

Cryptocurrency momentum:
Is it there?
Persistence and predictability

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Cryptocurrency Momentum: Is it there?

Persistence and predictability

*A momentum faktor jelenlétének és
előrejelezhetőségének empirikus vizsgálata a
kriptopiacon*

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Abstract

This study seeks to examine the enduring nature of cryptocurrency momentum and the capacity to forecast its profitability. In light of the distinguishing findings in the existing literature, this study thoroughly investigates the momentum anomaly. The findings of this paper demonstrate that the cryptocurrency momentum effect exists and is persistent, as indicated by the momentum portfolio's average weekly return of 2.60%. Enhancing this strategy conditional on the momentum gap—the difference between the returns of past winners and past losers in the formation period—as proposed by [Huang \(2022\)](#), increases the Sharpe ratio of the momentum strategy by nearly 9%, to 1.41. This strategy's superior performance remains robust across different time periods and for alternative portfolio constructions.

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1 Introduction

The strategy of purchasing stocks that have performed well in the past and selling those that have performed poorly generates significant profits. Since the findings of [Jegadeesh and Titman \(1993\)](#), this investment approach, popularly known as the *momentum strategy*¹, has been subject to a ton of investigations in various financial markets; [Rouwenhorst \(1998\)](#), [Rouwenhorst \(1999\)](#) assessed the momentum strategy in international and emerging markets, [Menkhoff et al. \(2012\)](#) and [Burnside et al. \(2011\)](#) investigated the effect in the foreign exchange market, [Jostova et al. \(2013\)](#) analyzed it in bonds, and [Miffre and Rallis \(2007\)](#) and [Erb and Harvey \(2006\)](#) tested it for commodities.

While evaluating the explanations given from numerous studies for the source of the profitability of the momentum strategy, [Jegadeesh and Titman \(2001\)](#) argue that momentum gains are not primarily linked to risk compensation ([Conrad and Kaul \(1998\)](#)) and could rather be associated with behavioral theories ([Daniel et al. \(1998\)](#), [Hong and Stein \(1999\)](#)), as the dissipation of momentum profits in the long run is rather consistent with a bias in investor attention. Considering the latter, delayed investor overreaction to information would result in the prices of previous winners exceeding their long-term values, thereby allowing the momentum effect to prevail. Besides the aforementioned explanations, numerous additional reasons were also suggested for the presence of the momentum effect (e.g., credit risk by [Avramov et al. \(2007\)](#) or substantial trading costs by [Korajczyk and Sadka \(2004\)](#)); however, a universally acknowledged explanation has not yet been adopted in the literature.

The credibility of the momentum strategy increased after [Carhart \(1997\)](#) demonstrated that incorporating momentum as a fourth factor into the three-factor asset pricing model proposed by [Fama and French \(1993\)](#) substantially improves the model's capacity to explain the cross-section² of stock returns. Nevertheless, the growing literature on the momentum factor has uncovered a few shortcomings of the strategy. As pointed out by [Daniel and Moskowitz \(2016\)](#), momentum strategies may encounter occasional periods of extreme negative returns, making the strategy unattractive³. To mitigate the risk of

¹For the sake of brevity, I only describe the detailed momentum strategy construction in [Section 2](#).

²While most of the literature focuses on cross-sectional momentum, [Moskowitz et al. \(2012\)](#) also present a different method; the time series momentum. This strategy analyzes the historical performance of each individual stock and buys assets that have shown positive momentum while simultaneously shorting assets that display negative momentum. [Huang et al. \(2020\)](#), [Georgopoulou and Wang \(2017\)](#), [Goyal and Jegadeesh \(2018\)](#), and [Kim et al. \(2016\)](#) all conducted further research on time series momentum.

³According to [Daniel and Moskowitz \(2016\)](#), the stock market momentum portfolio experiences a loss of almost 75% during the worst month.

momentum crashes, several strategies were introduced to scale the traditional momentum approach. [Daniel and Moskowitz \(2016\)](#) proposed the approach of dynamic scaling, [Barroso and Santa-Clara \(2015\)](#) developed the volatility-managed momentum⁴, whereas [Wang and Yan \(2021\)](#) focused solely on scaling the downside risk. All these strategies reduce the probability of momentum crashes and result in improved Sharpe ratios.

The proposal of [Huang \(2022\)](#) presents a different scaling approach for stock market momentum. It introduces the concept of the momentum gap, defined as the difference between the formation period returns of past winners and past losers. In the equity markets, the momentum gap is a successful predictor of momentum returns and therefore a valuable tool for risk-adjusted momentum investing⁵. The purpose of this paper is to test the predictive power of the momentum gap in the cryptocurrency market.

The cryptocurrency market has witnessed a rapid expansion over the last decade. After the launch of Bitcoin, a vast range of cryptocurrencies emerged, all relying on the blockchain technology. Given the ability to trade 24/7 and the absence of pricing constraints and physical backing, the virtual assets of this alternative market display extreme returns and enormous volatility, even within a day, unmatched by traditional securities ([Cheng et al. \(2019\)](#)). It is worth highlighting the relatively low impact of transaction costs in cryptocurrency trading, as this could make the momentum strategy more attractive to traders ([Tzouvanas et al. \(2020\)](#)). Another notable attribute of the coin market is its “fast metabolism” ([Dobrynskaya \(2021\)](#)), indicating that the processes in this market are carried out in much less time compared to regular investment markets. Therefore, in addition to traditional research methods, my analysis also considers these characteristics of cryptocurrencies. As an example, throughout my study, I examine weekly frequencies instead of the conventional monthly periods used in equity markets. This allows me to account for the “faster metabolism” of the market.

The quick evolution of the market was accompanied by a substantial number of studies on cryptocurrencies. The efficiency of the Bitcoin market was investigated by [Urquhart \(2016\)](#), [Bariviera \(2017\)](#), and [Nadarajah and Chu \(2017\)](#), while others examined the tendencies of conventional equity factors. Nonetheless, due to the unique nature of this market, the majority of factors and anomalies exhibit distinct behavior in contrast to traditional securities. Multiple papers aim to explain the cross-section of coins, with [Shen et al. \(2020\)](#) and [Liu et al. \(2022\)](#) both proposing a three-factor pricing model. All

⁴Further details regarding these strategies are presented in [Section 2](#).

⁵By including information on the momentum gap in momentum investing, the Sharpe ratio experiences a substantial enhancement of over 50%, rising from 0.52 to 0.78 ([Huang \(2022\)](#)).

of these models include some sort of price continuation, either in the form of reversal or momentum. Given the study of [Asness et al. \(2013\)](#), which provides evidence of a persistent momentum effect across eight different asset classes, it seemed inevitable that investigations into cryptocurrency momentum would eventually begin.

Unexpectedly, research conducted on momentum in the cryptocurrency market reveals wildly diverse results. [Grobys and Sapkota \(2019\)](#) were the first to explore the momentum effect. Remarkably, their work reveals that the conventional J/K strategy does not yield substantial momentum profits; instead, they exclusively document reversal. The following publications reveal that instead of applying the traditional monthly frequencies, weekly periods should be considered to recognize the cryptocurrency momentum effect. Among the numerous studies on the momentum strategy, certain writers have identified a significant momentum effect ([Yang \(2019\)](#), [Tzouvanas et al. \(2020\)](#), [Jia et al. \(2022\)](#)), while others have documented powerful reversal ([Kosc et al. \(2019\)](#)). Some even describe a very short-term, one-day momentum ([Zaremba et al. \(2021\)](#), [Li et al. \(2021\)](#)). The variations in the results can be attributed to disparities in the size and length of the sample, as well as differences in the lengths of the formation and holding periods.

In my research, I aim to examine the various aspects of portfolio construction discussed in these papers and determine the most effective approach for establishing a robust momentum portfolio, thereby making an important contribution to the existing literature.

Besides, this study adds to the growing body of research examining the momentum effect in alternative finance markets. This paper presents a comprehensive review of the existing literature discussing the momentum effect in cryptocurrencies and develops a momentum strategy through evaluating a wide range of portfolio construction possibilities that have been mainly overlooked in the majority of previous research.

My study aims to investigate a specific conditional momentum approach, the momentum gap proposed by [Huang \(2022\)](#), thereby deepening the literature on enhanced momentum methods in the cryptocurrency market. To the best of my knowledge, with the exception of [Tzouvanas et al. \(2020\)](#), who has tested and reported the superior performance of the volatility-managed momentum strategy ([Barroso and Santa-Clara \(2015\)](#)) compared to the unconditional momentum strategy, there is currently no detailed research available on the performance of scaled momentum strategies in the cryptocurrency market. Furthermore, the enhanced strategy developed throughout the study offers an intriguing alternative for cryptocurrency momentum investments. This is potentially critical given the exponential growth of the cryptocurrency market, which further emphasizes the importance of identifying profitable strategies.

