in their EMH analysis. Wei (2018) examined 456 different cryptocurrencies during 2017, a year of significant price fluctuations. The author classified cryptocurrencies into five distinct quintets based on their liquidity using the Amihud illiquidity ratio. Wei (2018) improved the tests used by Urquhart (2016) and concluded that as more informed and professional investors entered the market liquidity increases and creates an ecosystem that is less speculative. As a result, fewer arbitrage opportunities were present, making the overall market more efficient.

Similarly, Brauneis and Mestel (2018) used a sample of 73 cryptocurrencies from August 31, 2015, to November 30, 2017, to perform various efficiency tests based on liquidity measures. They concluded that cryptocurrencies tended to become less predictable as liquidity increased, resulting in more efficient markets.

Al-Yahyaee et al. (2020) analyzed the top six cryptocurrencies based on market capitalization levels from August 7, 2015, to July 3, 2018. They found similar evidence as Wei (2018), arguing that efficiency in the cryptocurrency market tended to increase as the market matured and liquidity increased. Overall, most existing studies suggest that the cryptocurrency market, although in a weak form of efficiency become more efficient as the market develops and matures.

Another strand of literature focuses on identifying pricing factors in the cryptocurrency market. Based on traditional financial markets, the idea of identifying the main pricing factor through the Capital Asset Pricing Model (CAPM) emerged. CAPM, first introduced by Sharpe in 1964, has become a common model to price financial assets and assess market efficiency due to its simplicity and reputation.

Liu et al. (2020) examined the effect of integrating cryptocurrency on the CAPM model using Bitcoin excess returns from July 20, 2010, to June 30, 2014. Their results indicated that Bitcoin does not have systematic risk. In other words, Bitcoin's risk profile may differ from traditional assets such as stocks and bonds and could be used to diversify risk.

Dunbar and Owusu-Amoako (2022) expanded on the work of Liu et al. (2020) by including several additional cryptocurrencies, namely XRP and ETH, using return data from September 1, 2014, to September 30, 2021. The authors provided new findings pointing toward the importance of the market risk premium in determining cryptocurrency returns. This suggests that investors' expectations of higher compensation for holding riskier assets are a significant predictor of cryptocurrency returns.

2.2 Traditional Factor Models

Following the Capital Asset Pricing Model (CAPM), Fama and French (1992) developed a three-factor model, which includes the market factor, the small minus big portfolio (SMB), and the high minus low portfolio (HML). These additions allowed researchers to capture new dimensions of the risk-return relationship.

The Size factor (SMB) classifies companies into two distinct categories. Small companies bear higher risk due to liquidity constraints, higher volatility levels, and lower levels of public information. In contrast, larger companies are defined as being more stable and, therefore, less risky. Smaller companies appear to offer a premium return over larger companies to compensate for the additional level of risk (Fama & French, 1992). The Value factor (HML) distinguishes different categories of firms based on their market valuation compared to their fundamentals, such as earnings. Fama and French (1992) found that value stocks, those with high book-to-market ratios, significantly beat growth stocks over the long run. A potential explanation for this phenomenon relies on the assumption that the market is more likely to overprice stocks with high valuations and underprice value stocks, creating higher return potential for the latter. Carhart (1997) later analyzed the momentum factor, previously introduced by Jegadeesh and Titman (1993). Momentum refers to the tendency of assets that have performed well (poorly) in the past to continue to perform similarly in the near future.

Early studies in the cryptocurrency market have built upon factors designed for traditional markets. While some factors are not applicable to this market, slight adjustments can be made. Shen et al. (2020) proposed a three-factor pricing model that includes market, size, and reversal factors, using 1,786 different cryptocurrencies from April 2013 to March 2019. Similar to the size factor in the equity market, the authors found that cryptocurrencies with lower market capitalization tend to obtain higher returns than their larger counterparts. Moreover, Shen et al. (2020) argued that reversal returns are significantly higher for smaller cryptocurrencies than larger ones. Overall, the three-factor pricing model strongly outperformed the cryptocurrency CAPM model. Liu et al. (2020) found similar results when analyzing more than 25 relevant factors, including size, momentum, volume, and volatility, in a cryptocurrency market setting. The data sample used was large, consisting of 1,70 coins weighed based on market capitalization. Their results indicated that a size or momentum strategy both yielded excess returns, while the results from the volume and volatility strategies were mostly not statistically significant.

2.3 Cryptocurrency Factor Models

2.3.1 Macro-Economic Factors

Literature tends to demonstrate a significant and negative relationship between cryptocurrencies, especially Bitcoin, and most exchange rates (Karaömer, 2022). However, conflicting evidence exists. Poyser (2019) found that the price of Bitcoin is negatively related to the exchange rate between the Yuan and the US Dollar. In contrast, Panagiotidis et al. (2018) used a Least Absolute Shrinkage and Selection Operator (LASSO) approach and found that various main exchange rates had a positive effect on Bitcoin returns. Hence, the effect of exchange rates on cryptocurrency prices remains unclear due to conflicting evidence.

Several studies indicate that interest rates play a key role in determining cryptocurrency prices. Nguyen et al. (2022) found that higher federal rates increase the price, volatility, and trading value of the top five cryptocurrencies. Panagiotidis et al. (2018) also found a positive effect of interest rates on Bitcoin returns using a LASSO approach. However, Havidz et al. (2021) and Zhu et al. (2017) found that the Federal Reserve interest rate has a negative impact on the price of Bitcoin, arguing that higher interest rates discourage investors from investing in risky assets like Bitcoin.

Research has assessed the effect of the commodity market as a macro-financial factor on cryptocurrency prices. Lamothe-Fernández et al. (2020) found that gold was positively correlated to Bitcoin prices using deep learning methods. Ciaian et al. (2015) and Panagiotidis et al. (2018) also found positive relationships between gold, oil, and Bitcoin price. However, Jareño et al. (2020) expose a negative relationship between oil and Bitcoin price using an asymmetric nonlinear cointegration approach, arguing that higher oil prices lead to lower household budgets and reduced investments in risky assets like Bitcoin.

Many studies have investigated the impact of the stock market on the cryptocurrency market, but conflicting evidence remains. Lamothe-Fernández et al. (2020) and Ciaian et al. (2016) found that the Dow Jones Index is positively associated with Bitcoin's price in the long term. Quoc Nguyen (2022), Jareño et al. (2020), and Bakas et al. (2022) found a significant and positive relationship between the S&P 500 Index and Bitcoin price, and a negative effect on Bitcoin volatility. Anamika et al. (2021) expanded their research to altcoins like Ethereum and Litecoin, finding that bearish periods in the equity market can cause cryptocurrency prices to rise, indicating potential hedging properties.

2.3.2 Supply and Demand

Researchers have shown that the fundamental concept of supply and demand plays a key role in determining cryptocurrency prices.

Lamothe-Fernández et al. (2020) found that the relationship between Bitcoin supply and demand is a key driver of Bitcoin pricing. Ciaian et al. (2016) and Dubey (2022) observed a negative correlation between the number of Bitcoin in circulation and its price, following classical economic rules. However, Wang and Vergne (2017) found a positive relationship between Bitcoin price and its supply, suggesting that other effects, such as holders' confidence or newcomers entering the market due to increased mining activities, may be at play.

Ciaian et al. (2016) argued that while the supply of a similar asset like gold is endogenous, responding to changes in production technology and capacity, the opposite is true for Bitcoin, indicating that Bitcoin could derive its value largely from demand-side shocks. Karaömer (2022) argued that growth in demand for Bitcoin ultimately leads to an increase in its price. Polasik et al. (2015) discovered that the returns of Bitcoin are mostly driven by the total number of transactions and popularity. Additionally, Liu and Tsyvinski

(2021) showed that network factors, such as the number of active wallets, payment, and transaction accounts, strongly influenced the inherent returns of several cryptocurrencies.

2.3.3 News Sentiment Analysis and Investor Attention

Investor attributes, such as attention and sentiment, have arguably been important determinants of cryptocurrency pricing. Shen et al. (2019) found that cryptocurrency-related tweet activity in previous days significantly drives the next day's price volatility and trading volume. Hakim das Neves (2020) investigated the impact of Google searches on the value of Bitcoin, concluding that an increase in worldwide interest for the digital currency usually follows a price increase, while an increase in market mistrust, defined by the term "bitcoin crash," is usually followed by negative returns. Urquhart (2018) found that past returns and volume predict future investor attention, while Liu and Tsyvinski (2021) noted that investor attention proxies significantly predicted future cryptocurrency returns. However, Smuts (2019) reported a negative correlation between Google trends as a proxy for investor attention and Bitcoin's price, contrasting with other findings.

2.3.4 Technological or Production Factors

Bitcoin mining is one of the most influential factors driving Bitcoin's returns (Ibrahim et al., 2020). Karaömer (2022) identified a positive relationship between the hash rate and Bitcoin's returns, which can be explained by the additional energy needed to mine Bitcoin as its hash rate increases. Kristoufek (2015) found that both hash rates and mining difficulty (the measure of computational power necessary to mine a new block) are positively related to Bitcoin prices. However, Sapkota and Grobys (2020) used portfolio analysis and found that energy consumption does not significantly impact cryptocurrency prices.

Meynkhard (2019) argued that reducing the supply and remuneration of miners every four years (halving) is a key driver to the growth of Bitcoin's market capitalization, with the effect appearing five months after the halving date, potentially the time needed for miners to adjust to the change in supply dynamics. Ramos et al. (2020) confirmed these results but argued that this effect tends to take more time after each occurrence. They also identified a positive correlation between the halving effect and alternative cryptocurrencies, suggesting that small projects can take advantage of Bitcoin's price rise to launch their own projects, effectively using the thrilled and enthusiastic investors to their advantage.

Empirical studies have also investigated other technology factors that affect prices and volatility, such as consensus protocols, blockchain type and information, and the number of emerging collaborators/proposals.

2.4 Idiosyncratic Volatility Puzzle

Fundamental principles in finance dictate that assets with high volatility should yield high expected returns to compensate investors for tolerating the extra risk over the risk-free rate, also known as the risk premium. However, a multitude of empirical studies disagree with this concept, and find conflicting evidence. Haugen and Heins (1975) were among the first researchers to point out the conceptual shortcomings of the positive relationship between risk and return. Their results indicated that, over the long run, stocks with lower volatility have historically outperformed riskier stocks.

