Do Risk Preferences Drive Momentum in Cryptocurrencies? **

Juliane Proelss*, Denis Schweizer† and Bastien Buchwalter‡

Abstract

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Keywords: Crypto-Assets, Momentum, Investing, Trading Strategy

JEL Classification: G10, G11, G15, G29, G40

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The cryptocurrency market's continuous operation, with 24/7 trading, results in constant price fluctuations and information flow, posing challenges for investors to keep up with market changes and causing delays in their reactions to news, a phenomenon known as investor's limited attention. Amidst factors like leveraged positions and the network effect, momentum strategies appear promising. However, existing research yields mixed outcomes. To refine our understanding, we analyze momentum effects using a dataset free from survivorship bias, while also considering cryptocurrency variations in market capitalization and trading volume. This differentiation is crucial due to retail investors' preference for smaller capitalized cryptocurrencies, driven by their higher risk tolerance and limited attention, in contrast to institutional investors who focus on the top seven cryptocurrencies. Consequently, we anticipate uncovering more successful momentum strategies among smaller capitalized cryptocurrencies, shedding light on this complex interplay between market dynamics, investor behavior, and trading strategies.

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1. Introduction

Cryptocurrency, the dynamic and swiftly evolving digital frontier, has attracted substantial interest and holds transformative implications for our comprehension of financial markets and investment strategies at large. The growing popularity of crypto assets has resulted in an influx of retail and institutional investors interested in new and rapidly evolving crypto assets space in the recent past. This growing interest in crypto assets is remarkable, because investments are associated with elevated levels of volatility, uncertainty about the investments itself and regulation as well as sharp market declines, also referred to as crypto winters. Furthermore, cryptocurrency markets are characterized by constant availability of trading opportunities. Unlike traditional stock markets which have set trading hours, cryptocurrency markets are open 24/7, 365 days a year results in continuous price changes and information processing. As a result, investors may miss important developments and consequently lag in their investment behaviour reacting to the news. This delayed reaction to news is commonly referred to as investor's limited attention. Jagadeesh and Titman (1993), Moskowitz and Grinblatt (1999), Rouwenhorst (1998), and Moskowitz et al. (2012), have studied the effect of investor's limited attention by testing momentum strategies in traditional financial markets. These studies demonstrated that assets with past winning (or losing) streaks tend to persist in their winning (or losing) trajectories. This momentum phenomenon has proven robust across varied timeframes and markets, and asset classes (see Chan, Hameed and Tong, 2000).

Besides the continuous trading in cryptocurrency markets, they also differ in comparison to tradition market by its market participants. The share of retail investors in the crypto space, having daily responsibilities besides monitoring the crypto markets and related news flow is significantly higher than in traditional markets. In addition to this investor's limited attention, investors in digital assets also tend to utilize leveraged trading and stop-loss orders more frequently, which can result in a more pronounced trend as e.g. stop-losses orders could trigger a sudden price reduction which could force losing leveraged position to be liquidated. Furthermore, the price of native blockchain cryptocurrencies, such as BTC or ETH, typically positively correlate with the growth of the related network. This is because the more users and developers joining and use the cryptocurrency the higher is the demand for the cryptocurrency. Taken together the more distinct investor's limited attention, higher share of retail investors, more leveraged positions, and the network effect present more arguments for successful implementation of momentum strategies in the cryptocurrency then traditional markets.

Studying momentum strategies in the realm of cryptocurrencies is a relatively fledgling field and results are surprisingly not unanimous especially for cryptocurrencies with low market capitalizations and weekly strategies. Research by Liu et al. (2022), Cheah et al. (2022), Chu et al. (2020), or Gutierrez and Kelly (2008) suggested significant momentum effects within cryptocurrencies, although these findings were far from unanimous, with some studies producing mixed or even contradictory results (see e. g. Grobys and Sapkota, 2019); Kosc et al., 2019; Li et al., 2020 and Shen et al., 2020). One of the reasons for the divergence in results are the unique data-related challenges. These include the prevalence of joke coins, pump-and-dump schemes, missing or inconsistent data, and issues surrounding deceased cryptocurrencies and double naming, among others. These complexities can introduce potential biases and inaccuracies into the analyses, emphasizing the necessity for meticulous data management and methodological rigor.

A further point is the high participation of retail investors in the cryptocurrency market in comparison to traditional markets. Previous studies have highlighted the distinctive decision-making processes of these two investor groups. Institutional investors are often characterized by their rationality, well-informed strategies, and disciplined approach (Ozdamar et al., 2022). In contrast, retail investors are commonly perceived as less informed and more prone to noisy trading behaviors.

Institutional investors exhibit a penchant for larger investments, underscoring the critical importance of liquidity in their chosen assets. Notably, hedge funds predominantly focus on established crypto assets such as Bitcoin (BTC) and Ethereum (ETH), both of which consistently rank among the top-ten by market capitalization (PricewaterhouseCoopers, 2022)[4]. Furthermore, major corporations like Tesla and MicroStrategy have demonstrated substantial commitments to Bitcoin as well as crypto asset insiders, such as Brian Armstrong (CEO of Coinbase) and Tech billionaire Tim Draper. Within the Ethereum ecosystem, key investors include institutional entities like Arbitrum Bridge, along with influential figures like Ethereum founder Vitalik Buterin and Jonathan Lubin, renowned for their expertise in software engineering and related domains.

In contrast to the well-versed institutional investors, survey-based research provides insights into the distinct characteristics of retail investors in the crypto market. Typically, these individuals are young, technologically savvy, and well-versed in crypto-related knowledge. Their primary motivation often centers around the prospect of rapid wealth accumulation and gravitate towards exploring opportunities in smaller capitalized crypto assets (Auer and Tercero-Lucas, 2022; Jalan, Matkovskyy, and Yarovaya, 2023). This demographic exhibits a higher tolerance for risk and a willingness to accept losses as part of their investment journey. Furthermore, their investment decisions are significantly influenced by media exposure, particularly on social platforms like YouTube and X (formerly Twitter). Online trading apps and platforms serve as gamification avenues, shaping their investment processes (Jalan, Matkovskyy, and Yarovaya, 2023).

Given the argumentation above, institutional investors primarily allocate their investments to crypto assets with high market capitalizations, while retail investors predominantly opt for smaller

[4] See https://www.pwc.com/gx/en/news-room/press-releases/2022/pwc-global-crypto-hedge-fund-report-2022.html.

capitalized crypto assets. Consequently, momentum strategy returns for smaller capitalized crypto assets are anticipated to diverge from those of their larger capitalized counterparts. This disparity stems from the distinct risk aversion and attention levels exhibited by these two investor groups.

In light of these challenges, this paper aims to contribute to the understanding of momentum in cryptocurrencies by reconciling conflicting findings from past research and addressing inherent data challenges. Specifically, we utilize the analytical model proposed by Koziol and Proelss (2021) to investigate the genesis of momentum in digital assets and shed light on the different levels of risk-aversion of investors types. Risk aversion, indicative of an investor's preference for less risky investments when faced with two options of identical expected return, plays a key role in the relationship between initial and subsequent returns in momentum effects.

Employing the most comprehensive and survivorship-free dataset used in this field to date, we focus on monthly and weekly strategies, incorporating robustness checks with various prediction periods. As compared to previous studies which all require cryptocurrencies to have information on market capitalization and thus limiting the dataset in the most comprehensive case to 2,500 cryptocurrencies at a time or a total 3,607 cryptocurrencies (Zaremba et al., 2021), we do not impose this restriction. Thereby our approach aims to provide a more nuanced and accurate understanding of momentum in cryptocurrency markets as previous studies did not adequately control and correct for data issues and assumed a "representative" investor irrespectively of the distinct differences between retail and institutional investors.