The subsequent sections of this study are organised as follows: [Section 2](#) offers an overview of the most relevant articles. The description of the dataset and a review of the applied methodology are provided in [Section 3](#). [Section 4](#) presents the results of this paper. At last, [Section 5](#) concludes.

2 Literature Review

2.1 The origins of the momentum strategy

The origins of the momentum effect can be attributed to [Jegadeesh and Titman \(1993\)](#). While investigating the abnormal returns generated by contrarian strategies in the US stock market, the authors document strong evidence for the profitability of relative strength strategies, which buy stocks that performed well in the past (past winners) and sell those that performed poorly (past losers). Since investors tend to overreact to information, the overreaction of stock prices leads to contrarian strategies earning abnormal returns. The construction of these strategies is as follows: Each month, stocks are ranked based on their performance over the past J months. To construct a portfolio, the highest performing decile of stocks is bought, while the decile with the lowest cumulative past return is sold. This portfolio is held for K months. J and K refer to the length of the formation and holding periods. The best-performing strategy, with a formation period of 12 months and a holding period of 3 months, has an average monthly return of 1.31% which improves to 1.49% if a one-week lag is considered. The performance of these strategies on the long run reveals the following effects: a short-term reversal is to be observed, as the portfolio yields negative returns in the first month after the construction. Additionally, there is even a long-term reversal, as the profits of the momentum strategies dissipate after two years.

2.2 Techniques for momentum scaling

Since [Jegadeesh and Titman \(1993\)](#), many have studied the momentum effect over various time periods and in multiple asset classes. However, despite its high profitability, the momentum strategy also encounters large drawdowns. As documented by [Daniel and Moskowitz \(2016\)](#), the negative skewness of momentum returns results in occasional extreme crashes. These crashes mostly occur during periods of market stress, after large market declines, when the stocks in the short leg of the WML (winner-minus-loser) port-

folio exhibit higher gains than the winners, as their up-market betas are very large. To avoid these crashes, the authors provide a dynamic scaling technique for the momentum strategy, which takes the forecasted mean momentum return and volatility into account. This approach significantly outperforms the traditional momentum strategy. [Barroso and Santa-Clara \(2015\)](#) find that market betas are not effective in predicting momentum crashes since most of the momentum risk is specific to the strategy and hedging only the market beta does not take specific risk into account. Thus, they introduce a method of volatility-scaling, which adjusts the risk of a momentum strategy to a desired level of volatility. This approach results in a significantly higher Sharpe ratio compared to the unconditional strategy. [Hanauer and Windmüller \(2023\)](#) provide a comprehensive overview of enhanced momentum strategies in international equity markets.

[Huang \(2022\)](#) establishes a new, successful predictor of momentum profits: the momentum gap. The momentum gap is defined as the difference between the formation period returns of former winners and losers. The lagged momentum gap exhibits a statistically significant, negative forecasting power for momentum profits, even after controlling for market return, market volatility and market illiquidity. The study reveals that an increase of one-standard-deviation in the momentum gap corresponds to a decline of 1.25% in the monthly adjusted return to the momentum approach. This negative relation demonstrates its resilience across international markets and remains consistent when tested out-of-sample. Logistic regressions confirm that the momentum gap can accurately predict momentum crashes defined by [Daniel and Moskowitz \(2016\)](#). Therefore, real-time investing strategies are developed conditional on momentum gap. All of them lead to enhancements in skewness and Sharpe ratio. The negative relation between momentum returns and the momentum gap contradicts risk-based explanations of momentum profits, suggesting instead a rather behaviorally motivated mechanism: Investors underreacting to information leads to a small momentum gap, while overreaction as consequence of investor overconfidence can be associated with the large momentum gap and higher probability of momentum crashes.

2.3 Momentum in the cryptocurrency market

The first investigation regarding the existence of momentum in the cryptocurrency market was conducted by [Grobys and Sapkota \(2019\)](#). They analyze monthly returns of 143 cryptocurrencies from 2014 to 2018, even focusing on a subset of coins with the highest market capitalization. The conventional J/K method, as proposed by [Jegadeesh and](#)

[Titman \(1993\)](#) is examined considering different lengths of formation and holding periods. The findings of the study indicate no significant momentum returns, except for the 1/1 approach. However, this strategy yields significant negative returns, suggesting a reversal effect rather than momentum. Even the subsample of the largest cryptocurrencies, to control for the high volatility of smaller coins, delivers no significant momentum profits.

Following the paper by [Grobys and Sapkota \(2019\)](#), many articles were written on cryptocurrency momentum. [Shen et al. \(2020\)](#) investigate weekly frequencies and document significant reversal effect for the strategy with a one-week-long formation and holding periods, which they include as factor in their three-factor pricing model for cryptocurrencies. However, they do not notice any significant momentum effect. Based on these findings, [Jia et al. \(2022\)](#) propose an alternative three-factor cryptocurrency pricing model, which incorporates momentum instead of reversal. Similarly, they consider weekly frequency, with the 1/4 combination delivering the highest momentum returns. With momentum as the third factor besides market and size, this new model exhibits higher explanatory power than the model proposed by [Shen et al. \(2020\)](#).

To understand the differences between previous research on cryptocurrency momentum, [Dobrynskaya \(2021\)](#) provides a comprehensive review of these studies as of 2020 and document that the main reasons for the disparities among these studies are differences in sample size, sample frame, and data frequency. In this study, all cryptocurrencies with a market capitalization over \$1 million are examined from 2014 to 2020. The daily returns are transformed into weekly data, as it is less noisy compared to the daily frequency. A total of 144 J/K strategies are tested, with both J and K ranging from 1 week to 100 weeks. The tests of these strategies reveal a short-term momentum and long-term reversal. As the formation period increases, the momentum returns become lower. The 2/2 strategy is the only approach delivering significant momentum profits. After a short-term momentum when the length of formation and holding periods remain below 1 month, a strong, long-term reversal can be noted. The shorter momentum and quicker long-run reversal provide evidence for the assumption of a “*faster metabolism*” among cryptocurrencies since events tend to escalate quicker within the coin market compared to conventional asset classes.

If a factor is included in an asset pricing model, it indicates that this factor is not strongly exposed to other standard risk factors, as these are unable to explain its premium. The most relevant pricing model for cryptocurrencies was introduced by [Liu et al. \(2022\)](#) including the following factors: market, size, and momentum. These three factors can explain all other successful long-short strategies that produce substantial excess returns.

Table 1: Summary of the most relevant studies of the momentum and reversal effects in cryptocurrency market

Article	Study period	Sample size	Frequency	Formation period	Holding period	Results
Grobys and Sapkota (2019)	2014-2018	143	monthly	1-12 months	1 month	insignificant, negative momentum returns
Kosc et al. (2019)	2014-2017	100	daily	1 week	1 week	powerful short-term reversal, no momentum
Shen et al. (2020)	2013-2019	over 1700	weekly	1-4 weeks	1-4 weeks	1-2 weeks: powerful reversal, 4 weeks: slight momentum
Liu et al. (2020b)	2015-2018	78	daily	1 year	1 week	momentum effect, more dominant among small cryptocurrencies
Tzouvanas et al. (2020)	2015-2019	12	daily	7, 5, 30 days	7, 5, 30 days	significant momentum for the 7/7 strategy
Dobrynskaya (2021)	2014-2020	2000	weekly	1-104 weeks	1-104 weeks	short-horizon momentum, significant reversal beyond 1 month
Jia et al. (2022)	2016-2019	1084	weekly	1-4 weeks	1-4 weeks	significant momentum effect, no reversal
Liu et al. (2022)	2014-2020	1827	daily	1-4 weeks	1 week	significant momentum profits, strongest for 2 and 3 week formations
Yang (2019)	2009-2018	63	daily	1-14 days	1 day	positive and significant momentum profits
Zaremba et al. (2021)	2015-2021	3607	daily	1 day	1 day	short-term reversal, momentum only among highest market cap
Li et al. (2021)	2014-2020	300	daily	1 month	1 week	MAX momentum effect

Notes: This table summarizes the major findings on the momentum and reversal effects in cryptocurrency markets. The sample period refers to the specific timeframe in which data is collected for the research. Sample size shows the number of cryptocurrencies fulfilling the data filtering requirements. Frequency refers to the frequency at which data are observed. Formation period is the period during which the past performance of cryptocurrencies is observed. Holding period shows how long the momentum portfolio is held for. The results column summarizes the key findings of each study. MAX momentum effect means that cryptocurrencies with a high extreme return in the previous month continue to perform well in the future

While constructing the factors, only cryptocurrencies with a market capitalization over \$1 million are considered. The formation period of the momentum strategy considered in this study varies from 1 to 4 weeks, while the holding period is always 1-week-long. The highest excess returns are generated by the 2/1 and 3/1 strategies. The finalized pricing model includes the latter. The authors conduct Principal Component Analysis (PCA) tests to investigate the explanatory power of the three-factor model. 45% of the time variation can be captured by the first two components, which exhibit notable correlation with the size and momentum factors. The study also reveals that the momentum strategy performs better in larger and more liquid portfolios, which aligns with the behavioral explanation of the momentum profits, as these coins attract greater investor attention.