Since then, several studies have been conducted on this topic. Ang et al. (2006) found that US equities with high lagged idiosyncratic volatility earned low future mean returns, with evidence that the Fama-French model mispriced these assets. The results were significant and robust across 23 developed markets from 1963 to 2000. Detzel et al. (2019) later replicated the main results of Ang et al. (2006), even when expanding the sample to 2016. None of the considered asset-pricing models could consistently account for or explain the pricing of aggregate-volatility risk.

Baker et al. (2011) argued that the low-volatility anomaly might be driven by institutional investors' ambitions to beat a fixed benchmark, which discourages risky strategies. Furthermore, they found that this anomaly is especially present in periods of high volatility and investor sentiment. An earlier study by Blitz and Vliet (2007) revealed that the anomaly is more pronounced in bear markets and periods of high market volatility. Regarding the cryptocurrency market, several studies have examined its volatility component. Baur and Dimpfl (2018) examined the asymmetric volatility effects regarding the 20 largest cryptocurrencies and found conflicting evidence with traditional markets. Surprisingly, they found that positive shocks in the cryptocurrency market increase volatility to a greater extent than negative shocks, indicating that cryptocurrencies may have different volatility characteristics than equity markets. On the other hand, Zhang et al. (2021) demonstrated that downside risk and future returns were positively correlated similarly to traditional asset classes.

Another strand of literature focuses on drivers of volatility in the digital currency market. Almaqableh et al. (2022) found that terrorist attacks could have positive effect for cryptocurrency returns, however such events could also alter the inherent risk behaviour for different cryptocurrencies, at least on the short term. The COVID-19 outbreak also had a large impact on the volatility and fluctuation of cryptocurrency returns due to heightened uncertainty and market disruptions (Apergis, 2022; Quoc Nguyen, 2022). Lastly, Wang et al. (2019) investigated the relationship between trading activity and price fluctuations of Bitcoin, finding that this relationship could be negative, suggesting that investors should pay attention to this phenomenon when constructing their portfolios.

While most existing research focuses on the predictability of cryptocurrency volatility, this paper investigates if volatility can predict differences in the cross-section of cryptocurrency returns. Traditional market methodologies, such as the work of Haugen and Heins (1975), are applied to a digital market context. To the best of the authors' knowledge, this study is the first to investigate the low-volatility anomaly in the cryptocurrency context, contributing to the existing literature on market efficiency and pricing of cryptocurrencies.

2.5 Hypothesis Development

Based on the existing literature and the unique characteristics of the cryptocurrency market, this study aims to analyze the profitability of specifics factors on the digital coins returns. To control for macroeconomic variables, American interest rates are chosen, while the halving event is chosen to proxy liquidity events. These variables' effects are then used to assess low-volatility anomalies in the market. The following sections present the Hypotheses.

Halving effect

Halving may influence investor behavior and the market, because of shifts in supply and demand dynamics. Based on the argumentation of Ramos et al. (2020), which states that price and volatility of cryptocurrencies tend to grow in the months succeeding the event, the following Hypotheses are constructed.

Hypothesis 1 (H1): Following halving occurrence, the price of cryptocurrencies should increase significantly more than compared to other periods.

Hypothesis 2 (H2): Following halving events, volatility increases significantly compared to other periods.

Interest rates

Following Havidz et al. (2021) results regarding the effect of interest rates on Bitcoin returns, based on the assumption that during high interest period, investors are less likely to invest in risky assets, the following Hypothesis is drafted:

Hypothesis 3 (H3): During periods of high interest rates, prices of cryptocurrencies should decrease.

Low volatility

Based on the findings from Baker et al. (2011) and Blitz and Vliet (2007), arguing that stocks with lower volatility perform better during bear and volatile markets based on a risk-adjusted perspective, therefore, the following Hypotheses are considered:

Hypothesis 4 (H4): Cryptocurrencies with lower volatility should yield higher risk-adjusted returns than cryptocurrencies with higher volatility during bear markets. Bear markets are proxied by the level of the interest rate.

Hypothesis 5 (H5): Cryptocurrencies with lower volatility should yield higher risk-adjusted returns during periods of high market volatility than cryptocurrencies with higher volatility. Market volatility is proxied based on halving events.

Chapter 3 Data

Daily Price and Market Capitalization

Trading data for several cryptocurrencies is collected via Coinmetrics.io, a leading provider of crypto financial intelligence. Coinmetrics.io offers market, network, technology, and volume data, collected from 30 of the world's leading spot and derivatives crypto exchanges. It excludes data from unreliable exchanges with low liquidity.

Around 270 top currencies are available through Coinmetrics.io. Although the exact criteria for inclusion are not specified, it can be inferred that market capitalization, liquidity, and the reputation of exchanges are assessed. For this research, cryptocurrencies must have daily information on price and market capitalization.

Daily closing prices for different cryptocurrencies quoted in reference to USD are collected from Coinmetrics. The data is then log-transformed to deal with skewness and ensure a normal distribution. The sample spans from April 1, 2010, when Bitcoin was priced at $0.085, to the end of April 2024, for a total of 122,033 observations. It is important to note that in 2010, only Bitcoin existed, while several of these coins have appeared in recent years. Therefore, this analysis will integrate additional currencies over time.

Market capitalizations of the coin sample are retrieved through the same provider and calculated as the sum USD value of the supply on a given day. Two metrics are used: "Market Cap USD" and "Market Cap Estimated USD." The latter is chosen for coins that are not supported for the former.

Several gaps are filled using the estimated market capitalization to ensure continuity of data. This was the case for several cryptocurrencies such as CRO, XLM, CRV, GAS, and QNT, for which the estimated market capitalization is used instead of the normal market capitalization. The reason behind this choice is that the information from the estimated market capitalization is more accurate when compared to other sources such as Coinmarketcap.com. Certain gaps are also filled using this estimated value, such as for XLM, which is lacking the original market capitalization from 2022/04/25.

An overview of the changes in market capitalization over time is provided in figure 1 for Bitcoin and Ethereum, and figure 2 for the next 8 largest cryptocurrencies.

Figure 1

Market Value Bitcoin and Ethereum

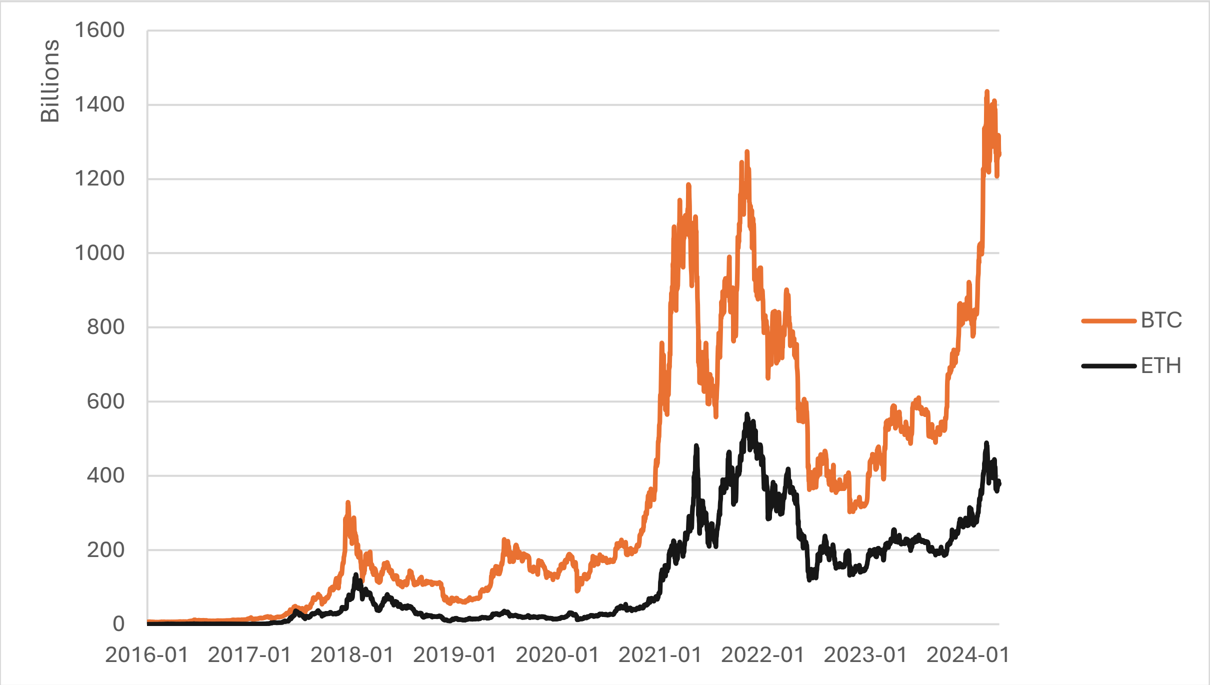
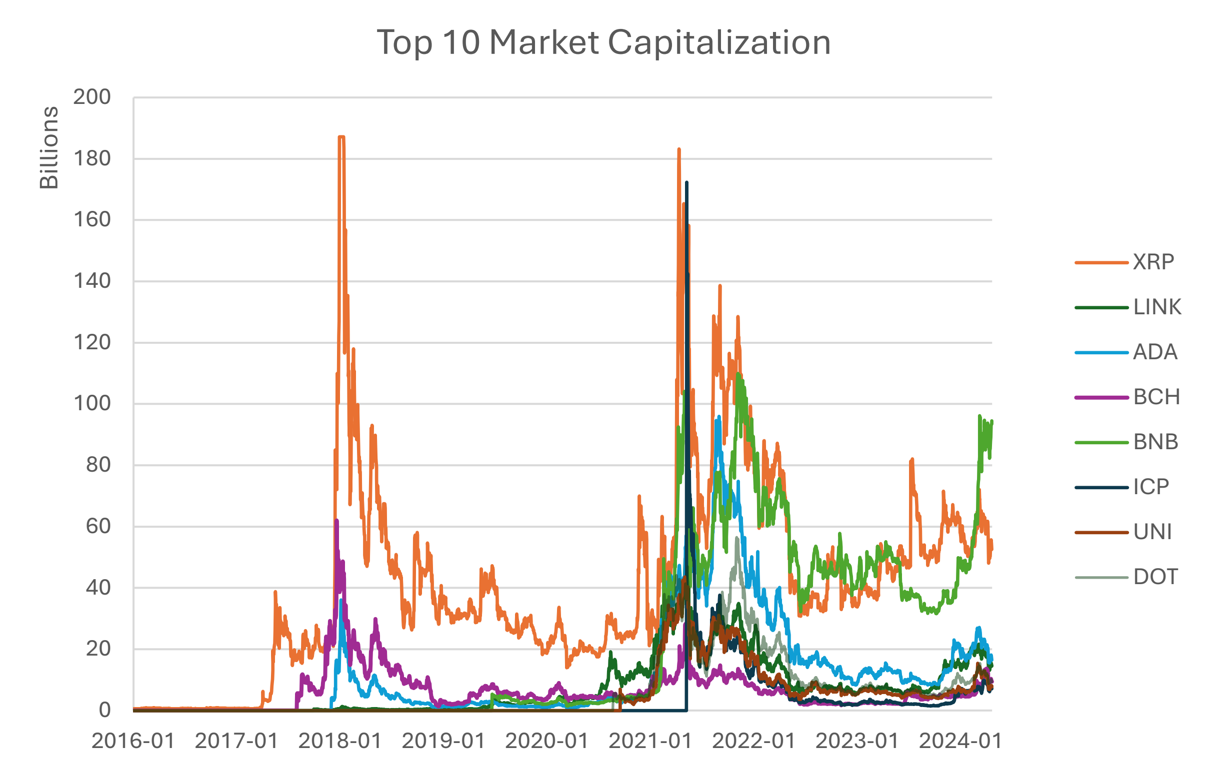


Figure 2

Market Value Top 10 Cryptocurrencies (excl. BTC and ETH)



Coins with market capitalizations inferior to $1,000,000 are excluded from this analysis to ensure a focus on more established and liquid cryptocurrencies. After applying this filter, the number of coins satisfying these conditions falls to 52.