The organization of this paper is as follows: A review of relevant literature is presented in Section 2, followed by an extensive description of the utilized dataset in Section 3. In Section 4, the employed methodology is delineated in detail. Section 5 furnishes the outcomes of our study, and Section 6 encapsulates our conclusions.

2. Literature Review

2.1. Momentum in Stock and Other Markets

The literature on momentum patterns in financial markets has explored various strategies, with notable studies by Jagadeesh and Titman (1993), Moskowitz and Grinblatt (1999), Moskowitz et al. (2012), Rouwenhorst (1998), Georgopoulou and Wang (2017), Kim, Tseb, and Wald (2016), Goyal and Jegadeesh (2018), and Huang et al. (2020). These studies employ monthly observations and examined variations in the duration of estimation and investment periods, ranging from 1 month to 48 months with a main focus on momentum strategies with a 1-3-6 or 12-month estimation and holding period showing that past winners (losers) continue to be winners (losers). A considerable body of research investigating the momentum phenomenon across different timeframes and internationally and has provided empirical support for the findings initially reported by Jegadeesh and Titman (1993), see e.g Kroencke et al. (2014) for currency markets or Fuertes et al. (2010) for commodity futures.

Studies that are more recent have examined short- and medium-term momentum using weekly, daily and intraday data in different markets. Gutierrez and Kelly (2008) or Chai et al. (2017) study holding periods of 1, 2, and 3 weeks and up to 52 weeks. Their findings reveal that stocks with high 1-week returns display a significant continuation in returns throughout the subsequent 52-week holding period, following reversals for (especially extreme) 1-week returns. Lin et al. also focusses on weekly periods from 1 to 12 weeks on Chinese stock markets. The findings indicate that a contrarian strategy performs better than a momentum strategy in these markets. Short-term strategies, particularly those with a one-week sorting period, do not generate significant returns. This contrasts with the findings from previous studies on mature stock markets, such as the U.S., where price momentum typically occurs over 1-12 months. Rakowski and Wang (2009) research daily momentum in the context of mutual fund suggest that investors tend to follow contrarian strategies rather than momentum strategies on a daily basis. Overall, daily flows of mutual funds exhibit mean-reversion tendencies. Gao et al. (2018), Elaut et al. (2018) or Baltussen et al. (2021) research intraday momentum in different markets including equity, currencies and as well as bonds and commodities and find significant evidence of time series intraday momentum.

2.2. Momentum in Cryptocurrencies

Momentum related cryptocurrency research encompasses various approaches to analyzing momentum effects. One stream of papers examines the use of moving averages as indicators of momentum, while another focus on traditional momentum strategies including time series momentum[5] (see Moskowitz et al., 2012) and cross-sectional momentum[6] (see Jegadeesh and Titman, 1993) using different data granularities including intraday-prices, daily price changes, weekly and also monthly data. These studies shed light on the dynamics of momentum in the cryptocurrency market and provide insights into the effectiveness of different momentum-based trading strategies. Table 1 presents a summary of the findings regarding momentum in cryptocurrencies.

2.2.1. Analysing Momentum in Cryptocurrencies using Moving Averages

Early papers on Momentum in cryptocurrency include Rohrback et al. (2017) who investigate the performance of momentum and trend-following trading strategies for six currencies and Bitcoin. The study employs daily cryptocurrency data from 2014 to 2017. Overall, their findings suggest that cryptocurrencies exhibit significant momentum, however, the limited data of the study and issues surrounding cryptocurrencies made it difficult to effectively apply a trading strategy. Chu

[5] Time series momentum, also known as trend-following, is a financial phenomenon where the positive or negative price trends of an asset in the past persist into the future. It is a strategy that involves buying assets with positive price trends and selling assets with negative price trends. Time series momentum takes advantage of the belief that asset prices show short-term persistence, allowing traders to capitalize on profitable trading opportunities.

[6] Cross-sectional momentum, also known as relative momentum, is a strategy that examines the performance of different assets relative to each other. It ranks assets based on their recent past returns and constructs a portfolio by buying the top-performing assets and selling the underperforming ones. This approach capitalizes on the belief that assets with strong historical relative performance are likely to continue outperforming in the future, aiming to generate excess returns by exploiting the momentum effect observed across assets.

et al. (2020) provide evidence supporting these findings, demonstrating that time series and cross-sectional momentum trading strategies using exponential moving averages (EMA) with hourly data in 2017 can generate positive returns, with signal-based strategies outperforming returns-based strategies for the seven largest cryptocurrencies. Grobys at al. (2020) also find support for the presence of momentum in seven cryptocurrency and show that a variable moving average strategy generates profits for a majority of cryptocurrencies, regardless of whether Bitcoin is included. Specifically, the short-term (20 days) strategy yields statistically significant profits for five out of ten cryptocurrencies, while the mid-term and long-term strategies generate profits for only three and one cryptocurrency respectively. Further Borgards (2021) investigated twenty cryptocurrencies and the S&P500 from 2014 to 2019 using a moving-average smoothing filter algorithm with momentum periods from 5 minutes to several months. The study found evidence of notable momentum periods in both asset classes following the initial price formation periods. The analysis further revealed that cryptocurrencies exhibited more extensive and prolonged momentum periods across various frequencies, indicating a more robust momentum effect compared to the stock market, which may be attributed to the inherent complexity associated with ascertaining the intrinsic value of cryptocurrencies.

Contrary to the previously studies which find support for momentum in the researched cryptocurrencies, there is a stream of literature which only find mixed results for the existence of momentum. Hudson and Urquhart (2021) employ daily data and find that a moving average rule is performing well for Ripple and Ethereum but not for Bitcoin using data from 2010 to 2014. Corbet et al. (2019) use intraday data to research fixed and variable moving average strategies related to momentum and find that variable moving averages generate significant returns using high-frequency Bitcoin returns while the fixed moving average strategy demonstrates that buy-sell differences are not showing significant differences. Applying mono- and multi-fractal analysis, Cheng at al. (2019), using Bitcoin, Ethereum, Ripple, EOS data from 2013 to 2018 find if significant fluctuations occur, there is a notable momentum effect observed in Bitcoin and Ethereum, while a market reversion effect is evident in Ripple and EOS.

2.2.2. Cryptocurrency Momentum with Monthly Prediction Periods

Grobys and Sapkota (2019) investigates momentum strategies in the cryptocurrency market using monthly time series data from 2014 to 2018 for 143 cryptocurrencies. Similar to Jegadeesh and Titman (1993) the authors employ monthly observations with the following strategies: 12-, 6- and 1-month prediction period with 1-month holding period, rebalanced monthly. Contrary to the earlier study by Rohrback et al. (2017), Liu at al. (2018) or Hong (2017) the paper does not find evidence supporting cross-sectional momentum in the cryptocurrency market.