Given that almost none of the aforementioned studies employ exactly the same methodology, I have compiled a summary of the key attributes of these articles on cryptocurrency momentum in [Table 1](#). This should help identify the cause of the disparities in the results. The results exhibit considerable differences across a wide range: the papers in the first three rows of [Table 1](#) provide evidence of a reversal effect, yet the articles in the last rows even describe a phenomenon of one-day momentum and reversal, with holding periods consisting of one single day. According to the displayed data, reversals occur over time periods longer than one month, whereas momentum appears to be consistent in the majority of articles that examine formation and holding periods of 1 to 4 weeks. The behavior of the largest cryptocurrencies may differ significantly from that of the smaller, less liquid coins; thus, sample size is crucial. None of the studies investigate the market beyond 2020, and the majority of the sample periods do not begin before 2014. To cover the majority of the cryptocurrency market’s history, I analyze a sample from 2014 to 2023, which is the most extensive period compared to the preceding articles and also provides the most recent information. Throughout my study, I primarily adhere to the methodology implemented by [Liu et al. \(2022\)](#), as this paper appears to offer the most extensive and proficient research. Evidently, I also take into account methods utilized in other works.

3 Data and Methodology

3.1 Description of data

I collect data from coinmarketcap.com⁶ to construct my sample, following [Liu et al. \(2022\)](#), [Shen et al. \(2020\)](#), [Kosc et al. \(2019\)](#) and almost every other study. This website provides a wide range of coin prices directly sourced from many exchanges. The listed cryptocurrencies cover approximately 97% of all coins. My sample consists of data from January 1, 2014 to December 31, 2023. This time period surpasses the majority of the sample periods examined in the most relevant current research studies. I obtain daily close prices, market capitalization and volume for all listed active and non-active cryptocurrencies, all converted to USD. Considering inactive coins helps to avoid survivorship bias and enables the replication of real-time tactics. For the risk-free rate, I download the daily rates of the one-month Treasury bill from Ken French’s data repository⁷ following [Daniel and Moskowitz \(2016\)](#) and many others.

$$R_{\text{Market}}^{\log} = \sum_{i=1}^n w_i R_i^{\log} \quad \text{where } w_i = \frac{MktCap_i}{\sum_{i=1}^n MktCap_i} \quad (1)$$

Based on the daily prices I calculate daily log returns ([Liu et al. \(2022\)](#)). I construct the market portfolio by computing the value-weighted average of the daily log returns of all cryptocurrencies in the sample. To determine the weights, I use market capitalization, as described in [Equation 1](#).

3.2 Momentum portfolio construction choices

Prior to forming momentum portfolios, I consider various data construction choices. [Fieberg et al. \(2024\)](#) places significant emphasis on these decisions due to the fact that just a few seemingly inconsequential choices can result in drastically different conclusions, thus creating an opportunity for non-standard errors. Non-standard errors refer to such seemingly unimportant decisions regarding data selection and portfolio construction. These considerations are critical since they can impact the results of the tests. [Table 2](#) provides a summary of the decisions I evaluated prior to establishing the momentum strategy.

Given the extreme volatility of cryptocurrency returns, I winsorize the cross-section

⁶<https://coinmarketcap.com>

⁷https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

Table 2: Dataset and portfolio construction design choices

Design choice	Decision	Reference
Dataset	coinmarketcap.com	Liu et al. (2022) , Shen et al. (2020)
Winsorization	1%	Liu et al. (2022) , Zhang et al. (2021)
Stablecoins	excluded	Bianchi and Babiak (2021)
Missing Values	0	Fieberg et al. (2023)
Market Capitalization Filter	\$1 million	Dobrynskaya (2021) , Liu et al. (2022)
Number of Portfolios	5	Jia et al. (2022)
Portfolio Weights	value-weighted	Liu et al. (2022) , Jia et al. (2022)
Lag	0	Liu et al. (2022)

Notes: This table provides an overview of dataset design choices made when constructing the momentum strategy. Non-standard errors considered, taking note of the findings of [Fieberg et al. \(2024\)](#).

of the returns at 1%. Winsorization involves replacing values that are below the 1st percentile and above the 99th percentile with the corresponding values at the 1st and 99th percentiles, respectively. This helps to mitigate the influence of extreme returns during the calculations. Regarding the other decisions, I primarily adhere to the procedures implemented by [Liu et al. \(2022\)](#). Stablecoins are excluded from the analysis considering their distinct behavior, which is influenced by their price being tied to the value of other currencies, such as the USD. Following [Fieberg et al. \(2023\)](#), I require all observations to feature full information for price, market capitalization, and volume on any given day during the formation period. In order to maintain sufficient liquidity in the sample, I remove all coins with market capitalization below \$1 million. At the end of each formation period, I sort all cryptocurrencies into five portfolios ([Jia et al. \(2022\)](#)). Thus, an adequate quantity of coins is ensured for each portfolio, even in the case of the smallest possible sample size. Lag control for reversal is not implemented in my approach, as it is commonly assumed in most studies that the portfolio is constructed immediately following the calculation of the signal.

In order to determine the most powerful momentum approach, I conduct tests on the strategy mentioned above using different formation and holding periods. The duration of the formation (J) and holding (K) periods varies from 1 to 4 weeks, following the works of [Shen et al. \(2020\)](#), [Jia et al. \(2022\)](#) and [Liu et al. \(2022\)](#). The momentum portfolios are rebalanced either every K week or weekly. The latter scenario involves overlapping portfolios, where each portfolio is allocated a weight of $1/K$, as described by [Dobrynskaya \(2021\)](#). This means 32 different strategies in total. In order to replicate an investment strategy in real time, the filtering criteria outlined in [Table 2](#) are exclusively applied to

the formation period. Although this eliminates the risk of look-ahead bias, it does not guarantee the avoidance of missing values during the holding period.

Once I have determined the most prominent momentum strategy, I proceed to evaluate several additional attributes of the portfolio. As [Fieberg et al. \(2024\)](#), I conduct experiments to assess the possibility of 3, 5, and 10 portfolios. Following [Liu et al. \(2022\)](#), besides considering zero lag, I also take into account a one-day lag and even a one-week delay controlling for short-term reversal, as discussed by [Fieberg et al. \(2023\)](#). These tests are run for both value and equal-weighted portfolios, resulting in a total of 18 additional tests. The subsequent analyses of this study are conducted on the approach that delivers the highest [Newey and West \(1994\)](#) t -statistics following these experiments.

3.3 Methodology of the momentum gap

In accordance with [Huang \(2022\)](#), I construct two momentum gap approaches. Using the momentum signal generated during the formation period, the formation period return difference between the 75th and 25th percentiles is referred to as MG, while the difference between the 90th and 10th percentiles is defined as MG_{idr} . Instead of using both measures, I mainly focus on MG since it is more robust to extreme values, which are even more prevalent in cryptocurrency returns compared to the stock market. MG_{idr} is primarily studied as a test of robustness.

To investigate whether the momentum gap accurately predicts momentum profits for cryptocurrencies, similar to how it does in the stock market, I perform both in-sample and out-of-sample tests. The out-of-sample predictions only use data prior to portfolio construction, preventing look-ahead bias⁸ and technically functioning as a real-time trading strategy. As I evaluate the momentum gap, I also assess the behavior of control variables. The factors in question include market return, market volatility, and market illiquidity. Momentum returns in the stock market are significantly correlated with these variables as documented by [Cooper et al. \(2004\)](#), [Wang and Xu \(2015\)](#), and [Avramov et al. \(2016\)](#). [Huang \(2022\)](#) estimates the market return and market volatility by analyzing data from the previous three years. Considering the disparities between cryptocurrencies and the stock market, my estimation period will consist of three months, thereby proportioning the length of these timeframes for the faster dynamics of the alternative market. Market return is calculated for each day as outlined in [Equation 1](#), and thereafter, I

⁸[Barroso and Santa-Clara \(2015\)](#) specifically highlights that the presence of a forward-looking bias hinders the practical implementation of various strategies for real-time investments.

construct weekly returns. The final market return variable is the cumulative return of the past three months, while market volatility is estimated from weekly returns in the three-month estimation window. Ascertaining market illiquidity requires calculating the value-weighted average of the [Amihud \(2002\)](#) illiquidity ratios. As recommended by [Liu et al. \(2022\)](#), the latter is calculated for cryptocurrencies by dividing the average absolute daily return by the price volume during the portfolio formation period.

One of the primary concerns regarding cryptocurrency WML methods are the short selling constraints. Such trading opportunities in the coin market are highly restricted. Shorting is only obtainable for a handful of the larger cryptocurrencies, while for the majority it is not even possible. To address this issue, I examine alternative WML strategies, which buy the long leg of the WML portfolio and short Bitcoin, or the risk-free rate, as recommended by [Liu et al. \(2022\)](#) and [Fieberg et al. \(2023\)](#). The efficacy of these approaches is reported alongside other robustness tests in the final part of the study.