To address potential outliers, daily price datapoints were initially winsorized at a 1% confidence level. However, upon further examination, this winsorized dataset was found to be unrepresentative of the real daily returns of certain cryptocurrencies. This discrepancy can be attributed to the extreme volatility inherent in the cryptocurrency market, where currencies can sometimes experience daily price fluctuations exceeding 50%.

Consequently, to better capture the true market dynamics of cryptocurrencies, this paper will utilize the unwinsorized data. While this approach preserves the extreme price movements, it provides a more accurate representation of the volatility and potential returns in the cryptocurrency market.

Market Index

An index is built to mimic the market portfolio and is used as a benchmark for the sorted portfolio strategies. This index is built following the methodology of Momtaz (2021) who builds a market capitalization-weighted benchmark, arguing that due to extreme daily returns value, an equal-weighted benchmark could produce deceptive results. Hence the market index is constructed as the sum of the products of the market capitalization of digital currency j on day d over the total market capitalization on day d multiplied by the daily raw return of digital currency j at day d.

$$MKT_d = \sum_{i=1}^{n} R_{i,d} * \frac{Cap_{i,d}}{TotalCap_d}$$

Risk-Free rate

The daily 1-Year Treasury Bill Secondary Market Rate is used as a proxy for the risk-free asset and obtained through the Federal Reserve bank database https://fred.stlouisfed.org/.

Interest rate

Data on interest rates is retrieved from the Federal Reserve bank database https://fred.stlouisfed.org/. The daily information on Federal Funds Effective Rate or (EFFR) is obtained. This information will later be used to construct a binary variable to explore the macroeconomic influence of interest rates on cryptocurrency returns.

Having dates

Halving dates of Bitcoin can be found in Table 1. On these dates, the reward provided to miners is divided by two as displayed in column 4. This event is usually associated with higher volatility levels. For this study, this event will be used as a dummy variable to proxy fluctuations in volatility.

Table 1

Overview of Halving Events

Date	Blocks mined	Halving number	Block reward
03-01-09	0	0	50
28-11-12	210000	1	25
09-07-16	420000	2	12,5
11-05-20	630000	3	6,25
19-04-24	840000	4	3,125

Summary Statistics

The summary statistics of the daily log returns are presented in Table 2, providing insights into the return characteristics of the top cryptocurrencies. For clarity and conciseness, only the top 10 coins, ranked by market capitalization on the last day of observations, are included, along with the market index. With this focused approach, the analysis displays the fluctuations of the largest and most traded coins in the market, which are likely to have a bigger impact on the overall market. Average returns and standard deviation are annualized, the rest of the data are provided considering daily units.

Table 2

Summary Statistics for the 10 Largest Cryptocurrencies

Variable |	Obs	Avg return	Avg. Vol	Min	Max	Skewness	Kurtosis

BTC	5,030	166.6%	94.5%	-66.49%	43.66%	-0.75	22.77
ETH	3,183	146.5%	108.4%	-56.56%	38.07%	-0.18	10.89
XRP	3,541	59.7%	125.9%	-63.64%	100.87%	1.56	32.98
LINK	2,400	78.3%	126.7%	-63.61%	47.49%	-0.07	10.60
ADA	2,337	22.3%	112.4%	-49.24%	66.39%	0.97	17.38
BCH	2,459	5.8%	121%	-56.08%	48.86%	0.53	15.05
BNB	2,476	275.3%	116.1%	-53.17%	68.55%	1.19	1.19
DOT	1,344	26.7%	107.4%	-43.17%	40.12%	0.22	10.76
ICP	1,080	-67.1%	117.1%	-35.71%	36.13%	0.15	8.35
UNI	1,315	3.6%	115%	-35.47%	42.78%	0.55	9.43
Market	5,030	198%	95.67%	-63.80%	43.66%	-0.74	21.03

The sample sizes vary across cryptocurrencies, ranging from 1080 daily observations for ICP to 5030 for Bitcoin. Average annual returns indicate that most coins yield positive and extremely high percentages. For instance, BNB stands out with an average annual return of 275%, in comparison, BTC and ETH stand at 166% and 146% return respectively. On the other hand, ICP yields on average an extremely negative annual return of -67%, which indicates that since its inception the digital currency has followed a declining trend. The annualized average standard deviation values indicate that cryptocurrencies can be extremely volatile. LINK and XRP display an average volatility of around 125%, while BTC and the market index have relatively lower estimates at around 95% per year. Overall, these values provide insights into the extreme price movement experienced by the market, but also its extreme return prospective. Interestingly the minimum and maximum values indicate that price movements can also be extreme on a daily basis. To illustrate this point, LINK's maximum daily return slightly surpasses 100%, indicating that its value doubled between the opening and the closure of the market. On the other hand, the highest decrease experienced by a cryptocurrency is Bitcoin which lost 66% of its value in a single day.

The skewness and kurtosis values offer information about the distribution of log return. Overall, XRP and BNB display extreme positive skewness values which indicate a higher probability of large positive returns compared to a normal distribution. Regarding kurtosis, it seems that most cryptocurrencies show significantly higher values than 3, indicating a higher probability of extreme returns compared to a normal distribution.

Chapter 4 Methodology

Subsection 4.1 describes the construction of the returns and other variables for each cryptocurrency. These other variables are market, size, momentum (reversal) and low-volatility. Two additional dummy variables, namely, Halving and interest rates allow the development of the analysis based on specific market conditions. Subsection 4.2 explains the characteristics and the formation of sorted portfolios based on variables discussed in 4.1. Subsection 4.3 describes the methodology used and applied to calculate pricing factors.

4.1 Variable Construction

4.1.1 Log Returns

Following the methodology of Falcon and Lyu (2021), the daily log return, R_d is calculated at day d, where P_d is the close price at day d and P_{d-1} is the close price at the day prior to day d:

$$R_d = \ln\left(\frac{P_d}{P_{d-1}}\right)$$

4.1.2 Market

The market is proxied as the value-weighted average of cryptocurrency returns.

$$MKT_d = \sum_{i=1}^{n} R_{i,d} * \frac{Cap_{i,d}}{TotalCap_d}$$

Where MKT_d is the returns of the market portfolio at day d, $R_{i,d}$ denotes the log returns for i_{th} cryptocurrency at day d, $Cap_{i,d}$ represents the market capitalization of a given cryptocurrency at day d, and $TotalCap_d = \sum_{i=1}^{n} Cap_{i,d}$.

4.1.3 Size

For the size variable, the market capitalization of a given digital currency in the previous period is used.

Cryptocurrency in the top decile of market capitalization and currencies in the bottom decile at day d-1 are considered to construct portfolios on day d. Holding periods considered are 1, 2, 3, and 4 weeks.

4.1.4 Momentum

The methodologies from Shahzad et al. (2021) and Shen et al. (2020) are adapted and used to construct J-K portfolios to predict momentum returns using daily observations. Portfolios are created based on the prior J weeks returns from which currencies are ranked in ascending order. The winner portfolio consists of the top 10%, in other words, cryptocurrencies with the highest returns in the formation period J. Whereas, the loser portfolio consists of the bottom decile. The formation periods J and the holding periods K are set to 1, 2, 3, and 4 weeks, one week consisting of 7 days as the cryptocurrency market trades 24/7. Portfolios are constructed at time d – J, based on the returns of the cryptocurrencies from d – 2J to d – J, and held until d.

Momentum signals are calculated as follows:

- $Momentum_{i,d}^{1w} = R_{i,d-7}^{1w}$

- $Momentum_{i,d}^{2w} = R_{i,d-14}^{2w}$

- $Momentum_{i,d}^{3w} = R_{i,d-21}^{3w}$

- $Momentum_{i,d}^{4w} = R_{i,d-28}^{4w}$

4.1.5 Volatility

The methodology of Jegadeesh and Titman (1993) is used to construct the J-K low volatility cryptocurrency portfolios. For the low-volatility variable, cryptocurrencies are ranked in descending order in any given week t based on their volatilities in the past J weeks and kept in the portfolios for K weeks. This study considers look-back and holding periods of 1, 2, 3, and 4 weeks to cater to the fast-paced environment of the cryptocurrency market. Digital currencies are then sorted into deciles based on their past volatilities. A long strategy is adopted for the top decile (lowest volatility) and a short strategy for the bottom decile (highest volatility). Volatility measures for each cryptocurrency are calculated as such:

- 7-day volatility V_7, is constructed as the standard deviation of log returns on a 7-day rolling window, where C_7 are the 7 daily log returns for cryptocurrency c:
$$V_7 = \sqrt{var(C_7)}$$
- 14-day volatility V_{14}, is constructed as the standard deviation of log returns on a 14-day rolling window, where C_{14} are the 14 daily log returns for cryptocurrency c:
$$V_{14} = \sqrt{var(C_{14})}$$
- 21-day volatility V_{21}, is constructed as the standard deviation of log returns on a 21-day rolling window, where C_{21} are the 21 daily log returns for cryptocurrency c:
$$V_{21} = \sqrt{var(C_{21})}$$
- 28-day volatility V_{28}, is constructed as the standard deviation of log returns on a 28-day rolling window, where C_{28} are the 28 log returns for cryptocurrency c:
$$V_{28} = \sqrt{var(C_{28})}$$

4.1.6 Dummy variables

The inclusion of dummy variables allows to control for certain characteristics of the market. This analysis focuses on the time varying effect of macroeconomic variables with a focus on interest rates, and the effect of the halving effect. This enables the analysis of variations in portfolio returns based on factors that influence the market. Dummy variables are presented in the next part.