Contrary to Grobys and Sapkota (2019), Dong et al. (2020) as well as Jia et al. (2022) find evidence that the momentum effect is a critical driver in cryptocurrency returns. In detail, Dong et al. (2020) shows that past 1- and 6- months returns are significantly related to the expected returns on up to 1887 researched cryptocurrencies for a comparable data period covering 2014 to 2019. Jia et al. (2022) study covers 1,084 cryptocurrencies from 2016 to 2019. The authors further show a positive association between the magnitude of momentum returns and smaller cryptocurrency size. Similarly, Li at al. (2021) and Lin at al. (2021) findings also indicate the presence of momentum. The authors show that cryptocurrencies with the largest extreme returns outperform those with the smallest extreme returns, suggesting the presence of a MAX momentum effect based on 1-month predicting and one-week ahead and one month ahead returns respectively for the up to 300 largest cryptocurrencies and a research period covering 2014 to 2020. According to Li at al. (2021) this effect is particularly pronounced during market upturns, low investor sentiment, and for underpriced cryptocurrencies. Furthermore, the results remain independent of idiosyncratic volatility and skewness, longer holding periods and size.

2.2.3. Cryptocurrency Momentum with Weekly Prediction Periods

In line with the findings of Grobys and Sapkota (2019), who do not find evidence for momentum, Kosc, at al. (2019) examines weekly momentum and contrarian effects in over 1,200 cryptocurrencies from 2014 to 2017, finding a strong contrarian effect but no momentum using lagged one week returns to predict next week returns. The authors attribute their findings to the early stage of the market with resulting informational inefficiency, market instability, liquidity limitations, regulatory constraints, and technical factors unique to the cryptocurrency market. Those results are supported by the findings of Li et al. (2020) researching 1803 cryptocurrencies from 2014 to 2018 with 1- to 4-week predicting and 1-week ahead returns where losers outperform winners especially for small cryptocurrencies. Similarly, Shen et al. (2020) using weekly data for 1786 cryptocurrencies from 2013 to 2019 and 1 to 4 weeks holding and symmetrical ahead returns find the performance of buy-sell portfolios, where winning assets are purchased and losing assets are sold to be mostly negative, except for the 4-1 strategy, indicating no significant evidence of a momentum effect.

In contrast, Liu et al. (2022) analyzed a dataset consisting of 1,827 cryptocurrencies with weekly data spanning from 2014 to 2020 and implemented various prediction periods, including 1-, 2-, 3-, and 4-weeks, and 1-month prediction period, together with a 1-week ahead forecast period. By employing a long-short strategy that involves buying cryptocurrencies with large positive returns and shorting cryptocurrencies with small positive returns, the researchers found that all investigated strategies yielded significant excess returns indicating the existence of momentum. Tzouvanas et al. (2020) also provide evidence supporting the presence of short-term momentum by utilizing a similar prediction period for one-week ahead returns. Liu et al. (2018), Liu et al. (2020) and Liu and Tsyvinski (2021) also find evidence of momentum across different time horizons for Bitcoin, Ripple and Ethereum in particular, 78 different cryptocurrencies as well as for a value weighted cryptocurrency portfolio from CoinMarektCap using weekly return strategies with data ranging as early as 2011 for bitcoin and up to 2020. Liu et al. (2018) study also find evidence for the existence of daily momentum effects for Bitcoin, Ripple and Ethereum and show that top-performing quintiles consistently outperform bottom-performing quintiles at 1-to-4-week horizons. More recently, Cheah et al. (2022) findings also demonstrate that time-series momentum, along with economic policy uncertainty, and financial uncertainty can predict one-to four-week ahead Bitcoin returns for Bitcoin data from 2011 to 2019.

2.2.4. Cryptocurrency Momentum with Daily Prediction Periods

An early study by Hong (2017) on Bitcoin returns, using daily data from September 2013 to February 2015, provides evidence for the presence of time series momentum for one day ahead forecasts with up to eight weeks prediction periods and a partial reversal over longer prediction timeframes. This suggests that short-term momentum exists in Bitcoin returns but tends to diminish over more extended periods. Yang (2019) provides support for these findings by examining one day-ahead momentum based on a prediction period of up to two weeks, using 63 core cryptocurrencies and data spanning from 2009 to 2018. Similarly, Nguyen et al. (2020) observe significant short-term momentum in the 100 largest cryptocurrencies, analyzing a data period from 2013 to 2019 and using past 3- and 7-day returns to predict 1-day ahead returns. However, their results do not show significance when considering a one-month prediction period after accounting for size. Zaremba et al. (2021) also show a clear association between cryptocurrency size and momentum effects for a sample of 3607 cryptocurrencies using daily winsorized data from 2015 to 2021 where lagged daily return predicts current return. While small and medium cryptocurrencies primarily exhibited a reversal pattern, larger cryptocurrencies gradually displayed a weakening reversal and eventually highlighted a positive slope coefficient, indicating momentum. This suggests that momentum is more prevalent and economically significant in the top 2% of the largest cryptocurrencies, which constitute the majority of the market capitalization.

2.2.5. Cryptocurrency Momentum with Intraday Prediction Periods

More recent studies shed light on the existence of intraday momentum. Shen et al. (2022) for example find evidence for the presence of intraday momentum in the Bitcoin market, suggesting that short-term price patterns persist throughout the trading days with stronger intraday momentum occurring on days characterized by higher trading volume and higher volatility during the first trading sessions. The study shows that intraday momentum is higher on days when past returns are positive rather than negative. This indicates that the direction of past returns influences the strength of intraday momentum in Bitcoin.

Contrary, Wen et al. (2022) examined price data for Bitcoin, Ethereum, Litecoin, and Ripple over an eight-year period starting 2013. Using hourly and half-hourly intervals in the cryptocurrency markets the authors found evidence of intraday return predictability, with both positive momentum effects and negative reversal effects.

Overall, the contradicting findings on momentum especially for monthly and weekly returns in cryptocurrency markets highlight the need for further research and exploration of momentum strategies in cryptocurrencies.

This study aims to shed more light on the existence of momentum in cryptocurrencies and tries to provide an explanation with cryptocurrency markets becoming more efficient. The study uses the most comprehensive so far employed in this context so far. We also address potential data problems surrounding cryptocurrencies including but not limited to missing market capitalization information for liquid cryptocurrencies, joke coins, pump-and-dump schemes, missing data, decreasing cryptocurrencies, double naming etc., which may have biased previous studies.

To ensure comparability with existing studies, our analysis primarily focuses on the strategy using monthly and weekly data. Following Grobys and Sapkota (2019), Dong et al. (2020), Lin at al. (2021), and Jia et al. (2022) we will use symmetrical 1-month prediction (initial return) for 1-month ahead (subsequent return) returns. As a robustness check we will also employ 2- and 6-month prediction period for the 1-month ahead return strategy. Inline with the literature we expect to find momentum for the 1-1 and 2-1 strategy but not for the 6-1 strategy. Additionally, in line with Liu at al. (2018), Kosc at al. (2019), Li et al. (2020), Liu et al. (2020), Shen et al. (2020), Tzouvanas et al. (2020), Liu and Tsyvinski (2021), Liu et al. (2022), and Cheah et al. (2022) we consider symmetrical 1-week prediction periods (initial return) combined with 1-week investment periods (subsequent return). The finding on this strategy is mixed and we contribute to shedding light on the origins for short-term cryptocurrency momentum. As a robustness check we will also employ 2- and 4-week prediction period for the 1-week ahead return strategy. To maximize the utilization of our datasets, we employ a rolling window method for all the strategies.

3. Data

We collected cryptocurrency trading data for all tokens and coins starting April 28, 2013 until July 9, 2023 from CoinMarketCap. This includes all "delisted," "inactive" or so-called "dead" cryptocurrencies, because CoinMarketCap either stopped tacking them or removed from their website. There can be multiple reasons why CoinMarketCap stops coverage, but predominantly because the lack of regular trading activity (see Varmaak, 2021)[7]. By including all inactive in addition to active cryptocurrencies, we ensure that our dataset is survivorship bias free resulting in a total of 24,827 different cryptocurrencies identified by their names.