4 Results

4.1 Construction of the momentum strategy in the cryptocurrency market

I analyze formation and holding periods spanning from one to four weeks in order to determine the most impactful momentum strategy. [Table 3](#) provides the results of the tests conducted. For both examined rebalancing approaches, the 2/2 strategy yields the highest and most significant momentum returns, with weekly returns of 2.63% and 2.11%, respectively. These results align with the conclusions drawn by [Dobrynskaya \(2021\)](#), who similarly identifies the two-week holding and formation period strategy as the most effective momentum approach. Similar to [Liu et al. \(2022\)](#), the 2/1 and 3/1 combinations also exhibit notable returns, although they do not consider holding periods over 1 week; therefore, these strategies are outperformed by the 2/2 approach in my study. Consistent with the long-term reversal, the significance of momentum profits diminishes as the formation and holding periods approach the length of four weeks, although negative average returns are still not observed.

Further tests of the 2/2 strategy reveal that including a 1-day lag results in even higher profitability. This is most likely evidence of a very short-term return reversal, consisting of only about a day ([Zaremba et al. \(2021\)](#)). Remarkably, equal-weighted

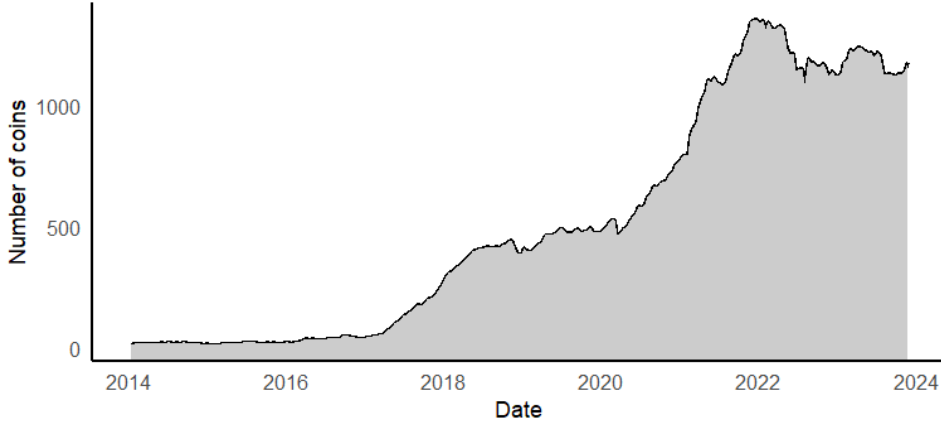
Table 3: Average momentum returns on different portfolio constructions

3/A: Different formation and holding periods								
J\K	rebalancing = K				weekly rebalancing			
	1	2	3	4	1	2	3	4
1	0.0160 (2.45)	0.0079 (1.20)	0.0252 (3.53)	0.0113 (1.59)	0.0160 (2.45)	0.0155 (2.84)	0.0144 (3.09)	0.0134 (3.05)
2	0.0244 (3.83)	0.0263 (4.76)	0.0162 (1.89)	0.0226 (3.80)	0.0244 (3.83)	0.0211 (3.94)	0.0177 (3.76)	0.0139 (2.96)
3	0.0212 (3.86)	0.0108 (1.67)	0.0138 (2.84)	0.0082 (1.57)	0.0212 (3.86)	0.0149 (2.78)	0.0100 (1.92)	0.0065 (1.32)
4	0.0146 (2.70)	0.0119 (2.16)	0.0076 (1.35)	0.0086 (1.39)	0.0146 (2.70)	0.0097 (1.73)	0.0060 (1.08)	0.0050 (0.90)
3/B: Different lags and number of portfolios								
reversal	Number of portfolios							
	value-weighted			equal-weighted				
	3	5	10	3	5	10		
0	0.0235 (4.76)	0.0263 (4.76)	0.0257 (4.03)	0.0088 (2.91)	0.0107 (2.50)	0.0071 (1.23)		
1	0.0260 (5.91)	0.0284 (4.94)	0.0253 (3.83)	0.0099 (3.17)	0.0108 (2.67)	0.0099 (1.56)		
7	0.0159 (3.46)	0.0138 (2.48)	0.0036 (0.49)	0.0010 (0.35)	0.0007 (0.20)	0.0023 (0.50)		

Notes: This table reports the average weekly returns of WML strategies, which buy past winners and sell past losers based on their performance in the formation period. In Panel A, the length of the formation and holding periods vary from 1 to 4 weeks. J is the length of the formation period in weeks, during which the performance of cryptocurrencies is observed. K is the length of the portfolio holding period in weeks. At the end of each formation period, stocks are sorted into 5 value-weighted portfolios. The portfolios are rebalanced weekly or every K week. In Panel B, the 2/2 momentum strategy is examined further. At the end of each formation period, cryptocurrencies are sorted into 3, 5 or 10 portfolios. Reversal is the number of days excluded at the end of each formation period to control for the short-term reversal effect. [Newey and West \(1994\)](#) t -statistics are reported in parentheses.

portfolios yield notably lower. This weighting scheme grants greater influence to smaller, less liquid currencies, which frequently exhibit extreme returns; as a result, the momentum strategy becomes unreliable. As their economic significance is likewise negligible (Fieberg et al. (2024)), applying value-weighted portfolios makes sense as it limits the influence of these coins.

Figure 1: Number of cryptocurrencies considered



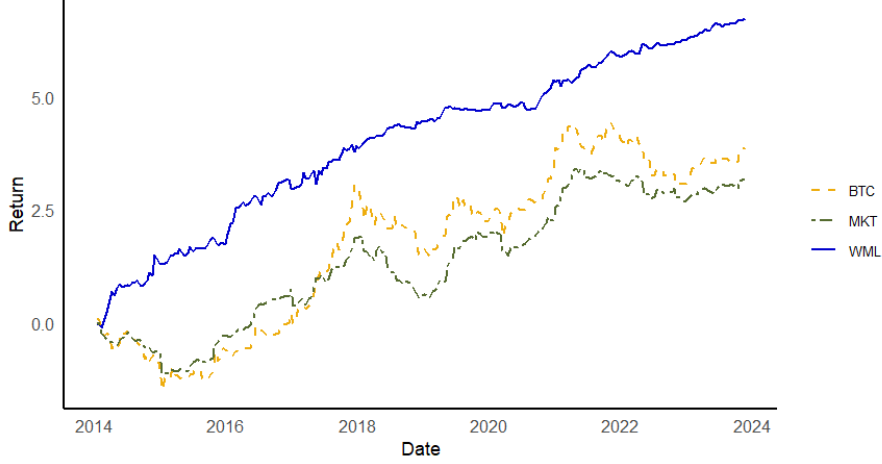
Notes: This figure shows the number of cryptocurrencies fulfilling the sample criteria for each formation period of the best-performing momentum strategy. This is the 2/2 momentum strategy, which sorts cryptocurrencies into 3 value-weighted portfolios based on their past performance. A 1-day lag is considered to control for reversal. The sample period is from 2014 to 2023.

Similarly to how the implementation of a one-day lag, increases momentum profits, sorting coins into tertiles instead of quintiles does the same. Lowering the number of portfolios ensures a sufficient number of cryptocurrencies for each group, thereby enhancing portfolio diversification and leading to more consistent returns. Figure 1 displays the number of cryptocurrencies fulfilling the that fulfilled the filtering criteria at the time of portfolio formation over the sample period. In the initial phases of the sample, only a minimum number of 16 coins is considered. Sorting 16 coins into 5 portfolios would result in each portfolio consisting of only 3 assets. While considering only 3 portfolios, this minimum limit could be raised to 5, enabling more effective diversification. The sample size experienced a rapid growth in 2017, peaking later at a maximum of 1352 assets.

The implementation of these portfolio construction measures lead to additional improvement momentum returns. Thus, the weekly return on the best momentum portfolio is 2.60%. The ten-year progression of the cumulative returns of the selected momentum strategy is depicted in Figure 2. In comparison to the returns of Bitcoin or the cryptocurrency market portfolio, the performance of the WML portfolio is substantially superior, yielding roughly double that of the latter two. Additionally, the momentum strategy

appears to be less volatile, as noticeable crashes only disrupt the monotonic growth on a handful of occasions.

Figure 2: Cumulative returns of the chosen WML strategy



Notes: This figure displays the cumulative weekly log returns of the chosen WML strategy. The best performance was exhibited by the 2/2 momentum strategy, which sorts cryptocurrencies into 3 value-weighted portfolios based on their past performance. A 1-day lag is considered to control for reversal. BTC is the cumulative log returns of Bitcoins. MKT shows the cumulative weekly log returns of the market portfolio, constructed as the value-weighted return of all cryptocurrencies. The sample period is from 2014 to 2023.