<u>Interest rates</u>

This paper considers the following threshold based on Borio and Gambacorta (2017) approach, to consider the interest rate level either low (less than 1.25%) or high (more or equal to 1.25%). Therefore, the dummy variable takes a value of 1 if the EFFR is higher or equal to 1.25% and takes a value of 0 otherwise.

<u>Halving</u>

Based on the argument that the effects of the halving event tend to be incorporated in the market with several months' time-lag (Ramos et al., 2020). The dummy variable H1 takes a value of 1 for dates that are included within 6 months succeeding the event, and 0 otherwise.

However, two additional dummy variables are constructed to test shorter term interactions H2 (3 months), and a dummy variable H3 that investigates the period before and after the halving's occurrence (6 months each).

4.2 Portfolios

The portfolios in this paper are constructed by sorting a selection of cryptocurrencies based on specific characteristics of the variables. Additionally, interactions between variables are considered using double sorts. Furthermore, Fama-MacBeth regressions are conducted to analyze the cross-section of cryptocurrency returns on the selected variables.

The use of top-minus-bottom portfolios is preferred, computed by ranking portfolios based on their exposure to the characteristics. However, long-only portfolio analysis is included to better represent trading patterns in practice. The portfolios are constructed with equal weights; if ten currencies are selected at time t, each will represent 10% of the overall portfolio. The top decile portfolio is included in a long strategy, while the bottom decile is shorted. Average and excess returns are then evaluated to draw conclusions on the effectiveness of the characterized factor. The excess returns are computed over the risk-free rate for each portfolio.

The portfolio creation begins when price information for at least 10 cryptocurrencies is available, allowing the creation of deciles and interesting comparisons. This occurs on August 8, 2015. However, the maximum lookback period required to compute the portfolios, which is 28 days, must be accounted for.

Consequently, the analysis in this paper spans from September 5, 2015, to the end of April 2024 which is the latest available data during the data collection effort. Due to the fast-paced nature of the cryptocurrency market, as highlighted by Fang et al. (2022), portfolios with short-term lookback and holding periods are typically adapted. These are, in most cases, defined as 7 days (1w), 14 days (2w), 21 days (3w), and 28 days (4w).

4.2.1 One-dimensional sorts

The analysis commences with a one-dimensional sort of cryptocurrencies. Each Saturday, cryptocurrencies are selected to construct both long portfolios and long-short portfolios based on their ranking in each of the chosen factors (size, momentum, and low-volatility). Subsequently, excess returns (accounting for the risk-free rate) over the next week(s) are computed, and the process is reiterated until the end of the available data period.

Table 3 reports the equal-weighted returns for the long-short portfolios in panels A (Size), B (Momentum), and C (Volatility), respectively, while Table 4 showcases similar results for long-only portfolios. The results from Tables 3 and 4 indicate that each strategy tends to yield positive average excess returns, except for the 4-week long-short momentum strategy, which exhibits an average return of -0.2% per week.

Long-short portfolios constructed based on the size variable yield an average return of approximately 0.5% per week, while long portfolios built on the size variable yield an average weekly return of 2%. Overall, the 2-week lookback and holding period seem to yield the most favorable results. As for the momentum strategies, long-short portfolios yield around 1% per week, and long portfolios yield around 1.85%, with optimal performance observed for the 3-week strategies. Lastly, the low-volatility portfolios yield average weekly rates of 0.1% and 1.6% for long-short and long portfolios, respectively. Short-term holding and look-back periods seem to outperform their long-term equivalent but may generate higher transaction costs which are not considered in this study.

Altogether, long portfolios tend to outperform long-short portfolios, which can be attributed to the overall positive returns that cryptocurrencies have displayed over the years. By shorting cryptocurrencies, an opportunity cost is created. The lack of significant t-statistic values for most variables may indicate a lack of explanatory power for subsequent returns, potentially due to the low number of cryptocurrencies in each portfolio resulting from the choice of decile portfolios.

The empirical relation between cryptocurrency returns and variables is further assessed by adjusting for standard measures of risk. The alphas presented in both tables represent the intercepts from the regression of portfolio returns on the cryptocurrency market return. These values are high and statistically significant for the short-term long-short portfolios consisting of momentum and low-volatility anomalies, indicating that these factors might be reliable indicators of cryptocurrency returns over and above the market returns.

Table 3

Weekly-Returns Single Long-Short Portfolios

			Excess Portfolio weekly returns (Long-Short)		
		K,J= 1	2	3	4
Panel A Size (Constant J=1/7)					
	Return	0.0053	0.0063	0.0052	0.0046
		(1.392)	(1.561)	(1.163)	(0.971)
	Alpha	0.0037	0.0040	0.0034	-0.0014
		(0.920)	(0.945)	(0.717)	(-0.304)
Panel B Momentum					
	Return	0.0099	0.0098	0.0125	-0.0017
		(2.579)**	(2.559)**	(1.33)	(-0.406)
	Alpha	0.0099	0.0122	0.0090	-0.0014
		(2.361)**	(2.796)**	(0.971)	(-0.314)
Panel C Low-Volatility					
	Return	0.0022	0.0127	0.0050	0.0078
		(0.656)	(2.167)**	(1.265)	(1.451)
	Alpha	0.0048	0.0132	0.0064	0.0101
		(1.244)	(2.142)**	(1.491)	(1.73)*

Table 4

Weekly-Returns Single Long Portfolios

		Excess Portfolio weekly returns (Long-only)			
	K,J=	1	2	3	4
Panel A Size (Constant J=1/7)					
	Return	0.01965	0.0218	0.0206	0.0181
		(1.994)**	(2.075)**	(1.780)*	(1.467)
	Alpha	0.0012	0.0054	0.0057	-0.0271
		(0.148)	(0.318)	(0.192)	(-0.755)
Panel B Momentum					
	Return	0.0169	0.0190	0.0294	0.0095
		(1.855)*	(1.955)*	(1.553)**	(1.003)***
	Alpha	0.00009	0.0064	0.019	-0.032
		(0.012)	(0.377)	(0.357)	(-1.056)
Panel C Low-Volatility					
	Return	0.0096	0.0239	0.01306	0.0182
		(1.792)*	(1.957)*	(2.169)**	(1.763)*
	Alpha	-0.0039	0.0127	-0.0064	0.0059
		(-1.246)	(0.576)	(-0.747)	(0.167)

Average weekly excess return for cryptocurrency portfolios formed on one-dimensional sorts, on size, momentum, and low-volatility. Portfolios are rebalanced every 1, 2, 3, or 4 weeks (K) based on a lookback period of 1, 2, 3, or 4 and traded at the end of Fridays for the period of 2015-09-04 to 2024-04-19. Long-(short) portfolios are created based on the top decile and (bottom) decile. T-stats and significance levels are presented in parentheses, moreover, alpha represents the intercept obtained from the regression between the portfolio return and the market return. Significance levels are represented by 10% (*), 5% (**), and 1% (***).

4.2.2 Double Sorts Analysis

This paper further investigates the interactions between the previously defined variables by employing the double-sorting methodology proposed by Liu et al. (2020). Digital coins are first organized into three groups based on a specific characteristic, such as size (small, neutral, and large). Subsequently, each group is subdivided into three subgroups based on another characteristic, for instance, momentum returns (low, medium, high). Finally, a 3x3 equal-weighted portfolio is constructed based on the intersection of both variables.

Lookback periods of one week are employed; however, this study analyzes both daily and weekly holding periods to assess the argument by Günther et al. (2020) that short-term reversal effects may be present when double sorting. Rebalancing daily permits a comparison with weekly rebalancing. Consistent with the single-sort portfolios, weekly returns are computed and transformed into excess returns relative to the risk-free rate.

The choice of a 3x3 matrix, rather than larger matrices, ensures that each subgroup contains an appropriate number of cryptocurrencies. Notice that the two-pass sort results may differ depending on the order of the first sort and the second. Based on the significance identified in the previous section, the first sorts prioritize the momentum and volatility anomalies. Consequently, the following pairs are created: momentum and size, momentum and volatility, volatility and size, volatility and momentum, as well as size and volatility. Weekly excess returns for both holding periods are presented in Tables 5 and 6, in panels A, B, C, D, and E, respectively.

Apart from the large-cap cryptocurrencies in the loser momentum group, all other subgroups yield positive returns, aligning with the common expectation that portfolios including underperforming assets should generate lower returns. Panels A from Tables 5 and 6 display the weekly weighted average return for portfolios formed on momentum and size. Most of the return values seem to indicate a downward trend from large cryptocurrencies to small cryptocurrencies, showing a significant size effect.

Panels A returns typically range around 1% per week, with a minimum of -0.34% and a maximum of 2.09%. There appears to be a clear momentum effect, as displayed by higher returns in the "Winner" rows compared to the "Loser" rows.

Panels B display similar results with higher returns for higher-ranked momentum portfolios. However, there is no clear distinction between low and high volatility subgroups in terms of returns based on the results. This indicates a weaker momentum effect for highly volatile coins.

Panels C indicate a clear size effect and confirm the idea that the volatility feature does not seem to have a large influence on returns.

Both Panels D clearly showcase the momentum effect, but an effect from the volatility feature is once again not present, except in Table 5 for the neutral and winner subgroups.

Lastly, Panels E do not display clear volatility effects within the size groups.