[7] For a complete list of reasons, see also https://coinmarketcap.com/academy/glossary/delisting.

Thereafter, we excluded stable coins, reducing the number to 24,625 cryptocurrencies within our observation period.[8] To filter out so-called "jokecoins" with at best limited economic value and most likely without a legit project backing the cryptocurrency, we analyze the lifespan, market capitalization (MC) and daily trading volume in USD of each cryptocurrency. Based on the findings of Cointelegraph (2019) showing that "jokecoins" have an average lifespan of 1.4 years (or about 500 days), we remove "young" cryptocurrencies with up to 500 observations as "jokecoins" if 1) the median MC is below 1 million USD and the maximum MC over the lifespan is less than 5 million USD. If MC was not reported, we remove the respective cryptocurrency as "jokecoin" if the median daily trading volume is below 1,000 USD and the maximum daily trading volume over the lifespan is less than 10,000 USD. Based on this analysis, we removed 2,993 out of 15,968 "young" cryptocurrencies, which do not meet the minimum criteria.

For cryptocurrencies with a trading history exceeding 500 trading days ("old" cryptocurrency), we remove them if 1) the reported maximum MC over the lifespan remains below 5 million USD and 2) if the maximum daily trading volume over the lifespan is less than 10,000 USD. The projects behind these cryptocurrencies were presumably never intended to create economic value. Consequently, we remove 1,754 of the 8,657 "old" cryptocurrencies which do not fulfill these criteria, leaving us with a total of 19,878 different cryptocurrencies.

We also aim to exclude cryptocurrencies that were not designed with a viable or economically sound project in mind. To achieve this, we analysed the MC and daily trading volume in USD after the first fourteen trading days. We removed 1,468 cryptocurrencies which did not reach a MC of 1 million USD or, if not reported, a trading volume of 1,000 USD. In total, we were left with 18,410 different cryptocurrencies and 8,782,361 daily cryptocurrency observations.

[8] The list of stable coins has been retrieved from https://coinmarketcap.com/view/stablecoin/ on May 15, 2023 and has been expanded through manual searches to encompass 114 verified stablecoins.

In sum, we retained all cryptocurrencies in our dataset, which had a sufficiently high market capitalization or trading volume at some point in their history. Thereafter, we checked if cryptocurrencies became "inactive" or “dead” during their lifetime. We excluded the daily observations of a respective cryptocurrency as soon as the cryptocurrency’s respective median daily trading volume over a 30-day consecutive trading period fell below USD 10,000 and MC (if reported) fell below 500,000 USD[9]. This resulted in a dataset of 6,711,047 cryptocurrency-trading-day observations for our remaining 18,410 cryptocurrencies. Figure 1 illustrates the identification when a cryptocurrency becomes "inactive" or “dead” showing "abel-finance" price development on CoinMarketCap. abel-finance first appears in our dataset on Jan 22, 2023, and is still available on CoinMarketCap. abel-finance’s daily trading volume fell below USD 10,000 for more than 30 consecutive trading days and was consequently dropped after 9 June 2023. In some instances, one could argue that this methodology might be somewhat conservative cost in removing potentially large parts of a time series for a respective cryptocurrency. However, in rare cases of a project's revival and it related cryptocurrency, it often comes at the of extreme one-time price fluctuations, primarily due to the exceptionally low trading volume and market capitalization of these "inactive" cryptocurrencies.

In the final step, we examined data gaps and total number of observations per cryptocurrency within the remaining dataset. We identified 994 cryptocurrencies with less than seven observations or data gaps of seven or more consecutive trading days. To maintain as many useful cryptocurrencies as possible without compromising data quality, we implemented the following procedure.

[9] In rare cases were 30-days median trading volume and if reported MC were not available we analysed 14-consequitve trading days to determine if a cryptocurrency is not “dead.”

For cryptocurrencies with less than 360 price observations (628 out of 994):

1. 86 cryptocurrencies were removed because the cryptocurrency had less than seven price observation in total.
2. If the average gap[10] between observations is 30 trading days or less, and the data gap represents 15%[11] or less of the total cryptocurrency observations, we classify the cryptocurrency time series as reliable. However, we observe this kind of infrequent but large data gaps, no return can be calculated from the previous observed price (before the gap) and first observed price following the data gap leaving us with infrequent missing return data. This applies to 185 out of the 628 cryptocurrencies.
3. We remove cryptocurrencies which exhibit data gaps more frequently than 15%[9] as we consider the data unreliable. This applies to 357 out of the 628 cryptocurrencies.

For cryptocurrencies with more or equal to 360 price observations (366 out of 994):

1. If we observe only one larger data gap or if the average gap between observations is 30 trading days or less, and the data gap represents 15% or less of the total cryptocurrency observations, we classify the cryptocurrency time series as reliable. Similar to case 1), no return can be calculated following the data gap leaving us with infrequent missing return data. This applies to 241 out of the 366 cryptocurrencies.
2. If the average gap between observations exceeds 90 trading days, but the data gap represents 15% or less of the total cryptocurrency observations, we assume that the first cryptocurrency vanished and was replaced by another cryptocurrency with the same name. Consequently, we assign a new ID to the cryptocurrency following the data gap. This scenario applies to 30 out of the 366 cryptocurrencies.

[10] The average data gap is calculated by the total number of trading days with no observed price divided by the number of data gaps in the time series.
[11] The relative number of missing observations per cryptocurrency is calculated as the total number of trading days with no observed price divided by the total number of observed prices for the respective cryptocurrency.

3. We remove the cryptocurrencies that do not meet either of the two criteria mentioned above, as we consider the data unreliable. This applies to 95 out of the 366 cryptocurrencies.

After applying these procedures, we are left with a total of 17,958 cryptocurrencies.

Lastly, we address missing data for data gaps that span seven or fewer subsequent trading days in the remaining dataset. We impute missing trading days in the cryptocurrency time series and replace non-observed returns with the mean daily return calculated from the total return observed over the duration of the respective data gap. For instance, if a cryptocurrency has two consecutive trading days with missing data we can calculate a total log-return over the complete gap from the last observed price before the data gap and the first observed price after the gap. Assuming the total log-return would be for example 6%, we can calculate the mean return over the respective three trading days as 2% per day. This mean return is imputed in the data gap. This approach has the drawback of underestimating volatility, but it would be impractical to remove data from the dataset each time.

Moving forward, we eliminate cryptocurrencies that appear to be frequent targets of pump-and-dump schemes. Specifically, we identify cryptocurrencies with absolute daily log returns equal or greater than 2 (1) more frequently than 10% (20%) of all respective cryptocurrency observations and exhibiting at least one (two) up-and-down circle(s). This exclusion removes a total of 80 cryptocurrencies, including examples such as “pumpeth," "red-eyed-frog," "all-in-ai," "ethereum-gold-project," "metagamble," "bedlingtonterriertoken," "burrow," or "baby-white-hamster." As a result, we are left with 17,791 cryptocurrencies and 6,448,883 cryptocurrency-trading day observations.