In contrast to what the infamously volatile nature of cryptocurrencies might suggest, the momentum strategy for cryptocurrencies does not appear to often experience catastrophic collapses that significantly reduce the WML return. The months⁹ during which the momentum gap encountered the most serious declines are detailed in [Table 4](#). A loss of 41.71% is incurred by the momentum portfolio during its worst month. Despite the substantial loss, this return represents only approximately half of the worst momentum crash month in the stock market (-74.36%), as documented by [Daniel and Moskowitz \(2016\)](#). All monthly returns of Bitcoin, except for January 2017, consistently show absolute monthly returns exceeding 10% during periods of cryptocurrency momentum crashes. This might indicate that Bitcoin was included in the momentum portfolio's long (short) leg when the coin experienced losses (gains) over 10%, thereby contributing to the momentum portfolio's losses. Nevertheless, it should be noted that the performance of Bitcoin cannot be attributed to momentum losses, as the strategy employs value-based weights. Given Bitcoin's substantial market capitalization, it would have a

⁹Although I examine weekly log returns of cryptocurrencies, I calculate monthly returns to simplify the comparison to the stock market data

significant influence on the performance of the momentum portfolio. Consequently, the momentum returns should closely approximate the absolute returns of Bitcoin. This is incorrect, as the returns of Bitcoin are significantly lower compared to the altitude of cryptocurrency momentum crashes.

Table 4: Worst cryptocurrency momentum crash months

Rank	Month	WML_t	BTC_t
1	2016-07	-0.4171	-0.1617
2	2017-05	-0.4080	0.3891
3	2014-12	-0.3905	-0.1789
4	2017-01	-0.3869	-0.0089
5	2015-11	-0.3599	0.1097

Notes: This table presents the five worst months for the chosen cryptocurrency momentum strategy. WML_t is the log return of the 2/2 momentum strategy in month t . As WML portfolios are rebalanced every two weeks, the monthly momentum returns are calculated as the sum of two following momentum portfolios. BTC_t is the log return of Bitcoin in the given month. The sample period is from 2014 to 2023.

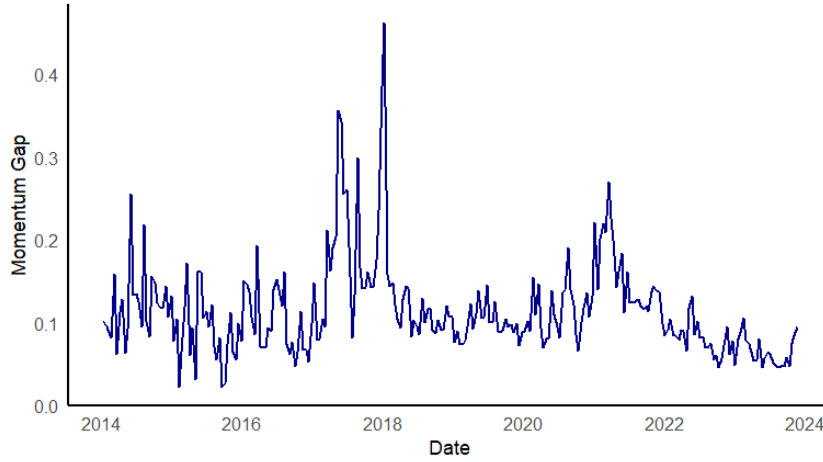
Given that the analyzed cryptocurrency momentum portfolios are rebalanced at a higher frequency compared to momentum portfolios constructed in the stock market, the comparatively lower losses experienced during crashes appear rational. Considering that investors make portfolio adjustments more often, coins experiencing long-lasting losses or gains would strictly impact the strategy for a duration of two weeks. For instance, in May 2017, the cryptocurrency momentum strategy experienced its second-greatest loss. Despite an enormous average weekly decline of 31.09% during the second half of the month, the preceding and subsequent periods generated considerably positive returns. This helped compensate for the big loss and restricted the whole monthly decline to just 40.80%.

Once I have identified the optimal approach for constructing a momentum portfolio and confirmed that it is comparatively less vulnerable to extreme market downturns than the stock market, my focus shifts to the examination of the momentum gap. I anticipate that the behavior of the momentum gap among cryptocurrencies will be different from that of the equity market due to the distinctions between the stock market and cryptocurrencies with regard to the extreme losses of the momentum portfolio.

4.2 Prediction of momentum returns using the momentum gap

Figure 3 displays the time-series evolution of the momentum gap, constructed as the difference between the 75th and 25th percentiles of the momentum signal generated during the two-week formation period. I prioritize this measure, while the alternatively defined MG_{idr} primarily functions as a control variable for robustness tests. The momentum gap exhibits substantial time variation. The peak MG values are observed during the mid and late periods of 2017, as well as in February and March of 2021. Although there were a limited number of crashes in 2017, there is no obvious indication that the momentum gap reaches its maximum during periods of the worst momentum, unlike in the stock market. Calculating the momentum gap for the latter market reveals that the time series of the variable exhibits its maximum values in 1932 and 2009, periods when monthly losses of stock market momentum exceeded even 50%.

Figure 3: Time-series of the momentum gap



Notes: This figure illustrates the time-series progression of the momentum gap. The momentum gap is defined as the difference between the 75th and 25th percentiles of cumulative coin returns over 24-weeks formation periods. The momentum signal is generated by the 2/2 momentum strategy with 1-day lag controlling for reversal. Cryptocurrencies are sorted into 3, value-weighted portfolios.

Table 5 validates this assumption, as WML returns do not show a statistically significant correlation with either the MG or MG^{-+} , MG^{-} , and MG_{idr} . Table 5 provides descriptive statistics for the main analyzed throughout the study. The momentum returns exhibit a noteworthy positive skewness of 0.82 and a kurtosis of 4.30. As a contrast, Barroso and Santa-Clara (2015) estimates that equity momentum has a kurtosis of 18.24 and a skewness of -2.47. The decrease in kurtosis is desirable, as it reduces the tail of the distribution of returns. The momentum in the equity market demonstrates a pronounced fat tail, indicating a higher frequency of extreme returns. Hence, the substantially lower

Table 5: Descriptive statistics

	WML	WML ⁺	WML ⁻	MG	MG ⁺	MG ⁻	MG _{idr}
4/A: Moments							
Count	258	258	258	258	258	258	258
Mean	0.0260	-0.0154	0.0421	0.2160	0.1139	0.1021	0.4794
Standard deviation	0.08	0.17	0.17	0.09	0.06	0.04	0.18
Skewness	0.82	-0.20	-0.17	2.20	2.25	1.77	1.66
Kurtosis	4.30	1.71	1.27	8.47	8.18	5.80	4.84
4/B: Correlations							
WML		0.32	0.15	-0.04	-0.05	-0.02	-0.07
WML ⁺			-0.89	-0.31	-0.31	-0.25	-0.31
WML ⁻				0.31	0.30	0.26	0.29
MG					0.94	0.90	0.92
MG ⁺						0.71	0.89
MG ⁻							0.81
4/C: Subsample means							
2014	0.0503	-0.0016	0.0495	0.2357	0.1220	0.1138	0.5331
2015	0.0163	0.0049	0.0124	0.1704	0.0860	0.0844	0.3677
2016	0.0482	-0.0096	0.0568	0.2022	0.1017	0.1006	0.4453
2017	0.0362	-0.0748	0.1121	0.3423	0.1877	0.1546	0.7138
2018	0.0206	0.0189	0.0026	0.2428	0.1256	0.1171	0.5076
2019	0.0095	-0.0187	0.0271	0.1841	0.0978	0.0863	0.4315
2020	0.0252	-0.0283	0.0575	0.2026	0.1118	0.0908	0.4785
2021	0.0205	-0.0428	0.0681	0.2838	0.1565	0.1272	0.6310
2022	0.0130	0.0116	0.0027	0.1616	0.0812	0.0804	0.3664
2023	0.0200	-0.0130	0.0317	0.1279	0.0647	0.0632	0.3053

Notes: This table presents a summary of descriptive statistics for the main variables examined in this study. WML shows the weekly log returns of the 2/2 momentum strategy with 1-day lag controlling for reversal. Cryptocurrencies are sorted into 3, value-weighted portfolios. WML⁺ is the weekly log return of the long leg of the momentum, buying the top tertile and selling the market portfolio. WML⁻ is the weekly log return of the short leg of the momentum, buying the market portfolio and selling the lowest tertile. MG is the momentum gap, defined as the difference between the 75th and 25th percentiles of cumulative coin returns over 2-weeks formation periods. MG⁺ is the difference between the 75th and 50th percentile, MG⁻ is calculated as the difference between the 50th and 25th percentile of the momentum gap. MG^{idr} is an alternative definition of momentum gap, the difference between the 90th and 10th percentile. Panel A reports the counts and the moments of each variables. Panel B shows the correlations. Panel C displays the subsample means of the variables. The significance of the correlations in Panel B is solely evaluated in the textual analysis section of the study.

kurtosis of cryptocurrency momentum returns implies a smaller probability of extreme WML returns occurring. As negative skewness is associated with an increased probability of extreme losses, the 0.82 skewness observed in the cryptocurrency market should also be regarded as a positive development relative to equities.