Table 5

Weekly-Returns Double Sorted Portfolios with Daily Rebalancing

(J=1/7)	Equal-weighted		
Panel A			
Momentum&Size			
	Small	Neutral	Big
Loser	0.0105	-0.0018	-0.0034
	(1.4257)	(-0.249)	(-0.5264)
Neutral	0.0190	0.0085	0.0121
	(2.672)***	(1.2136)	(1.9716)**
Winner	0.0093	0.0142	0.0121
	(1.1817)	(1.8542)*	(1.7812)*
Panel B			
Momentum&Volatility			
	Low	Medium	High
Loser	0.0036	0.0047	0.0027
	(0.5883)	(0.6451)	(0.3407)

Neutral	0.0176	0.0124	0.0107
	(2.992)***	(1.8178)*	(1.4491)
Winner	0.0118	0.0175	0.0077
	(2.0048)**	(2.1796)**	(0.8388)
Panel C			
Volatility&size			
	Small	Neutral	Big
Low	0.0174	0.0065	0.0079
	(2.706)***	(1.0912)	(1.5283)
Medium	0.0158	0.0065	0.0080
	(2.1126)**	(0.9171)	(1.2134)
High	0.0120	0.0009	-0.0002
	(1.4666)	(0.1067)	(-0.0303)
Panel D			
Volatility&Momentum			
	Loser	Neutral	Winner
Low	0.0038	0.0136	0.0188
	(0.6668)	(2.311)**	(3.2075)***
Medium	0.0054	0.0142	0.0170
	(0.7759)	(1.9933)**	(2.3486)**
High	0.0025	0.0025	0.0091
	(0.3218)	(0.3129)	(0.9812)
Panel E			
Size&Volatility			
	Low	Medium	High
Small	0.0192	0.0129	0.0052
	(2.8478)***	(1.5633)	(0.6216)
Neutral	0.0124	0.0068	-0.0005
	(2.0464)**	(0.999)	(-0.052)
Big	0.0078	0.0044	0.0111
	(1.5044)	(0.6557)	(1.4572)

Table 6

Weekly-Returns Double Sorted Portfolios with Weekly Rebalancing

(J=1)		Equal-weighted	
Panel A			
Momentum&Size			
	Small	Neutral	Big
Loser	0.0052	-0.0010	-0.0028
	(0.7356)	(-0.1444)	(-0.4197)
Neutral	0.0104	0.0103	0.0095
	(1.4723)	(1.3891)	(1.6723)*
Winner	0.0186	0.0070	0.0209
	(1.9812)**	(0.9235)	(2.798)***

Panel B			
Momentum&Volatility			
	Low	Medium	High
Loser	0.0018	0.0003	0.0027
	(0.2858)	(0.0341)	(0.3538)
Neutral	0.0129	0.0159	0.0055
	(2.05)**	(2.0966)**	(0.8002)
Winner	0.0141	0.0196	0.0181
	(2.264)**	(2.3879)**	(1.6436)

Panel C			
Volatility&size			
	Small	Neutral	Big
Low	0.0103	0.0033	0.0089
	(1.5618)	(0.5626)	(1.5995)
Medium	0.0092	0.0125	0.0074
	(1.2972)	(1.5596)	(1.1434)
High	0.0135	0.0110	0.0042
	(1.4269)	(1.136)	(0.5227)

Panel D			
Volatility&Momentum			
	Loser	Neutral	Winner
Low	0.0004	0.0113	0.0129
	(0.0689)	(1.7254)*	(2.1101)**
Medium	0.0060	0.0073	0.0156
	(0.8081)	(1.0509)	(2.138)**
High	0.0052	0.0111	0.0173
	(0.6184)	(1.3636)	(1.6173)

Panel E			
Size&Volatility			
	Low	Medium	High
Small	0.0088	0.0180	0.0113
	(1.3371)	(1.9428)*	(1.1432)
Neutral	0.0100	0.0058	0.0031
	(1.5887)	(0.8345)	(0.3704)
Big	0.0082	0.0080	0.0087
	(1.5014)	(1.1618)	(1.1074)

Average weekly excess returns for cryptocurrency portfolio formed on two-pass sorts as previously described. In Table 5 cryptocurrencies are traded each day, while Table 6 presents a holding period of 1 week. For either holding period, digital currencies are allocated to three groups based on terciles of the first variable. Each group is divided into three sub-groups based on the second variable. Significance levels are represented by 10% (*), 5% (**), and 1% (***).

4.3 Pricing Model

4.3.1 Fama-MacBeth Regressions

The Fama and MacBeth (1973)'s cross sectional regressions methodology is chosen to further assess the relationship between returns and selected variables. Each day, the following regression is carried out on the features, namely, size, momentum, and low volatility.

$$(1) \quad r_{i,t+1} = \alpha_{o,t} + \beta_{1,t}Log(Size_{i,t}) + \beta_{2,t}Momentum_{i,t} + \beta_{3,t}vol_{i,t} + \epsilon_{i,t+1}$$

Where $r_{i,t+1}$ represents the daily log return of the cryptocurrency i, at t+1. $Size_{i,t}$ is the log value of the market capitalization of cryptocurrency i estimated based on the value from the prior day. $Momentum_{i,t}$ represents the lagged return of the past 7 days of the ith cryptocurrency. Lastly, $vol_{i,t}$ denotes the lagged volatility in the past 7 days.

Interaction effects between dummy variables and the dependent variable can be found in the following five regressions, which are described beneath. Furthermore, interaction effects with the volatility variable are also described.

$$\begin{aligned}(2) \quad r_{i,t+1} = \alpha_{o,t} + \beta_{1,t}Log(Size_{i,t}) + \beta_{2,t}Momentum_{i,t} + \beta_{3,t}Vol_{i,t} + \beta_{4,t}Vol_{i,t} * IR_t \\ + \beta_{5,t}IR_t + \epsilon_{i,t+1}\end{aligned}$$

$$\begin{aligned}(3) \quad r_{i,t+1} = \alpha_{o,t} + \beta_{1,t}Log(Size_{i,t}) + \beta_{2,t}Momentum_{i,t} + \beta_{3,t}Vol_{i,t} + \beta_{4,t}Vol_{i,t} * H1_t \\ + \beta_{5,t}H1_t + \epsilon_{i,t+1}\end{aligned}$$

$$\begin{aligned}(4) \quad r_{i,t+1} = \alpha_{o,t} + \beta_{1,t}Log(Size_{i,t}) + \beta_{2,t}Momentum_{i,t} + \beta_{3,t}Vol_{i,t} + \beta_{4,t}Vol_{i,t} * H1_t \\ + \beta_{5,t}H1_t + \beta_{6,t}Vol_{i,t} * IR_t + \beta_{7,t}IR_t + + \epsilon_{i,t+1}\end{aligned}$$

$$\begin{aligned}(5) \quad r_{i,t+1} = \alpha_{o,t} + \beta_{1,t}Log(Size_{i,t}) + \beta_{2,t}Momentum_{i,t} + \beta_{3,t}Vol_{i,t} + \beta_{4,t}Vol_{i,t} * H2_t \\ + \beta_{5,t}H2_t + \beta_{6,t}Vol_{i,t} * IR_t + \beta_{7,t}IR_t + + \epsilon_{i,t+1}\end{aligned}$$

$$\begin{aligned}(6) \quad r_{i,t+1} = \alpha_{o,t} + \beta_{1,t}Log(Size_{i,t}) + \beta_{2,t}Momentum_{i,t} + \beta_{3,t}Vol_{i,t} + \beta_{4,t}Vol_{i,t} * H3_t \\ + \beta_{5,t}H3_t + \beta_{6,t}Vol_{i,t} * IR_t + \beta_{7,t}IR_t + + \epsilon_{i,t+1}\end{aligned}$$

Where $H1_t$, $H2_t$, and $H3_t$ represent the halving effect dummy variables for 6 months, 3 months forward looking, and 3 months lag/forward looking, respectively. IR_t is the interest rate dummy variables that takes a value of 1 if the rate is above 1.25% at time t. Interaction effects with the volatility variable are represented as such $\beta_{x,t}Vol_{i,t} * DV_t$.

The results of the Fama-MacBeth cross-sectional regressions are presented in Table 7. Across all model specifications, the size factor exhibits a significant and negative relationship with cryptocurrency returns, confirming previous findings and supporting the existence of a Small-Minus-Big (SMB) factor. Consistently, the momentum factor displays a significant and positive association with returns, aligning with the results from the double-sorted portfolios and reinforcing the use of a Winner-Minus-Loser (WML) factor.

Most notably, the volatility factor demonstrates a positive and significant correlation with returns, contradicting the assumption of a low-volatility anomaly in the cryptocurrency market, at least in the long-term. Consequently, a High-Minus-Low (HML) factor will be considered for the pricing model. To further investigate the role of volatility on returns, interaction effects with interest rates and halving events are examined.

The results from the interest rate dummy variable indicate that the effects of volatility on returns are lower when interest rate levels are high. Furthermore, the interest rate term exhibits a significant negative relationship with the dependent variable, consistent with the Hypothesis that returns should be lower during periods of high interest rates.

Regarding the halving dummy variables (H1, H2, and H3), the findings suggest that H1 and H2 have a significantly negative influence on returns, while H3, which captures the period prior to and after the halving event, displays a significant positive correlation with returns. This observation highlights the anticipation effect of the halving, where prices tend to rise in anticipation of the event, indicating that the market may price in the event before it occurs.

Concerning the interaction effects on the volatility variable, H1 seems to increase the positive effect of volatility, although the coefficients are not statistically significant, hence no meaningful conclusion can be made. In contrast, H2 exhibits a strong, significant, and positive impact on the volatility factor's effect on returns. Lastly, H3 shows a significant negative relationship with the impact of volatility on returns.

Overall, the results are highly significant, except for the dummy variable H1 in the third and fourth regressions, and the interaction effect between interest rates and the volatility variable across all model specifications.

Table 7

Fama MacBeth Cross Sectional Regressions

	1	2	3	4	5	6
Intercept	(0.0602)***	(0.0819)***	(0.0657)***	(0.0992)***	(0.0797)***	(0.0927)***
Log(Size)	(-0.003)***	(-0.004)***	(-0.003)***	(-0.005)***	(-0.0039)***	(-0.004)***
Momentum	(0.0064)***	(0.0062)***	(0.0057)***	(0.0056)***	(0.0059)***	(0.0053)***
Vol	(0.0187)**	(0.0188)*	(0.0226)***	(0.01734)*	(0.0184)*	(0.0393)***
H1			(-0.0072)	(-0.0108)*		
H2					(-0.0277)**	
H3						(0.0032)**
Vol * H1			(0.1002)	(0.106)		
Vol * H2				(0.5171)**		
Vol * H3					(-0.070)***	
Vol % IR	(-0.0062)		(-0.0022)	(-0.0074)	(-0.0141)	
IR		(-0.0036)*		(-0.005)***	(-0.004)***	(-0.004)***
Multiple R^2	0.00432	0.0056	0.00544	0.00696	0.00631	0.00677

Day-by-day cross-sectional regressions of cryptocurrency returns on variables and dummy variables. Columns represented by numbers display regressions based on the formulas provided above. Significance levels are represented by 10% (*), 5% (**), and 1% (***).

4.3.2 Pricing Factor

The pricing factors are built based on previous findings and follow the methodology of Liu and Tsyvinski (2021) and (Shen et al., 2020). The first factor is the market excess return which is defined as MKT_d - Rf_d.