Following the data cleaning process, we categorize our cryptocurrencies into LargeCap, MidCap, and SmallCap, using seven-day median Market Capitalization (MC) and if not available seven-day median daily trading volume, similar to the methodology outlined in the S&P Digital Market Indices Methodology of February 2023. Rebalancing is performed at the beginning of each quarter. The algorithm is a simplified version of a k-means algorithm and has the following parameters: 1) It uses the natural logarithm of MC as the only dimension for clustering; 2) The clusters are fixed as LargeCap, MidCap, and SmallCap; 3) The initial points for the Large and Small clusters are set as the third largest[12] and smallest digital assets in the eligible set in the respective quarter. In this algorithm, each constituent is classified into a cluster based on the closest centroid. The process iterates through each constituent. The distance used for classification is the absolute difference between the natural logarithms of the MCs. To categorize each cryptocurrency on a quarterly basis, we adhere to the following steps:

1. Calculate the seven-day median MC (volume)
2. Determine large centroid as the cryptocurrency with the largest MC (volume) and calculate the distance to the large centroid for each cryptocurrency.
3. Determine small centroid as the cryptocurrency with the smallest non-zero MC (volume) and calculate the distance to the small centroid for each cryptocurrency.
4. Determine the mid centroid as the cryptocurrency with the largest MV (volume) for which the distance calculated in Step 2 is greater than or equal to the distance calculated in Step 3 and calculate the distance to the mid centroid for each cryptocurrency.
5. Perform the classification in decreasing order by MC (volume):
    a. A cryptocurrency is classified as "Large" if the distance to the large centroid (from Step 2) is smaller than the distance to the mid centroid (from Step 4)

[12] We have intentionally omitted the two largest crypto-assets, Bitcoin and Ethereum, to ensure a more representative estimation for the project with the highest MC. This choice is driven by the SEC's recognition of Bitcoin's potential commodity-like attributes and Ethereum's exceptional role as a host blockchain for numerous other projects.

    b. A cryptocurrency is classified as "Mid" if it is not classified as "Large" and the distance to the mid centroid is smaller than the distance to the small centroid (from Step 3)
    c. All remaining cryptocurrencies are classified as "Small".
6. The primary classification is determined based on Market Capitalization (MC). If MC classification is not available for a cryptocurrency, the classification based on trading volume is used instead.

The categorization procedure requires that a cryptocurrency need to be traded at least one week before rebalancing. We are losing 212 cryptocurrencies as they do not meet the minimum number of trading days to be classified leaving us with a final sample of 17,580 different cryptocurrencies over the complete observation period. Table 2 provides an overview of the number of cryptocurrencies in each size bucket based on the quarterly rebalancing alongside the mean market capitalization in million USD (if available) as well the mean daily trading volume in thousand USD (if available) at the beginning of each quarter. In comparison, the dataset used by Zaremba et al. (2021), which has been among the most extensive used in this context, included a total of 3,607 assets and up to 2,500 assets at any one time. The reason for the huge difference between assets used in past research and our research is that CoinMarketCap only provided MC data for about 4,702 cryptocurrencies over time. Reasons for the lack of information on MC include the way how CoinMarketCap collects the data from other exchanges, some of which do not report MC. However, only because CoinMarketCap does not report MC this does not mean the respective cryptocurrency has no economic use biasing previous results to cryptocurrencies listed at MC reporting exchanges. Figure 2 shows an example for this bias. The cryptocurrency "gains-network," was listed since November 2021, but CoinMarketCap only reports MC data since March 2023 and MC jumped from 0 to 240 Mio USD between two days because the cryptocurrency started to be traded at an exchange reporting MC. Concluding, any research solely relying on MC would have excluded this cryptocurrency systematically biasing analysis. We circumvent this problem of observation bias by classifying cryptocurrencies according to their daily trading volume if MC is not available extending the dataset from 4,702 cryptocurrencies to 17,580.

Table 3 presents the return distribution characteristics across different cryptocurrency sizes (Small, Mid, Large) and Bitcoin, Ethereum, Ripple, Dash, Litecoin, MaidSafeCoin, Monero (Top 7 henceforward) representing cryptocurrencies which have been appearing frequently in related research if the respective dataset was focussing on selected cryptocurrencies only (see e.g. Chu et al., 2020). Note, if a cryptocurrency becomes listed between the rebalancing of the size buckets it remains unclassified and will not be included in further analysis. A significant portion of return-cryptocurrency observations fall within the Mid-cap category, a predictable outcome given the limited number of very large cryptocurrencies such as Bitcoin, Ethereum, Binance Coin or Ripple. The market capitalization for other cryptocurrencies drop sharply beyond these. Throughout our observation period, both the mean and median daily returns were negative across all cryptocurrency sizes except for the largest 5 cryptocurrencies, with Small-Cap cryptocurrencies exhibiting the most pronounced negative return in the mean and Large-cap cryptocurrencies presenting the least negative return. Irrespective of size, all cryptocurrencies exhibited a non-normal distribution. The data in the table further suggests that smaller cryptocurrencies carry increased risk, as indicated by standard deviation and 5th percentile (an approximation for Value at Risk). However, smaller cryptocurrencies also offer some potential, as seen in their positive 95th percentiles. We, therefore, hypothesize that investors in smaller cryptocurrencies are likely to exhibit lower risk aversion compared to those investing in Large and Mid-sized cryptocurrencies.

4. Methodology

To analyze momentum, we follow the framework suggested by Koziol and Proelss (2021) to research not only the origin of momentum in cryptocurrencies but also shed light on the risk-aversion of investors. Risk aversion plays a significant role in the relationship between initial returns and subsequent returns in the context of momentum effects. In the following we briefly summarize the model and subsequently comment how risk aversion can measured.

In line with past research on momentum we examine how the initial return $\underline{r}$ (or predicting return) of an asset is influencing the magnitude of an asset's subsequent return $\overline{r}$ (or ahead return). We consider three states where information about the true value of the asset is gradually revealed. In state 1, investors have knowledge of the asset's distribution. In state 2, investors receive a biased signal (s) which is a combination of the asset's true payoff (x) and additional noise (ε). In state 3, the true value becomes public. The initial return, $\underline{r}$, as the asset log return between state 1 and state 2 and the subsequent return, $\overline{r}$, is the asset return between state 2 and state 3. The magnitude of the signal, s, influences the asset price in state 2, thereby impacting the initial return, $\underline{r}$. Therefore, it is important to investigate the relationship between different signals (and consequently different initial returns) and the subsequent return. A sequence of two returns with consistent signs is commonly referred to as momentum. The curve formed by the combination of initial and subsequent returns provides insights into the risk aversion of investors engaged in trading the studied asset.

We assume payoff (x) and noise term (ε) are log-normal distributed. In line with asset pricing literature the representative investor is pricing assets using the uncertainty equivalent concept and is assumed to have constant relative risk aversion (CRRA) with following type of utility function

$$u(x) = \frac{x^{1-\lambda}}{1-\lambda} \; with\, \lambda \neq 1 \tag{1}$$

Where λ measures the relative risk aversion. A higher value of lambda indicates a greater aversion to risk, while a lower value implies a lower aversion to risk. A negative lambda means an investor receives higher utility from taking more risk. We use CRRA type of utility function as it very flexible allowing for all different kinds of utility from taking risks, from the most conservative risk avoiding investor to the most risk loving investor, not requiring increasing return for taking on extra risk.