Based on these statistics, it appears that momentum investing in cryptocurrencies carries less risk compared to equities, as the likelihood of momentum crashes occurring is lower. This prompts the question of whether it makes sense to examine the momentum gap’s forecasting power. The relatively low returns in 2015 and 2022, as indicated by the subsample means of WML returns, suggest that momentum returns are not consistent over time; consequently, investors may wish to devise a method to reduce the historical variation of this strategy.

While there is no statistically significant correlation between WML and MG, a significant relationship exists between MG and the distinct long (WML^+) and short legs (WML^-) of the momentum strategy, nevertheless in the exact opposite direction. Following [Huang \(2022\)](#), WML^+ involves purchasing the long leg of the momentum portfolio and selling the market portfolio, while WML^- buys the market portfolio and shorts past losers. This way, both strategies should deliver positive returns, as past winners are expected to beat the performance of the market, while past losers should yield less than the market portfolio. This is confirmed by WML^- ; however, the average weekly returns of WML^+ are -1.54%, which means that the performance of the market surpasses the returns of the coins in the long leg of the momentum portfolio. This prompts inquiries about the adequate definition of past winners or an alternative long leg for the momentum portfolio.

Although the correlations are not significant, I employ univariate sorting and order the momentum returns based on the momentum gap in the past period. This allows me to further evaluate the relationship between these two variables. [Table 6](#) presents the results for these sortings. Neither the utilization of quintiles nor the process of separating into tertiles establishes a definitive and linear correlation. Still, in both scenarios, it seems that the highest quantiles contain the lowest average returns. This suggests that although there is no obvious and monotonic relationship, as in the equity market, high momentum gap values tend to coincide with low momentum returns.

I conduct further tests in order to determine whether this fact gives momentum gap the capacity to accurately forecast momentum returns. [Table 7](#) presents a comprehensive summary of the regression results. In addition to analyzing the momentum gap, I also account for other potentially influential variables. Consequently, I control for market

Table 6: Momentum returns by the lagged momentum gap

Rank	Num.	Average MG	WML	WML ⁺	WML ⁻
5/A: Tertiles					
1	86	0.1381	0.0237 (3.75)	0.0037 (0.29)	0.0197 (1.48)
2	86	0.1983	0.0333 (3.46)	0.0232 (1.29)	0.0097 (0.58)
3	86	0.3116	0.0211 (2.03)	-0.0730 (-3.20)	0.0970 (4.54)
1-3			0.0025 (0.20)	0.0767 (3.00)	-0.0773 (-3.18)
5/B: Quintiles					
1	52	0.1239	0.0202 (2.53)	0.0257 (1.59)	-0.0047 (-0.29)
2	52	0.1653	0.0305 (3.86)	-0.0260 (-1.84)	0.0548 (3.65)
3	52	0.1985	0.0382 (2.60)	0.0367 (1.50)	0.0006 (0.03)
4	51	0.2366	0.0246 (2.25)	-0.0251 (-0.95)	0.0517 (2.04)
5	51	0.3590	0.0164 (1.13)	-0.0898 (-2.79)	0.1098 (3.65)
1-5			0.0038 (0.22)	0.1155 (3.01)	-0.1145 (-3.13)

Notes: This table displays mean weekly momentum log returns by the lagged momentum gap. MG is the momentum gap, defined as the difference between the 75th and 25th percentiles of cumulative coin returns over 2-weeks formation periods. WML shows the weekly log returns of the 2/2 momentum strategy with 1-day lag controlling for reversal. Cryptocurrencies are sorted into 3, value-weighted portfolios. WML⁺ is the weekly log return of the long leg of the momentum, buying the top tertile and selling the market portfolio. WML⁻ is the weekly log return of the short leg of the momentum, buying the market portfolio and selling the lowest tertile. *t*-statistics are reported in parentheses.

volatility, illiquidity, and market return.

Panel A, in which WML is the dependent variable, exhibits regression coefficients that are close to zero and low R^2 values. Although MG explains a higher proportion (0.21%) of the variance in momentum returns compared to the explanatory power of all three variables combined (0.10%), the t -statistics continuously exhibit low values and are all statistically significant. The R^2 value does not exceed 0.27%, even when all four explanatory variables are included in the model. In this model, the coefficient of MG remains fairly stable, while the presence of multicollinearity significantly affects the coefficients of market return and market volatility. Yet all t -statistics remain statistically insignificant, indicating that none of these variables have a substantial impact on the momentum returns.

Panel B and Panel C present the results of regressions conducted on MG^+ and MG^- . On this occasion, there are statistically significant t -statistics. MG explains 8.45% and 8.38% of the variation in WML^+ and WML^- returns, respectively. Besides MG, market return also exhibits statistically significant betas. In fact, when considering models that incorporate all four independent variables, the impact of market return turns out to be superior in comparison to the MG. It is noteworthy that the directions of the relationships are opposite. An increase in the MG by one standard deviation corresponds to a decrease of 2.48%¹⁰ in WML^+ returns and an increase of 2.15%¹¹ in the returns of the WML^- portfolio. This contrary relationship eliminates the predictive potential of the momentum gap, given that the WML strategy entails a combination of WML^+ and WML^- .

Despite the fact that these findings provide an explanation for the lack of the momentum gap's explanatory power, I also conduct out-of-sample tests. By exclusively considering data prior to the examination, these tests effectively alleviate concerns regarding look-ahead bias. The predictions of the tests previously conducted in [Table 7](#) cannot be used throughout the strategy to improve the investment because the estimation period of these regressions covers the whole sample period between 2014 and 2023 and no real-time forecasts are provided.

[Table 8](#) presents a brief overview of the out-of-sample tests. The regressions use an expanding estimation window that initially covers 60 weeks, which corresponds to 30 momentum formation periods. Thus, only information that was available prior to the estimation time is utilized. As confirmed by the $\Delta RMSE$ as well as by the $\bar{R}^2$ computed as the mean R^2 of 222 observations, the MG fails to demonstrate significant out-of-

¹⁰ 0.09×-0.2758

¹¹ 0.09×0.2350

Table 7: Prediction of momentum returns

	MG	Market Ret	Market Vol	Market Ill	R ²
6/A: Regression of WML					
	-0.0407 (-0.73)				0.21%
		-0.0051 (-0.45)	0.0196 (0.15)	-0.4954 (-0.18)	0.10%
	-0.0487 (-0.65)	0.0008 (0.06)	0.0493 (0.35)	-0.3314 (-0.12)	0.27%
6/B: Regression of WML⁺					
	-0.5534 (-4.92)				8.45%
		-0.1486 (-6.67)	0.3157 (1.21)	3.2320 (0.61)	14.64%
	-0.2758 (-1.91)	-0.1149 (-4.06)	0.4838 (1.76)	4.1611 (0.79)	15.53%
6/C: Regression of WML⁻					
	0.5230 (4.90)				8.38%
		0.1445 (6.90)	-0.2728 (-1.11)	-3.7556 (-0.75)	15.44%
	0.2350 (1.72)	0.1158 (4.32)	-0.4161 (-1.60)	-4.5472 (-0.91)	16.10%

Notes: This table summarizes the results of following time-series regressions: $y_t = \alpha + \beta x_{t-1} + \epsilon_t$. The explanatory variables are MG, Market Ret (Cooper et al. (2004)), Market Vol (Wang and Xu (2015)) and Market Ill (Avramov et al. (2016)). *MG* is the momentum gap. *Market Ret* is the the 3-month market return of the value-weighted portfolio of all cryptocurrencies. *Market Vol* is the market volatility, calculated from weekly market log returns from the last 3 months. *Market Ill* is the Amihud (2002) illiquidity measure, calculated as the average 2-week market illiquidity. In Panel A, the dependent variables are weekly WML log returns. In Panel B and Panel C, the dependent variables are WML⁺ and WML⁻. *t*-statistics are reported in parentheses.

sample predictive capability for momentum returns. Furthermore, both market return and market illiquidity exhibit greater efficacy. Additionally, I evaluate the effects of a quadratic specification in A.1, which, although it demonstrates a minor enhancement in terms of $\bar{R}^2$, does not yield notably different outcomes.