The weekly breakpoints of past returns to construct the momentum factors are the 30th and 70th percentiles. Regarding the size factor, cryptocurrencies with top 80% market capitalization are considered big, and the bottom 20% as small. The original methodology is adjusted to cater for the limited number of currencies in the sample. The intersection of the size and the momentum factors portfolios are represented by abbreviations where B and S indicate big and small, U, M, and D represent up, medium and down respectively. Lastly, for the volatility factors, V represents volatile, while S denotes stable cryptocurrencies.

The size factor is defined as Small minus Big:

$$SMB_t = \frac{SD_t+SM_t+SU_t}{3} - \frac{BD_t+BM_t+BU_t}{3}$$

The momentum factor is defined as Up minus Down based on previous finding:

$$UMD_t = \frac{BU_t+SU_t}{2} - \frac{BD_t+SD_t}{2}$$

A volatility factor is constructed with similar percentiles as the momentum factor (terciles) and defined as Volatile minus Stable (VMS) based on Fama-MacBeth regression results.

$$VMS_t = \frac{BV_t+SV_t}{2} - \frac{BS_t+SS_t}{2}$$

To test the low volatility anomaly a factor is designed between the volatility and the momentum variable. This factor goes long in stable cryptocurrencies and shorts volatile cryptocurrencies. A double sorting is made based on the momentum feature.

$$SMV_t = \frac{US_t+DS_t}{2} - \frac{UV_t+DV_t}{2}$$

Panel A and B from Table 8 display the summary statistics and the correlation matrix for the pricing factors, respectively. The VIF scores from each factor are presented in panel C. It is important to note that 47 weeks from September 2015 are dropped due to missing values when computing sorted factor portfolios.

Findings indicate that the UMD factor is the sole occurrence that beats the market over the period analyzed with a mean return of 1.78%. Unfortunately, this strategy creates higher volatility than a passive value weighted investment, this is reflected in its lower Sharpe ratio level. Surprisingly, the SMV factor perform better than the VMS factor and indicates that lower volatility could yield higher returns, contradicting previous results. Correlations, which can be found in panel B, between the factors and the market factor are very low, ranging from -0.022 and 0.076. The correlation between factors can be considered moderate, ranging from -0.7749 to 0.538. The highest correlation value between VMS and SMV factors can be explained by the similar construction design for each factor. Due to the high negative correlation between VMS and SMV, the factor providing higher return is selected for the factor model, hence VMS is excluded from future models. Panel C displays the VIF test applied on each factor, values are within reasonable range, hence multicollinearity concerns are mitigated.

Table 8

Pricing Model Summary

Panel A Weekly Return Factor Model

	RM-RF	SMB	UMD	VMS	SMV
Mean	0.0143	0.0016	0.0178	-0.0046	0.0102
Median	0.0086	-0.0058	0.0004	-0.0176	0.0156
Skewness	0.0302	2.4129	4.2324	4.4784	-1.2188
Kurtosis	55.63	19.4419	35.7795	43.3269	14.0072
SD	0.1128	0.1085	0.1431	0.1388	0.1118
Tstat	2.55	0.29444	2.5025	-0.66558	1.8318
Sharpe R.	0.9164	0.1056	0.8978	-0.2387	0.6572

Panel B Correlation Matrix

	RM-RF	SMB	UMD	VMS	SMV
RM-RF	1				
SMB	-0.0219	1			
UMD	0.0411	0.3926	1		
VMS	0.0568	0.5382	0.4730	1	
SMV	0.0757	-0.5794	-0.3837	-0.7749	1

Panel C VIF

Factors	VIF scores
SMB	1.607
UMD	1.335
VMS	2.788
SMV	2.762

Panel A reports the descriptive statistics including the mean, median, skewness, kurtosis, volatility, t-stat, and Sharpe-ratio for each of the constructed factors. Returns are displayed weekly. Panel B displays the correlation matrix between the market factors and the other factors. Finally, Panel C included the Variance Inflation Factor scores for each factor.

Chapter 5 Results

Section 5.1 presents the factor model and provides the main results from the factor models. Section 5.2 presents further analysis on interaction effects to provide conclusions on the Hypotheses. Lastly, section 5.3 displays robustness checks on the construction of portfolios and the model.

5.1 Factor Models

Regressions are run on each cryptocurrency's excess return as dependent variable and factors as independent variables. This paper first analyses the market factor or CAPM defined as:

(1) $R_{i,t} - Rf_t = \alpha_o + \beta_1(RM_t - Rf_t) + \in_t$

where Ri,t , Rft and RMt are the return of cryptocurrency i in t, the risk-free interest rate, and the market return at time t, respectively.

The second factor model, which includes SMB, UMD, and SMV factors is presented beneath:

(2) $R_{i,t} - Rf_t = \alpha_o + \beta_1(RM_t - Rf_t) + \beta_2 SMB_t + \beta_3 UMD_t + \beta_4 SMV_t + \in_t$

Table 9 presents a summary of the average statistics for the weekly regressions performed between cryptocurrencies returns and the CAPM/4-factor models. Findings indicate that both models have very low R^2 values, suggesting little explanatory power of cryptocurrencies returns. Notice that the second model, which includes three additional factors increases the explanatory power by a factor of four compared to CAPM model. Overall, the average standard error of the intercepts remains constant. Hence, it can be concluded that despite the low explanatory power of each model, the second factor model explains digital coins returns better.

Table 9

Factor Model Regressions with (1) CAPM and (2) 4 factors

	|a|	R^2	s(a)
(1)	0.00054	0,00403	0.00263
(2)	0.00039	0.01759	0.00266

Summary statistics from weekly regressions on CAPM (1) and the four factors model (2). Results represent the average of the 52 regressions performed on each cryptocurrency's returns. |a| is the average absolute intercept, $R^2$is the average adjusted R squared value, s(a) is the average standard error on the intercepts.

5.2 Interaction effects

To further analyze the effect of the dummy variables on the low volatility anomaly it is first important to understand their effect on the volatility and return characteristics of the cryptocurrency market. Thus section 5.2.1 presents the impact of halving events on the cryptocurrency market and discusses the first two Hypotheses. Section 5.2.2 discusses the impact of interest rates on the overall market and answers the third Hypothesis. Lastly, section 5.2.3 assesses the impact of each interaction effects on the performances of portfolios constructed based on volatility characteristics.

5.2.1 Halving events

Figure 3 depicts the value-weighted average return of the cryptocurrency market around halving occurrences, represented by red vertical lines. Notice that there is usually a large variation in the return pattern prior or after halving occurrence. In 2016, prior to the halving, a large increase can be noticed, indicating abnormal returns. Six weeks before the second occurrence, a substantial drop of around 50% occurs, followed by positive returns over the subsequent three months. Regarding the most recent event, a large decline of 25% occurred around the halving occurrence, which could suggest that the market had already priced the event. However, it is hard to conclude from this table solely if the halving has a substantial impact on returns as large fluctuations also occur during other periods.

Figure 3

Value-Weighted Average Weekly Return of the Cryptocurrency Market

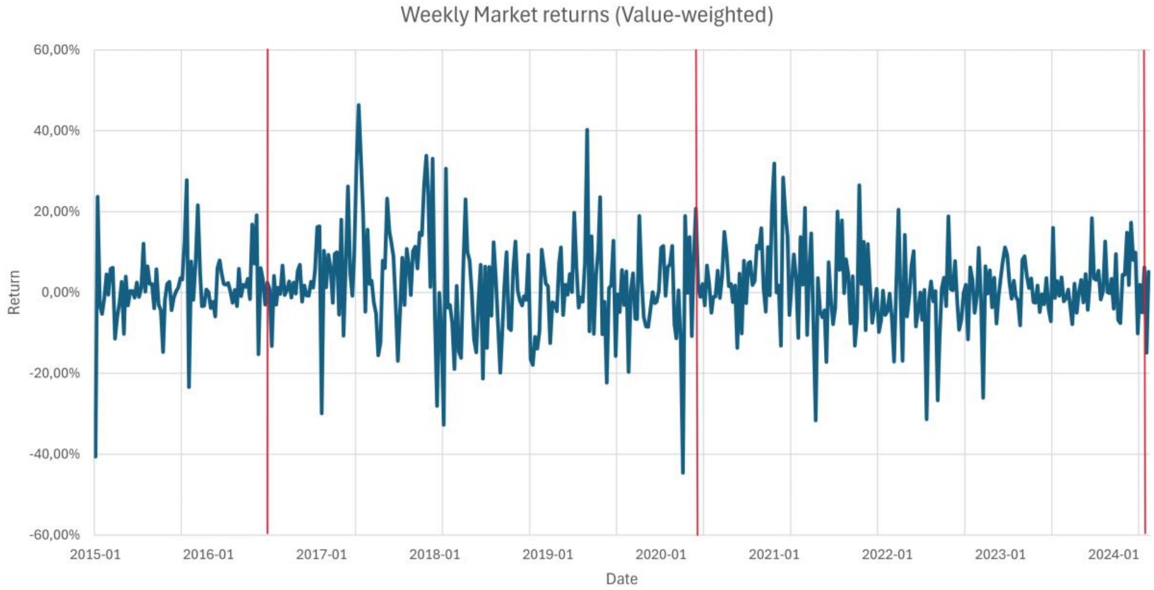


Figure 4 represents the value-weighted average volatility of the market. Overall, it appears that halving events are often preceded by large spikes in volatility and followed by steadier market movements.

These observations suggest that halving events can be associated with fluctuations in returns and volatility. The market appears to present anticipatory behavior, with abnormal returns and increased volatility preceding the occurrence of the halving.