Based on a density function of the payoff in state 1 ($f_1(x) \sim log\ normal\ (\mu_x, \sigma_x)$), Koziol and Proelss (2021) show that the asset price in state 1 is only determined by μ_x, σ_x and λ as follows:

$$p_1 = \exp\left(\mu_x + \frac{1}{2}\sigma_x^2(1-\lambda)\right) \tag{2}$$

In state 2 the noisy signal becomes available revealing additional information about the asset. Assuming $0 \leq x \leq s$ the authors show that the price in state 2 and consequently the initial return $\underline{r}$ are a function of the distribution function of payoff x, the signal s and the representative investors risk aversion as follows:

$$p_2(s) = \sqrt[1-\lambda]{EU_2(s)(1-\lambda)} \tag{3}$$

and

$$\underline{r}(s) = \log\left(\frac{P_{2(s)}}{P_1}\right) \tag{4}$$

Furthermore, the asset price in state 3 and thus the subsequent return is then a conditional function of the signal strength s as follows:

$$\overline{r}(s) = \log\left(\frac{\mathrm{E}(x|s)}{P_2(s)}\right) \tag{5}$$

where $\mathrm{E}(x|s)$ is the expected conditional payoff.

Ceteris paribus being able to measure signal s and the distribution of payoff x allows us to draw conclusions on the risk aversion of the representative investor. Koziol and Proelss (2021) show that a lower degree of risk aversion still exhibits a monotonic relationship between the initial return $\underline{r}(s)$ and subsequent return $\overline{r}(s)$. However, the sensitivity of the subsequent return to higher initial returns decreases, and the curvature of the relationship is no longer uniformly convex. In regions where a higher signal results in a lower standard deviation of returns, the subsequent return only experiences marginal increases, leading to a concave curve in that part. Overall, risk aversion influences the relationship between initial and subsequent returns, shaping the sensitivity and curvature of the relationship in the presence of momentum effects.

In the following analysis, we apply the previously established model, investigating the potential implications of its role on the initial and subsequent distribution of returns. We focus, in particular, on standard deviation and skewness, conditional on an observed signal, s, and the resulting momentum effects. Our sample comprises 5,516 cryptocurrencies that adhere to the criteria outlined in the preceding data section.

We also investigate whether the size of the cryptocurrency influences the observed momentum effects and if these effects can be explained by the representative's investors risk aversion. Literature reveals mixed findings on the topic. Jia et al. (2022), Liu et al. (2020), and Liu et al. (2022) assert a stronger momentum in smaller cryptocurrencies, whereas Li et al. (2020) conversely suggests contrarian effects, particularly for smaller cryptocurrencies. From a theoretical standpoint, the price and returns of smaller cryptocurrencies are likely to be more susceptible to individual trading behaviors compared to larger cryptocurrencies, which are influenced by a broader demographic of investors where investor base spans corporations, institutional investors, cryptocurrency funds, investment firms, and retail investors, amongst others. The model proposed by Koziol and Proelss (2021) is hypothesizing that greater risk aversion would generate more robust momentum effects. As a natural extension of this theory, we anticipate stronger momentum effects in smaller cryptocurrencies compared to larger ones, echoing the findings of Jia et al. (2022), Liu et al. (2020), and Liu et al. (2022).

Thus, we expect our model's application to shed further light on the complex interplay between cryptocurrency size and momentum effects, while providing insights into the mechanisms of return distribution characteristics and its effect on momentum for cryptocurrencies.

5. Results

In the model proposed by Koziol and Proelss (2021), a representative investor examines the payoff x of an asset, and thereby gets to know its distribution characteristics, standard deviation σ_x and mean payoff μ_x . To demonstrate these assumptions empirically, we assume that in case of monthly [weekly] observation the expectation about the payoff x are formed over the prediction period with length 30 day (or 1 month) [7 days (or one week)] for each cryptocurrency on a rolling window basis. We use daily rolling window method for 30 and 7 days estimation periods. The daily rolling method has the advantage that it captures also short-term fluctuations in the data, however, this may result in a noisy estimate as it is usually better suited for short term forecasts. Thus, we also use monthly rolling and weekly rolling window for our monthly and weekly estimation periods respectively. Prices are normed by the first observed price of the prediction period of the respective cryptocurrency to ensure comparability across cryptocurrencies and over time and to make our results comparable with the theory presented in Koziol and Proelss (2021).

Table 4 provides our empirical estimates for the different estimation periods for mean μ_x and standard deviation σ_x of our normed cryptocurrency payoffs x as well as the signal, which is not exceeded in 90% of all cases. The table shows that the mean normed payoff is between 1.00 for large cryptocurrencies and 1.08 (1.13) for mid (small) cryptocurrencies indicating that on average prices increased somewhat for small and mid-cap cryptocurrencies during the estimation period.

According to theory, the observation of a signal alters the investor's perception of the payoff x and its distributional parameters, as the signal helps predict realized returns. Stronger signals lead to a more pronounced deviation from the initial distribution of payoff x in the view of the investor.

Table 4 provides, and overview of the average received signal μ_s and the signal which is not exceeded in 90% of all cases s_{90}. The table shows that the subsequent received signal is largest (smallest) for small (large) coins using monthly estimation periods with an average signal of 1.21 (1.08) which signifies an average price increase of 21% (8%) as compared to the first price observed in the estimation period. The weekly estimation period shows a similar picture but with on average smaller signals. Signals of 1.55 (1.25) are not exceed in 90% of cases over all caps for monthly (weekly) estimation periods.

In line with the theory, we analyse the impact of new information on the conditional standard deviation. Specifically, as uncertainty diminishes, the standard deviation should decrease. When the signal s is low, the possible payoff range is narrow, resulting in lower standard deviation. With a high signal, a higher payoff is probable and reducing uncertainty. Medium signals introduce a chance of both low and high payoffs, with varying noise levels, which increases the uncertainty for investors. In line with the theory, Figure 3 shows that the condition standard deviation, after observing the signal is low for small signals and decreasing for larger signals. This is especially pronounced for Bitcoin (label 1 in the figure), Bitcoin and Ethereum (label 2 in the figure), Top 7 (label 7 in the figure) and large-caps and less pronounced for our small and mid-caps, where standard deviation only starts decreasing for very high signals or not at all for mid-cap weekly observations, which may be an early indication that no momentum can be observed for mid-cap and small-cap weekly strategies.

In our empirical investigation of momentum effects within cryptocurrency markets, we compute the mean log of initial $\underline{r}(s)$ and subsequent returns $\overline{r}(s)$ for distinct signal brackets spanning from ±0.0125 to ±0.025. Our findings prove to be robust to alterations in bucket sizes. Figure 4 together with Table 5, show the observed relationship between initial return and subsequent return. Given the preliminary outcomes displayed in Figure 3, we anticipate a more accentuated momentum effect for the largest cryptocurrencies as well as for large-cap as opposed to small- and mid-cap cryptocurrencies, given that the observed standard deviation aligns more consistently with the theoretical pattern proposed by Koziol and Proelss (2021) to explain momentum. Furthermore, as previously asserted, a lower risk aversion level would induce a monotonic relationship and a relatively flat line (low increase) when plotting initial return and subsequent return. In contrast, high level of risk aversion would increase subsequent return sensitivity, resulting in a convex curve and a stronger increase in the relationship. As risk aversion decreases the relationship between initial return and subsequent return may even result in a downward slope, indicating a contrarian pattern as opposed to momentum.

It should be noted that this pre-assessment does not include the important factor of risk aversion of the representative investors in different cryptocurrency sizes where we do not find evidence in the literature. As shown in Table 3 small cryptocurrencies tend to be riskier as compared to large cryptocurrencies and also show greater risk of being the target of pump-and-dump schemes or being fraudulent. As previously theorized, we anticipate that investors investing in smaller cryptocurrencies are likely to demonstrate less risk aversion or even a preference for risk taking than those investing in large and mid-sized cryptocurrencies. This should show in a smaller slope for small-cap cryptocurrencies as compared to mid- or even large-caps.