4.3 Enhanced momentum strategies

While I was unable to identify a significant relationship between momentum returns and the momentum gap, univariate sorts in Table 6 indicate that momentum returns are at their lowest subsequent to high momentum gap values. Hence, I examine whether it is

Table 8: Results of out-of-sample regressions

	$\bar{R}^2$	ΔRMSE
MG	0.55%	0.0027
Market Return	1.71%	0.0039
Market Volatility	0.04%	0.0011
Market Illiquidity	2.71%	0.2600

Notes: This table summarizes results of out-of-sample regressions predicting WML returns. MG is the momentum gap. Market return is the the 3-month log return of the value-weighted portfolio of all cryptocurrencies. Market Volatility is calculated from weekly market log returns from the last 3 months. Market Illiquidity is the [Amihud \(2002\)](#) illiquidity measure, calculated as the average 2-week market illiquidity. $\bar{R}^2$ is the average R^2 of out-of-sample regressions, using an expanding window with an initial length of 30 periods. ΔRMSE is the difference between the root-mean-squared errors of out-of-sample and predictive regressions. Positive ΔRMSE values indicate a superior out-of-sample prediction.

possible to predict momentum losses with the help of the momentum gap. I run logistic regressions and report the results in [Table 9](#). For the dependent variable, I construct a dummy, which is assigned a value of 1 if the period is classified as a momentum crash period and a value of 0 otherwise. As demonstrated across the panels of [Table 9](#), I evaluate different thresholds to define momentum crashes. Amidst the analyzed time frame, the momentum portfolio experiences declines over 2.5% 47 times, while losses exceeding 10% transpire merely 14 times.

With the exception of momentum losses above 10% analyzed in Panel D, MG demonstrates its unequivocal superiority in terms of predictive ability. For momentum returns lower than -2.5%, -5% or -7.5%, the momentum gap exhibits significant explanatory capability. When incorporating market return, market volatility, and market illiquidity into the same model, its coefficients hardly change. The Pseudo- R^2 values lack any notable enhancements when including all four factors compared to the simple regression model that only relies on the MG variable. This indicates that the predictive capacity of the MG is distinctive and cannot be explained by the other control variables. All of the momentum gap coefficients are positive, suggesting that increased MG values correspond to substantial momentum losses. In cases of losses exceeding even 10%, the coefficient of the MG becomes statistically insignificant in the four-variable model. While this could be a consequence of multicollinearity among the four variables, it is important to note that with only 14 occasions of such momentum crashes, the results might be spurious because of the low number of data points examined.

This significance of the momentum gap in predicting momentum crashes justifies

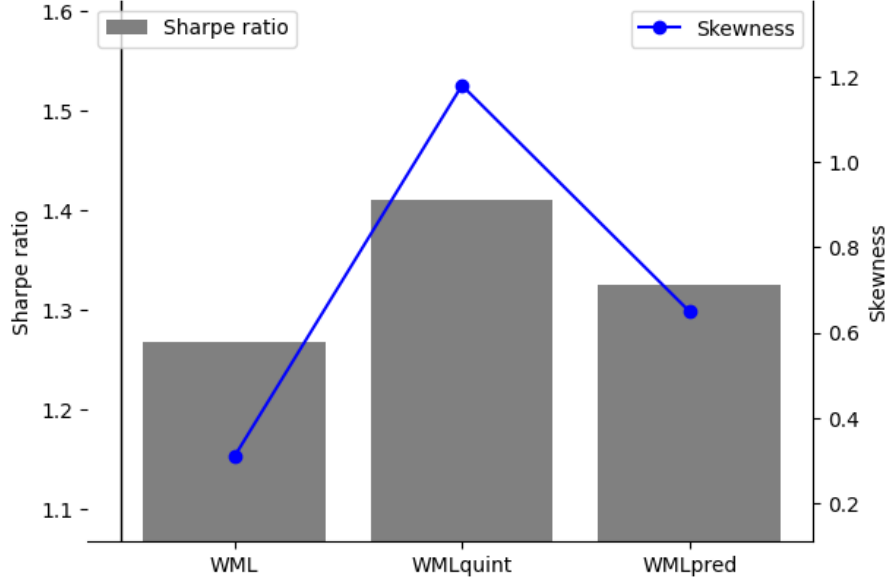
Table 9: Prediction of momentum crashes

	Num. Crashes	MG	Market Ret	Market Vol	Market Ill	Pseudo-R ²
8/A: WML $\leq$ -2.5%						
	47	4.3714 (2.75)				3.17%
		4.6089 (2.03)	0.0361 (0.08)	-2.8861 (-0.63)	-71.2241 (-0.37)	3.48%
8/B: WML $\leq$ -5%						
	31	6.1827 (3.45)				6.64%
		5.5980 (2.10)	0.3226 (0.60)	-4.5966 (-0.80)	-51.9500 (-0.26)	7.33%
8/C: WML $\leq$ -7.5%						
	21	6.7345 (3.44)				8.42%
		6.3887 (2.11)	0.2660 (0.42)	-5.6436 (-0.81)	-34.1431 (-0.18)	9.09%
8/D: WML $\leq$ -10%						
	14	4.8681 (2.36)				4.41%
		2.4411 (0.74)	0.8631 (1.10)	-4.1004 (-0.50)	-0.4279 (0.00)	5.86%

Notes: This table displays results of logistic regressions. Num. Crashes is the count of momentum crashes for each threshold. The variables to predict momentum crashes are the momentum gap, market return, market volatility, and market illiquidity. In Panel A, a period is defined as momentum crash period if the weekly log return is lower than -2.5%. In Panel B, C, and D the thresholds are -5%, -7.5% and -10%. The length of each period is 2 weeks. z-statistics are in parentheses.

the utilization of enhanced investment strategies conditional on the momentum gap. The strategies I formulate are identical to those [Huang \(2022\)](#) proposed. WML_{quint} only invests in momentum when the momentum gap computed from the formation period momentum signal is below the 80th percentile, thus avoiding large momentum gaps, which appear to coincide with momentum portfolio losses. WML_{pred} employs the predictions of out-of-sample regressions described in Table 8 and refrains from investing in momentum when the momentum gap predicts negative WML returns. Based on the limited, insignificant predictive power demonstrated by the momentum gap in the preceding sections of this study, I do not anticipate substantial improvements from the latter conditional strategy.

Figure 4: Performance of conditional momentum strategies



Notes: This figure displays the Sharpe-ratio of the benchmark momentum strategy and the momentum strategies conditional on momentum gap. WML is the unconditional 2/2 momentum strategy. WML_{quint} invests in momentum unless the momentum gap calculated at the end of the formation is above the 80th quintile. WML_{pred} does not take position in momentum if negative returns are forecasted by the out-of-sample predictive regression described in Table 7. Annualized Sharpe ratios are calculated from weekly excess log returns.

To ensure precise out-of-sample prediction, I analyze the performance of these conditional investing strategies first in May 2015, thereby granting an estimation window of at least 60 weeks. As a benchmark, Figure 4 illustrates the unconditional momentum strategy in addition to a summary of the performance of these enhanced investment approaches.

Remarkably, even WML_{pred} produces noticeable improvements in skewness and Sharpe ratio; yet, the Sharpe ratio increase is hardly significant (z -statistics 1.67). Considering that negative returns were predicted on a mere five occasions, this shows an impressive development. On the other hand, WML_{quint} results in a massively significant Sharpe ratio improvement (z -statistics 4.36), as the risk-adjusted return of this conditional strategy experiences an increase of nearly 9% (from 1.27 to 1.41). Additionally, both approaches enhance skewness, thereby reducing the likelihood of suffering serious losses.

When evaluating the performance of these strategies in comparison to the equity market, it is observed that all of the strategies built for cryptocurrencies exhibit superior Sharpe ratios. Even the enhanced equity strategies fail to demonstrate a Sharpe ratio

over 1, and all skewness values remain below 0. Nevertheless, when compared to the unconditional benchmark strategy, both conditional approaches demonstrate economically significant growth in the stock market. Regarding cryptocurrencies, only the strategy conditional on the top quintile of the momentum gap shows significant improvement hence confirming the notion that the momentum gap’s ability to predict is notably stronger in the stock market. Still, the considerably larger Sharpe ratios suggest that investing in cryptocurrency momentum could result in substantially greater profits, particularly when accounting for the information regarding the momentum gap. Still, fully replicating these strategies may prove to be a more challenging endeavor. One of the primary concerns associated with the momentum strategy is the constraints on short selling. As a part of the robustness tests that follow, I analyze, among other things, the limitations and alternatives of short selling.

4.4 Robustness tests

Asserting whether the superior performance of the enhanced momentum strategies conditional on the momentum gap persists across various subperiods and alternative constructions of the main variables, I undertake robustness tests in this section. [Table 10](#) presents a summary of the performance of the unconditional WML, as well as the enhanced WML_{quint} and WML_{pred} approaches.

At first, I examine MG_{idr} , a modified MG measure that takes into account the difference between the 90th and 10th percentiles of the returns over the formation period. The Sharpe ratio of the conventional momentum strategy remains the unchanged, in addition the enhanced momentum strategies also exhibit barely any variation in their Sharpe ratios. This indicates that whilst the strategies are conditional on the momentum gap, their effectiveness is not influenced by its construction.