Figure 4

Value-Weighted Average Weekly Volatility of the Cryptocurrency Market

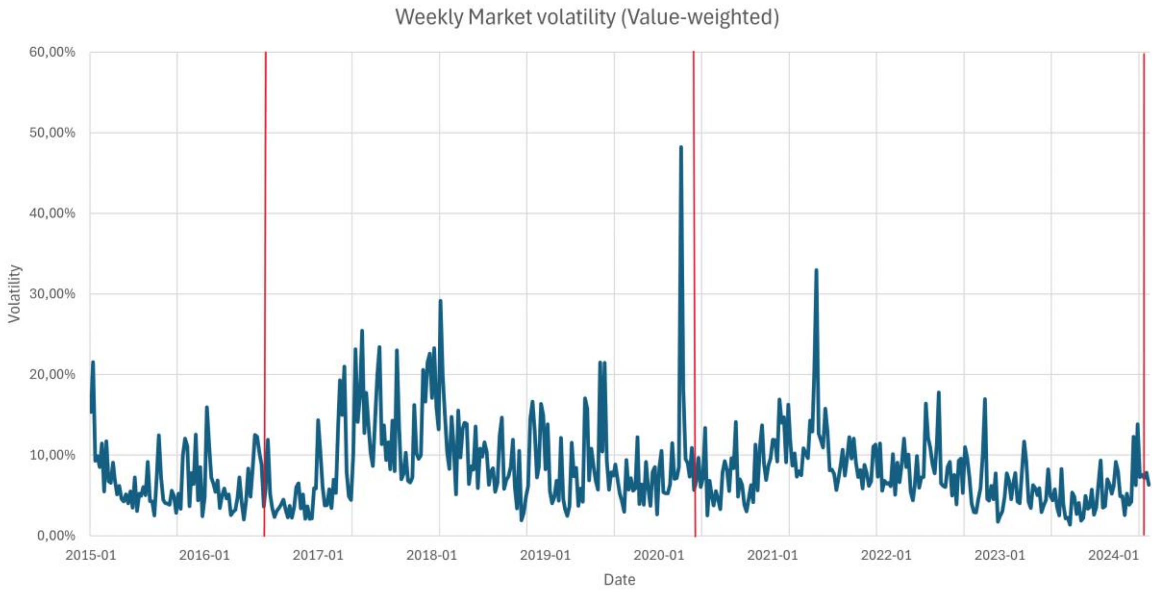


Table 10 represents return and volatility characteristics of the market around halving events. Panel A displays the average weekly return and volatility, based on equal weighting, of the past and future periods. Panel B on the other hand focuses on a value-weighted approach, both panels are compared.

It appears clear that on average volatility is significantly larger prior to halving occurrences than after. For instance, in panel A, the market experiences 11.71% average volatility in the three months leading to the event, while this figure decreases to 8.93% after the event. Looking at a range of six months yields to the same conclusions. Panel B, which considers value-weighted average, confirms this finding with pre-event volatilities of 8.22% and 7.17% and post-event volatilities of 5.62% and 5.5%.

Panel A and B display conflicting empirical evidence regarding returns pattern. When investigating the average returns from an equally weighted perspective, the period yielding the highest return is observed in the three months following the halving with a return of 3.24%. On the other hand, the period of three months before the halving event yields the lowest return with on average only 0.9%. These results conflict with panel B in which the highest return of 1.92% can be identified in the three months preceding the event, while the lowest returns are found in the three months succeeding the halving with a rate of 0.87%. This result could indicate that large capitalization cryptocurrencies gain additional returns as anticipation to the halving events while smaller cryptocurrency only benefit from the changes in supply and demand dynamics once the halving occurred.

Table 10

Overview of Market Characteristics Around Halving Periods

Panel A: Equally Weighted

	Past			Future		
Period	3 months	6 months	Last	3 months	6 months	Next

			occurrence			occurrence
Average weekly return	0.90%	2.17%	1.21%	3.24%	1.01%	1.32%
Average weekly volatility	11.71%	11.22%	12.07%	8.93%	9.56%	12.09%

Panel B: Value Weighted

	Past			Future		
Period	3 months	6 months	Last occurrence	3 months	6 months	Next occurrence
Average weekly return	1.92%	1.80%	1.32%	0.87%	1.46%	1.47%
Average weekly volatility	8.22%	7.17%	7.97%	5.62%	5.50%	8.27%

Panel A displays average equal-weighted weekly return and volatility for the entire market, proxied by the sample. Panel B focuses on value-weighted averages. Past indicates periods prior to the halving occurrence, while future indicates periods that occurred after. The last (next) occurrence column simply takes each week since (until) the previous (next) halving occurrence into account.

Results from Table 10, panel A confirm Hypothesis 1, which states that following halving events, prices of cryptocurrencies should increase significantly more than usual. However, this effect only lasts during the three months following the event in which a 3.24% average return is achieved compared to a 1.01% return when considering a period of six months. On the other hand, average volatility values from panel A and B indicate that the market experienced higher levels of fluctuations in periods leading to halving than periods which follow it. Therefore, Hypothesis 2 is rejected.

5.2.2 Interest rates

In this part, the effect of interest rates on the overall cryptocurrency market is assessed. Earlier, the idea that higher periods of interest rates led to lower returns was introduced. The rationale being that investors would be less likely to invest in risky assets under these circumstances. Hence, Figure 5 displays the relationship between interest rates and the value of 1000 euros invested in the cryptocurrency market to confirm if this assumption is indeed correct. The red line indicates the threshold for the interest rate, any value above 1.25% is considered high.

At the end of 2017 when the interest rate remained reasonable, prices soared to all-time highs. On the other hand, the interest rate hike from 2018 until 2020 led to a large reduction in the value of cryptocurrencies. The massive bull market which took place between 2020 and 2022 was accompanied by extremely low interest rate. Prices significantly dropped months before the interest rate started rising again to a value of around 5%, the point at which the market found a consolidation zone. Overall, the graph indicates that the market tends to reach the top while the interest rates find a bottom, and decreases when the rate increases. This supports the overall idea that prices decrease when interest rates increase, therefore supporting Hypothesis 3.

Figure 5

Market Value Compared to Interest Rates

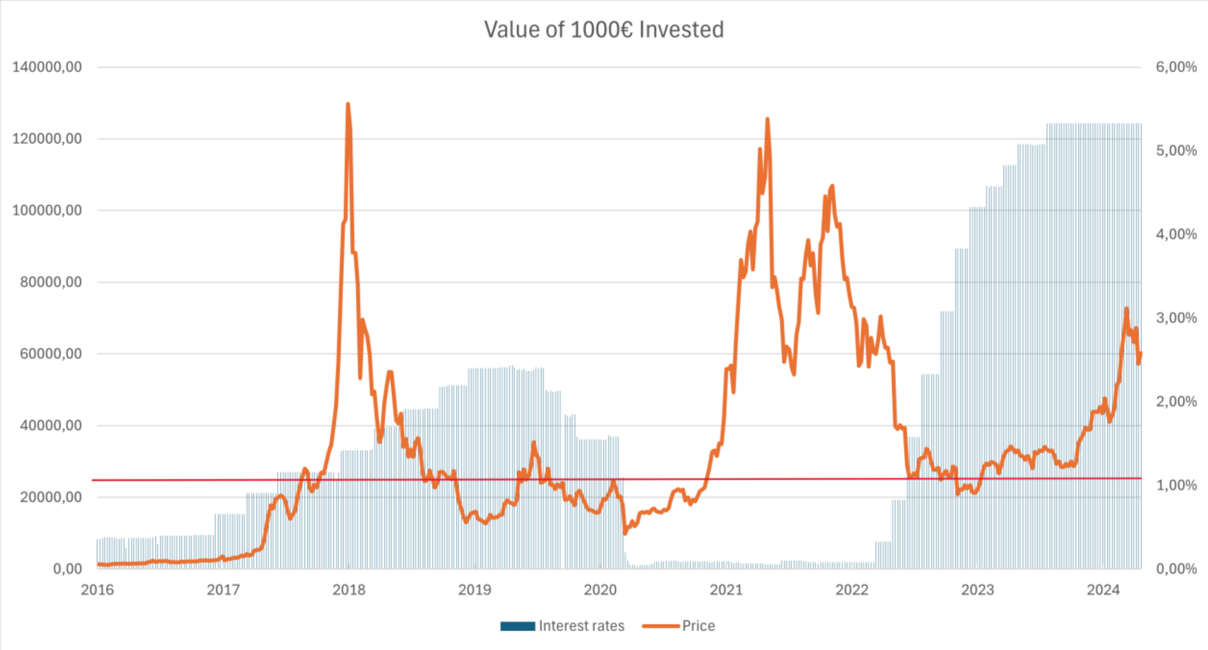


Table 11 indicates the average return per week in periods of high and low interest rates. The average weekly return for the sample is 1.5% while the average return during high interest rates period diminishes to 0.25%. In comparison, the average weekly return during low interest rates period is 2.62%. This conclusion remains when selecting a threshold of 2% for the frontier between low and high interest rates as can be seen in the table. Overall, this result supports previous conclusions and indicates that cryptocurrencies yield higher returns in periods of low interest rates.

Table 11

Average return during low and high interest rates

Average return	Low-IR	High-IR
Return	2.62%	0.25%
Return (Threshold 2%)	1.82%	0.8%

5.2.3 Low-Volatility Anomaly

Lastly, this paper performs a subsample analysis to address Hypotheses 4 and 5, providing insights into two key problems. The first question examines whether the low-volatility anomaly shows a stronger and more significant presence during bear market when compared to bull markets periods. The second question examines the anomaly depending on the level of market volatility.

To answer these questions, two different portfolios are built. The first portfolio, defined as, “high volatility” takes a long position in the top 20% of cryptocurrencies ranked by their volatility over the last week. The second portfolio “low volatility” takes a long position in the bottom 20% of cryptocurrency ranked on their volatility level. Both portfolios are rebalanced daily over the defined periods and are divided into 2 samples depending on the effect analyzed. For instance, this paper defines bear markets as the aggregated days for which the interest rate is higher or equal to 1.25%, conversely, bull markets are defined as days for which the interest rate is lower than this rate. This assumption follows from findings in section 5.2.2.

To proxy volatility level, this paper defined the 3 months preceding halving events as high volatility periods, and the succeeding 3 months as low volatility periods. The performance of each portfolio is assessed using average yearly return, standard deviation and the risk-adjusted return, represented by the Sharpe Ratio.

Table 12 describes returns from volatility strategies based on the state of market and provides evidence to support Hypothesis 4. A comparison of the risky and stable strategies indicates that during bear market periods, the risky strategy yields yearly returns of -49%, significantly lower than the -12.5% of its steady counterpart. Moreover, Table 4 clearly indicates that low volatility portfolios have lower standard deviations than highly volatile portfolios, as expected. This finding suggests that the low volatility strategy is more resilient during bear market and therefore preferable from a risk-adjusted return perspective. Remarkably, during bull markets, the higher volatility strategy yields a higher average return of 255.4% compared to the 222.5% return of the low volatility portfolio. However, when assessing the risk adjusted return of both strategies via the Sharpe ratio, it becomes obvious that the low volatility portfolio outperforms with a ratio of 2.56 compared to 1.96 for the high-volatility portfolio. This highlights the superior risk-adjusted performance of the low-volatility strategy, even during bull market conditions, hence this paper does not reject Hypothesis 4.