Figure 4 consolidates our results for winner cryptocurrencies, the monthly strategy with a 30-day prediction and symmetric ahead return for daily rolling (Panel A-1) and monthly rolling (Panel A-2), along with the weekly strategy that employs a 7-day forecast and symmetric ahead return for daily rolling (Panel B-1) and weekly rolling (Panel B-2) across all cryptocurrency sizes. We exclude loser cryptocurrencies in this figure, because retail investors tend not speculate on price decreases ("shorting") of cryptocurrencies to the same extend speculating on price increases.

Appendix Figures 1 shows the results for winning as well as losing cryptocurrencies. Table 5 consolidates all our findings.

In line with Chu et al. (2020), Rohrback et al. (2017), Cheng at al. (2019), Corbet et al. (2019) and other researcher we find consistent momentum pattern in the largest cryptocurrencies over all estimation windows represented by the significant positive slope shown in Table 5 for those cryptocurrencies independent of including losing cryptocurrencies. Consistent with the findings of Dong et al. (2020) and Jia et al. (2022), we discern momentum effects for large-cap cryptocurrencies across all signals for the monthly strategy, for winner as well as winner and loser cryptocurrencies, as evidenced by the statistically significant positive gradient. However, in accordance with Grobys and Sapkota (2019), we do not discern significant momentum effects for mid-sized and especially small cryptocurrencies. Instead, we observe reversal patterns, where a positive monthly return is succeeded by a negative return, regardless of the signal size. Corresponding with the extant literature, our results for the weekly strategy are mixed. In congruence with Li et al. (2020), who find that contrarian effect dominates especially for small- as compared to large-cap cryptocurrencies where losers outperform winners significantly for weekly estimation and investment periods. We also find that small-cap cryptocurrencies show contrarian effects. This may be explained with a lower risk aversion or even negative lambda indicating utility from risk taking for investors in small cryptocurrencies. These findings are in contrast to the findings of Liu et al. (2020) for weekly momentum and Jia et al. (2022) for monthly momentum. However, it should be noted that both studies only included observation in their analysis with reported MC and that could cause a selection bias as previously discussed. These cryptocurrencies are mostly classified as mid- or even large-cap in our analysis.

In accordance with Shen et al. (2020) and mirroring our findings for the monthly strategy, we do not detect momentum effects for mid-cap cryptocurrencies. These results confine our conclusions on investor risk aversion in cryptocurrencies to those dealing with small and larger capitalized cryptocurrencies. A robustness check using loser and winner cryptocurrencies are reported in Figure A1 in the Appendix and mostly confirms our results.

To further analyse which cryptocurrencies and strategies display significant momentum effects - potentially attributable to larger risk aversion - we do a linear regression for each cryptocurrency size and strategy, as follows:

$$\overline{r}(s)_{i,j} = \beta_0 + \beta_1 \cdot \underline{r}(s)_{i,j} + \varepsilon_{i,j} \ \ with\ min\ obs\ \geq\ 150, \tag{6}$$

with i representing the cryptocurrency size, j the corresponding strategy, $\overline{r}(s)_{i,j}$ the mean subsequent return for an observed signal s, and $\underline{r}(s)_{i,j}$ the initial mean return for an observed signal s. In aggregate, we analyse six distinct strategies (inclusive of the previously introduced strategies) for three different cryptocurrencies capitalizations (Small, Mid, Large). Aggregated regression outcomes are shown in Table 4. '$Est.$' stands for the estimation/initial period required to procure signal s, and '$Inv.$' denotes the investment/subsequent period necessary to observe the subsequent return for the detected signal s. %M (%R) refers to how often out of the six researched strategies we observe significant momentum (reversal) effects measured by a positive β_1 with statistical significance at the 10%-level.

In line with our preceding findings and the extant literature, momentum effects prove significant for 5 out of 6 strategies for small-cap cryptocurrencies, the exception being the strategy involving a 1-week prediction with a 1-week investment period. In contrast, mid-cap cryptocurrencies exhibit significant reversal effects for all investigated strategies. Large cryptocurrencies yield mixed outcomes, with significant momentum effects observed only for the strategy entailing a 2-week prediction and a 1-week investment period. The results presented in Table 4 enable us to infer about risk aversion. Generally, a larger β_1 corresponds to greater risk aversion from the investor, suggesting that risk aversion is lowest amongst those investing in mid-sized cryptocurrencies.

Summarizing, our findings offer mixed validation for our model, including its implications on the subsequent return distribution and purported momentum effects within cryptocurrencies. Mid-cap cryptocurrencies exhibit reversal effects rather than momentum effects, which could be accounted for by the lower risk aversion demonstrated by the average investors in these cryptocurrencies, thus leading to weaker momentum effects. It is noteworthy that our model presumes rational expectations on the part of investors, a presumption that may not always hold true. Investors may, for instance, exhibit ambiguity aversion, which could impact our results. The momentum effect appears to persist for small- and mid-cap cryptocurrencies until signals approximately reach 1.5 (a 50% increase in market price). Our data proposes that contrarian strategies might be more effective in explaining the return distribution for larger signals.

6. Conclusion

This research provides a summary and fresh look into the momentum effects and risk aversion of investors in the cryptocurrency market, an area of increasing interest. Amid the growing adoption of cryptocurrencies, understanding the dynamics of investment returns becomes crucial for both investors and regulators. We have undertaken a detailed study, using the largest dataset employed in this context so far addressing potential biases, to bring clarity to momentum and reversal in cryptocurrency markets.

Our study uses a model proposed by Koziol and Proelss (2021) to examine these dynamics. The approach allows us to investigate the relationship between initial and subsequent returns, and the impact of an investor's risk aversion on these parameters. All cryptocurrency categories researched exhibit negative mean and median daily returns and non-normal distribution with positive skewness. The findings also indicate that smaller cryptocurrencies carry increased risk but also offer larger potential. This adds another layer of complexity to the interplay between cryptocurrency size, momentum effects, and return distribution characteristics.

In alignment with previous studies, we employed symmetrical 1-month and 1-week prediction periods for corresponding ahead returns, including additional 2-, 4-, and 6-months robustness checks, with the aim of examining momentum and exploring the roots of short-term cryptocurrency momentum. Our findings demonstrate significant momentum effects for small-cap cryptocurrencies in five out of six strategies, but mid-cap cryptocurrencies showcase reversal effects across all strategies. Large-cap cryptocurrencies display mixed results, suggesting varied risk aversion across cryptocurrency sizes, with the lowest seen in mid-cap cryptocurrency investors. Additionally, our model's assumptions and their implications, such as rational expectations, might not always align with real-world investor behaviors, impacting results. Moreover, the momentum effect primarily persists for smaller signals, proposing contrarian strategies as potentially more effective for larger signals.

Our study is a step towards a comprehensive understanding of the cryptocurrency market's momentum effects and risk aversion dynamics. However, given the evolving nature of this landscape, further research is warranted to capture its full complexity.

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Table 1: The following table summarizes the findings on momentum in cryptocurrencies sorted by method and data frequency.