I also analyze the behavior of the unconditional and conditional strategies across multiple subperiods. From 2014 to 2023, there were several significant economic shocks that had a substantial impact on the financial markets. December 2017, the launch date of Bitcoin futures, is one of the dates I used to split the sample in half. This event marked a major turning point, as it significantly reduced the challenges associated with shorting Bitcoin. As [Liu et al. \(2020a\)](#) explains, the price of Bitcoin experienced an 80% decline the year following the introduction of Bitcoin futures, while the performance of other cryptocurrencies maintained a positive trend.

Although the outbreak of the Russian-Ukrainian war and the COVID-19 pandemic

Table 10: Robustness tests of conditional momentum strategies

	WML	WML _{quint}	WML _{pred}
Original sample	1.2680	1.4110	1.3262
MG _{idr} as predictor	1.2680	1.4397	1.3291
2014 - December 2017	1.4939	1.6644	1.6030
December 2017 - 2023	1.2813	1.5195	1.2719
2014 - December 2020	1.3690	1.5423	1.4454
December 2020 - 2023	1.7010	1.8084	1.7100

Notes: This table shows the robustness of the annualized Sharpe-ratio of the conventional 2/2 momentum strategy and the momentum strategies conditional on momentum gap. WML is the unconditional 2/2 momentum strategy. WML_{quint} invests in momentum unless the momentum gap calculated at the end of the formation is above the 80th quintile. WML_{pred} does not take position in momentum if negative returns are forecasted by the out-of-sample predictive regression described in Table 7. MG_{idr} is an alternative definition of momentum gap, the difference between the 90th and 10th percentile. December 2017 marks the date of the introduction of Bitcoin futures. December 2020 is when the significant surge of DeFi and Web 3.0 occurred.

were also noteworthy events, I opted to utilize a breaking point that is more specific to cryptocurrencies: the convergence of DeFi¹² and Web 3.0 in December 2020. While investigating whether factor momentum (Gupta and Kelly (2019)) exists in the cryptocurrency market, Fieberg et al. (2023) employs the identical breaking point for robustness tests.

In every subperiod, the enhanced strategies continue to perform better than the traditional momentum strategy. The period subsequent to the introduction of Bitcoin futures witnessed the most significant enhancement (t -statistics: 9.71), wherein the Sharpe ratio of WML_{quint} demonstrated an almost 20% improvement in comparison to the unconditional momentum strategy (1.28 vs. 1.52). The improvements of WML_{quint} in other subperiods are also all economically significant, while WML_{pred} continues to perform relatively inadequately and even degrades the performance of the basic WML approach between December 2017 and 2023.

At last, in consideration of short selling constraints, I evaluate an alternative momentum strategy that sells Bitcoin and buys past winners. While evaluating a three-factor pricing model for cryptocurrencies, Liu et al. (2022) observes that the size factor behaves similarly when constructed in this alternative manner; nevertheless, the momentum strategy's profits diminish. I observe a similar outcome: the momentum portfolio constructed

¹²decentralized finance

alternatively does not generate substantial profits, and its weekly average return of 0.26% does not deviate substantially from zero (t -statistics: 0.34). Even the Sharpe ratio falls below zero, as shown in Table 11. This indicates that investing solely in T-Bills generates higher earnings compared to this momentum strategy.

Table 11: Robustness test of Bitcoin momentum strategy

	WML	WML _{quint}	WML _{pred}
Conventional WML	1.2680	1.4110	1.3262
WML _{BTC}	-0.1640	0.2789	0.0887

Notes: This table shows the robustness of the annualized Sharpe-ratio of the conventional 2/2 momentum strategy and the momentum strategies conditional on momentum gap. WML is the unconditional 2/2 momentum strategy. WML_{quint} invests in momentum unless the momentum gap calculated at the end of the formation is above the 80th quintile. WML_{pred} does not take position in momentum if negative returns are forecasted by the out-of-sample predictive regression described in Table 7. WML_{BTC} is an alternative momentum approach, which buys past winners and sells Bitcoin.

The question of whether further information on the momentum gap could result in significant improvements becomes even more crucial in light of the strategy’s declining appeal. By improving the Sharpe ratio up to 0.28, the conditional WML_{quint} strategy achieves an economically significant (t -statistics: 5.93) enhancement. WML_{pred} yields a statistically significant improvement as well, although WML_{quint}’s increase is still more severe. This further substantiates the notion that the momentum gap demonstrates greater efficacy in forecasting only exceptionally low momentum returns, whereas its predictive ability with respect to all WML returns remains comparatively weaker.

In regard to a synthesis of robustness test outcomes, it is evident that significant developments are achieved by implementing a condition that restricts investment in the momentum strategy to instances where the momentum gap ranks in the top quintile. This fact remains unchanged regardless of alternative portfolio constructions or time periods. This suggests that, similar to the stock market, momentum strategies for cryptocurrencies can be improved with the help of information regarding the momentum gap.

5 Conclusion

The expanding body of literature on cryptocurrencies comprises numerous studies that examine the momentum effect in the cryptocurrency market. Momentum is undeniably present among cryptocurrencies; however, it manifests itself in a way that’s distinct

from that of the stock market: The phenomenon of short-term return reversal is only evident for a few days, after which a strong momentum effect persists until a one-month time frame. After one month, the momentum returns gradually decrease, and a long-term reversal takes place, in which the momentum portfolio no longer generates substantial profit.

I analyze the cryptocurrency momentum effect spanning from 2014 to 2023, making it one of the longest time periods ever studied in the field of cryptocurrency research. Successfully identifying momentum profits for a single portfolio construction may appear to be the result of data snooping, but I demonstrate that the momentum effect is, in fact, persistent in the cryptocurrency market by examining a variety of portfolio construction options. The most effective momentum strategy entails utilizing two-week intervals for both the formation and holding periods. It sorts cryptocurrencies into three value-weighted portfolios while also controlling for the short-term reversal by implementing a one-day lag. The average weekly return on this portfolio is 2.60%.

Differences in comparison to the equity market also occur when establishing the momentum gap from the signal of the cryptocurrency momentum strategy. While a large momentum gap might forecast losses of the stock market momentum strategy, it fails to demonstrate a significant relationship with cryptocurrency momentum returns. This may be due to the fact that momentum losses on cryptocurrencies are typically less detrimental to momentum profits, given that even the unconditional strategy displays a remarkably higher Sharpe ratio and skewness in comparison to enhanced equity momentum strategies.

The superior performance of the strategy, which is conditional on the momentum gap, remains robust across various time periods and even for different constructions of the strategy. This provides further evidence that the momentum gap has the potential to enhance momentum profits in the cryptocurrency market; however, the economic explanation for this phenomenon remains largely unknown.

An important issue to consider regarding this highly appealing investment technique is the constraints associated with short selling. Due to the limited availability of coins for shorting, it can be challenging to sell previous losers as part of the cryptocurrency momentum strategy. The complexity of this issue is increased by the lack of significant profits generated by the alternative strategy, which includes Bitcoin in the short leg of the momentum portfolio; however, the performance of the strategy is enhanced when the momentum gap is utilized as a predictor of crash periods.

Hence, the construction of a completely reproducible cryptocurrency momentum portfolio remains a topic that requires additional investigation, as reproducibility has

emerged as a significant concern in recent times ([Christensen and Miguel \(2018\)](#), [Hou et al. \(2020\)](#)). Once such a strategy is developed, it remains an open question how to measure its performance with regard to p-hacking ([Feng et al. \(2020\)](#), [Harvey and Liu \(2021\)](#)) and the false discovery rate ([Harvey et al. \(2016\)](#)). Additionally, concerns may arise from the uncertainty surrounding different choices in data selection and portfolio construction, commonly referred to as non-standard errors ([Menkveld et al. \(2021\)](#)). Finally, the identification of a variable that demonstrates a substantial ability to anticipate cryptocurrency momentum returns, similar to the momentum gap in the stock market, is still open for further research.

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Appendices

A Appendix A

A.1 Quadratic specification of out-of-sample predictions

Table A.1.1: Results of quadratic out-of-sample regressions

	$\bar{R}^2$	ΔRMSE
MG	1.11%	0.0066
Market Return	1.85%	0.0133
Market Volatility	0.20%	0.0017
Market Illiquidity	3.71%	0.2709

Notes: This table summarizes results of quadratic out-of-sample regressions predicting WML returns. MG is the momentum gap. Market return is the the 3-month log return of the value-weighted portfolio of all cryptocurrencies. Market Volatility is calculated from weekly market log returns from the last 3 months. Market Illiquidity is the [Amihud \(2002\)](#) illiquidity measure, calculated as the average 2-week market illiquidity. $\bar{R}^2$ is the average R^2 of out-of-sample regressions, using an expanding window with an initial length of 30 periods. ΔRMSE is the difference between the root-mean-squared errors of out-of-sample and predictive regressions. Positive ΔRMSE values indicate a superior out-of-sample prediction.