Table 12

Low-volatility Anomaly Subject to Market State

Volatility	Market	Bear	Bull
Low			
	Return	-12.58%	225.47%
	Std dev	73.28%	87.96%
	Sharpe Ratio	-0.17	2.56
High			
	Return	-49.25%	255.39%
	Std dev	93.79%	130.11%
	Sharpe Ratio	-0.52	1.96

Cryptocurrencies are divided into 2 groups, namely "Low" in which the bottom 20% is selected each day, and "High" for which the top 20% is selected based on the level of volatility. The portfolios are divided into two samples using interest rate as a threshold. Returns and standard deviation are annualized.

Table 13 describes the returns from volatility strategies based on the volatility characteristics of the overall market. Overall, findings generally support Hypothesis 5. Regarding the period prior to halving events, both portfolios display impressive returns. However, while the high volatility portfolio generates slightly higher returns, it demonstrates higher volatility patterns compared to its low volatility counterpart. As a result, the low volatility portfolio outperforms the high volatility portfolio on a risk adjusted basis before the halving occurs. This is displayed by the Sharpe Ratio of 1.38 and 1.76 for the low volatility portfolio compared to 1.07 and -0.36 for the high volatility portfolio, before and after halving events respectively. Interestingly, after the halving occurrence, during which the volatility is typically lower, the low volatility portfolio strongly outperforms the higher volatility portfolio. In particular, the former portfolio yields a return of 85.2% which is significantly higher than the -34.3% return of the latter. In conclusion, the risk-adjusted return from the low volatility portfolio is higher than the high volatility portfolio during periods of high volatility based on Sharpe Ratio values. Hence, this paper does not reject Hypothesis 5.

Table 13

Low-volatility Anomaly Depending on Volatility

Volatility	Halving	Before	After
Low			
	Return	102.41%	85.26%
	Std dev	73.93%	48.35%
	Sharpe Ratio	1.38	1.76
High			
	Return	118.07%	-34.34%
	Std dev	110.11%	95.51%
	Sharpe Ratio	1.07	-0.36

Cryptocurrencies are divided into 2 groups, namely "Low" in which the bottom 20% is selected each day, and "High" for which the top 20% is selected based on the level of volatility. The portfolios are divided into two samples using halving dates as a threshold. Before and after taking a period of 3 months prior and after halving occurrences. Returns and standard deviation are annualized.

5.3 Robustness checks

This study incorporates robustness elements in its original methodology. This includes comparing different lookback and holding periods to assess the homogeneity of results, the inclusion of interaction effects, and the analysis of subsamples. However, the results presented in the previous sections may still be sensitive to certain biases and assumptions introduced by the sorting methodology. Hence this study conducts robustness tests on the two pass portfolios, by adjusting the weights given to each variable. Each variable now consists of the bottom and the top half creating 2x2 equal-weighted portfolios. Results are presented in Appendix A under Table 1.

Moreover, this study conducts robustness tests on the 4-factor models by adjusting the original methodology used to construct the factors of the pricing model. The division for the size factor changes from [0%, 20%] and [80%, 100%] to [0%, 50%] and [50%, 100%]. Momentum and size factors follow a similar approach in which the small component represents the lower half, and the big component represents the upper half. Results, including the pricing model summary and the average regression coefficients for each model are displayed in Appendix B under Table 1 and 2, respectively.

Overall, the findings from robustness analysis led to similar conclusions as the original models, which implies that previous findings and conclusions are robust to the methodology used and the impact of potential methodology bias is therefore limited.

Chapter 6 Discussion

The study of the low volatility in the cryptocurrency market has yielded several key findings. Firstly, several pricing factors are identified, including, market, size, momentum, and volatility, all of which significantly influence the returns of the cryptocurrency market. The research also explores the effects of halving events and interest rates on the returns and volatility characteristics of the cryptocurrency market. The paper confirms that high interest rate periods are associated with lower returns. Surprisingly, volatility is found to be significantly lower after halving occurrences. Moreover, this paper reveals the presence of low volatility anomalies in which risk adjusted returns are higher for digital coins with lower volatilities in every subsample period tested. This includes periods of high and low volatility, and periods of bear and bull markets. Hence, the results from this paper showcase the similarities between the cryptocurrency market and traditional markets in which the low volatility anomaly has been researched in detail. This provides insights into effective risk management strategies in different market states.

However, the findings from this study are influenced by several limitations and must therefore be interpreted with care. One potential limitation from this study is the limited sample size of cryptocurrencies analyzed which included only 52 cryptocurrencies, compared to the thousands of coins existing. This issue arises because of the provider chosen and could be eliminated in further studies by selecting several data providers and compiling data. This would allow researchers to extrapolate findings to a broader cryptocurrency market context. It is also important to note that cryptocurrency as an asset class is still in its infancy stage which does not provide enough historical data to draw generalized conclusions. For example, in the sample chosen, price information for 10 cryptocurrencies were available from the end of 2015 only. Therefore, research should continue in the future to assess if results remain persistent with time. Moreover, this paper finds low R^2 values when investigating the explanatory power of the factors on the cryptocurrencies returns. These low R^2 values could be improved by exploring additional cryptocurrency-specific factors such as network effects, investor sentiments, or technology factors. Another limitation of this study has been to disregard transaction costs in the portfolios chosen, especially due to the daily and weekly rebalancing design which will most likely make any of the strategies discussed unprofitable. Hence, future research should focus on implementing frameworks to model the impact of transaction costs on portfolio strategies to improve the practical implications of findings. Lastly, this research is subject to biases in the modeling assumptions regardless of the robustness checks performed. Thus, future research could analyze different settings for the portfolios formation to confirm the conclusion drawn from this paper.

Additionally, future research could further explore the pricing of the cryptocurrency market in several ways. Firstly, researchers could build upon existing literature to conduct analysis on other cryptocurrency variables when creating sort portfolios strategies such as network activity, developer activity, or regulatory developments. Secondly, researchers could focus on applying machine learning models to enhance the predictive power of cryptocurrency price forecasting models. Lastly, further research is needed to understand key elements affecting the cryptocurrency market supply and demand dynamics, this includes for instance, the Halving effect, which is not well studied and for which conflicting evidence exists.

Chapter 7 Conclusion

This study examines the low-volatility anomaly over different market conditions for a sample of 52 cryptocurrencies for a period of 8 years. Additionally, this paper explores several pricing factors of the cryptocurrency market, namely, the market, size, momentum and volatility factor. Results are robust to alterations of pricing factors and portfolio construction. Similarly to (Shen et al., 2020), this paper finds strong evidence that small cryptocurrencies obtain higher returns than larger ones, and that the reversal returns increase from large to small cryptocurrencies. On the other hand, cryptocurrencies with low volatility measures appear to underperform their higher volatility counterpart, thus the volatility factor is defined as volatile minus stable. Overall, the four-factor model strongly outperforms the CAPM model in explaining returns.

Additional subsample analyses of the low-volatility anomaly during periods of low and high volatility, and during periods of bear and bull market are performed. Periods of high interest rates are found to be typical of bear markets while the opposite is true for periods of low interest. As hypothesized, cryptocurrencies with lower volatility are found to yield higher returns during periods of bear markets. Moreover, low volatility cryptocurrencies yield on average higher adjusted risk returns in bull market periods than their riskier counterparts. This finding has dire implication on the market efficiency of the cryptocurrency market, but also to its resemblance with traditional markets. The subsample based on overall market volatility proxied by halving events provides a similar conclusion on the existence of low volatility anomaly, in either setting. Interestingly, a low-volatility strategy displays higher risk-adjusted returns during periods of low volatility.

The results from this study provide relevant information to stakeholders such as investors, researchers and regulators regarding the efficiency of the cryptocurrency market and its similarities with traditional markets such as the equity market. Investors can use this information to adjust portfolio allocation depending on the state of the market and to mitigate risk. On the other hand, regulators can use this information as an indication that the cryptocurrency market may reflect similar patterns as other markets and therefore implement similar risk management regulations.

The fast-paced environment in which the cryptocurrency market thrives requires additional empirical research and analysis. This paper serves as a foundation for future research aiming to expand the body of literature on pricing determinants, risk mitigation approaches and market dynamics. Through additional research, collective comprehension can be expanded, and will ensure that actors of the market make decisions based on founded judgment.

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Appendices

Appendix A

Table 1

Weekly-Returns Double Sorted Portfolios with Weekly Rebalancing #2

Weekly excess returns of two-pass sorts (J=1)

	Equal-weighted	
Panel A		
Momentum&Size		
	Small	Big
Loser	0.0088	-0.0003
	(1.314)	(-0.055)
Winner	0.0165	0.0114
	(2.185)**	(1.867)*
Panel B		
Momentum&Volatility		
	Low	High
Loser	0.0042	0.0051
	(0.727)	(0.763)
Winner	0.0140	0.0175
	(2.323)**	(2.065)**
Panel C		
Volatility&size		
	Small	Big
Low	0.0109	0.0051
	(1.777)*	(0.951)
High	0.0123	0.0087
	(1.525)	(1.265)
Panel D		
Volatility&Momentum		
	Loser	Winner
Low	0.0025	0.0156
	(0.451)	(2.520)**
High	0.0067	0.0162
	(0.964)	(2.013)**
Panel E		
Size&Volatility		
	Low	Higher
Small	0.0088	0.0150
	(1.385)	(1.780)*
Big	0.0074	0.0067
	(1.374)	(1.031)

Average weekly excess returns for cryptocurrency portfolio formed on two-pass sorts as previously described. This Table presents a holding period of 1 week. Digital currencies are allocated to two groups based on an equal split of the first variable. Each group is divided into two sub-groups based on the second variable.

Appendix B

Table 1

Pricing Model Summary #2

Panel A	Weekly return factor model				
	RM-RF	SMB	UMD	VMS	SMV
Mean	0.0143	0.00133	0.0076	-0.0062	0.0056
Median	0.0087	-0.0043	0.0029	-0.0102	0.0121
Skewness	0.0301	2.0662	2.2522	0.9082	-0.9483
Kurtosis	5.5629	15.7319	19.5479	9.7608	9.1238
SD	0.1127	0.0711	0.0691	0.0760	0.0765
Tstat	2.554	0.375	2.226	-1.6566	1.4678
Sharpe R.	0.9164	0.1348	0.7988	-0.5943	0.5266

Table 2

Factor Model Regressions with (1) CAPM and (2) 4 factors #2

	Weekly regressions		
	|a|	R^2	s(a)
(1)	0.0005385	0.0040328	0.0026273
(2)	0.0004732	0.0200305	0.0026449

Summary statistics from weekly regressions on CAPM (1) and the four factors model (2). Results represent the average of the 52 regressions performed on each cryptocurrency's returns. |a| is the average absolute intercept, R^2 is the average adjusted R squared value, s(a) is the average standard error on the intercepts.