Moving Average Strategies and related Methods				
Author	**Crypto-Asset**	**Data-Period**	**Strategies**	**Results**
Rohrback et al. (2017)	Bitcoin, Dash, Dogecoin, Litecoin, Maidsafecoin, Monero and Ripple.	Daily, June 2014 to February 2017	Exponential moving average (EMA) Cross-Sectional Momentum, Time Series Momentum	Evidence for momentum with cross-sectional approach being more suitable
Cheng at al. (2019)	Bitcoin, Ethereum, Ripple, EOS	Daily, June 2013 to July 2018	Mono-fractal analysis (de-trended fluctuation analysis, DFA) and multi-fractal fluctuation de-trended analysis (MF-DFA)	When significant fluctuations occur, notable momentum effects are observed in Bitcoin and Ethereum, while a market reversion effect is evident in Ripple and EOS
Corbet et al. (2019)	Bitcoin	Intraday, January 2014 to June 2018	fixed and variable moving average	Significant returns for variable moving average but not fixed moving average
Hudson and Urquhart (2021)	Bitcoin, Bitstamp, Litecoin, Ripple, Ethereum	Daily, July 2010 (Bitcoin) until December 2017	exponential moving average (EMA), Calmar ratio	moving average rules are the best performing for Ripple and Ethereum but not Bitcoin
Chu et al. (2020)	Bitcoin, Ethereum, Dash, Litecoin, MaidSafeCoin, Monero, Ripple	Intraday, February 2017 to August 2017	Exponential moving averages (EMA) hourly rebalanced	Time series and cross-sectional momentum trading strategies have the potential to generate positive returns, with signal-based strategies outperforming returns-based strategies
Grobys at al. (2020)	Bitcoin, Ripple, Litecoin, Ethereum, Dogecoin, Peercoin, BitShares, Stellar Lumen, Nxt, MaidSafeCoin, Namecoin	Daily, January 2016 to December 2018	variable moving average (20, 50 and 100 days)	Significant returns for most currencies in the short run for less currencies in the mid to long run
Borgards 2021	Bitcoin, Ripple, Dash, EOS, Ethereum Classic, Ethereum, Iota, Litecoin, Neo, Monero, Stellar Lumens, Zcash, Metaverse ETP,	Intraday, January 2014 to December 2019	moving-average smoothing filter algorithm with momentum periods	Time-series momentum is found in cryptocurrencies and the S&P500 across different frequencies and price directions.

	0x, Tezos, Bitcoin SV, LEO, Bitcoin Gold, Tron, Batcoin		from 5 minutes to several months	
Momentum with Monthly Data				
Author	**Crypto-Asset**	**Data-Period**	**Strategies**	**Results**
Grobys and Sapkota (2019)	143 from CoinMarketCap	Monthly, January 2014 to December 2018	momentum with 12, 6, 1 month predicting 1 month ahead returns	Cross-sectional momentum tends to generate non-significant results, time series moment tends to show only marginally significant momentum returns with a 1-month reversal effects
Dong et al. (2020)	1,887 with minimum price history of 5 months and total MCap of 25 Mio USD	Monthly, January 2014 to April 2019	momentum with 1, and 6 months predicting 1 month ahead return	Past 1 and 6 month are significantly related to the expected returns on the researched cryptocurrencies
Li at al. (2021)	Largest 300 of 2805 from CoinMarketCap with weekly rebalancing	Weekly, January 2014 to June 2020	momentum with 1-month predicting 1-week ahead return	Evidence of a MAX momentum effect, which is most prominent during market upturns, low investor sentiment, and for undervalued cryptocurrencies. These findings hold regardless of idiosyncratic volatility, skewness, longer holding periods, and size
Lin at al. (2021)	64 most active from the CoinMarketCap	Daily, February 2014 to June 2019	momentum with 1-month predicting 1-month ahead return	Evidence of a MAX momentum effect, persisting after accounting for general momentum
Jia et al. (2022)	1,084 with minimum 1-year price history from CoinMarketCap	August 2016 to August 2019	momentum with 1 to 4 month predicting and 1 to 4 month ahead returns	Evidence for momentum effect with the magnitude of momentum returns being larger for smaller cryptocurrency size
Momentum with Weekly Data				
Author	**Crypto-Asset**	**Data-Period**	**Strategies**	**Results**
Liu at al. (2018)	Bitcoin, Ripple, Ethereum	January 2011 (Bitcoin), August 2013 (Ripple), August 2015 (Ethereum) to Mai 2018	momentum with current daily (weekly) predicting 1, 3, 5, 6 (1, 2, 3, 4) day (week) ahead returns	Evidence of momentum across different time horizons

Kosc et al. (2019)	TOP100 rebalanced daily of 1223 from CoinMarketCap	Weekly, May 2014 to October 2017	momentum with 1-weekly predicting and 1-week ahead returns	Short-term contrarian effect clearly outperforms momentum effect, with frequent up to two-digit returns depending on reallocation period and ranking window
Li et al. (2020)	1,803 from coinmarektcap with reported MCap	January 2014 to May 2018	momentum with 1- and 1 to 4 weekly predicting and 1-week ahead returns	Contrarian effect dominates especially for small as compared to large cryptocurrencies where losers outperform winners significantly
Liu et al. (2020)	78 with complete time series	Weekly, August 2015 to December 2018	momentum with 1-weekly predicting and 1-week ahead returns	Significant momentum effect especially for small cryptocurrencies
Shen et al. (2020)	1,786 from CoinMarketCap with reported MCap	Weekly, April 2013 to March 2019	momentum with 1-, 2-, 3-, and 4-week predicting and 1-, 2-, 3-, and 4-week ahead returns	Buy-sell portfolios, with buying (selling) winning (loosing) assets tend to generate negative returns, except for the 4-1 strategy. No significant evidence of a momentum effect
Tzouvanas et al. (2020)	12 from CoinMarketCap with minimum total MCap of 100 mio USD and min 3 year data	December 2015 to January 2019	momentum with 7-, 15-, and 30-day predicting and with 7-, 15-, and 30-day ahead returns	Winners generally dominate Losers, only shorter-term momentum (7/7, 7/15, 7/30, and 15/7) is significant also after controlling for volatility
Liu and Tsyvinski (2021)	Value-weighted portfolio bases on all CoinMarketCap with reported MCap	January 2011 to December 2018	momentum with current weekly predicting 1 to 8 week ahead returns	current cryptocurrency market returns positively and significantly predict one-week- to five-week-ahead returns
Liu et al. (2022)	1827 from CoinMarketCap with minimum total MCap of 25 mio USD	Weekly, January 2014 to July 2020	1-, 2-, 3-, and 4-weeks and 1-month predicting and 1 week ahead	A long-short strategy buying (shorting) cryptocurrencies with large (small) positive returns produces significant excess returns for all researched strategies
Cheah et al. (2022)	Bitcoin	Daily, October 2011 to January 2019	Compound daily excess Bitcoin return over the prior 12 days predicting 7-, 14-, 21- and 28 day ahead	Evidence that time-series momentum can predict bitcoin prices

Momentum with Daily Data				
Author	**Crypto-Asset**	**Data-Period**	**Strategies**	**Results**
Hong (2017)	Bitcoin	Daily, September 2013 to February 2015	1, 3, 5, 8, 10 and 15 week predicting period predicting 1 day ahead returns	Evidences for time series momentum in Bitcoin returns, observing persistent returns over one to eight weeks, which partially reverse over more extended periods
Yang (2019)	23 core cryptocurrencies and 40 ERC20 cryptocurrencies from Coin Metrics	January 2009 to July 2018	Past 1-, 3-, 5-, 7-, and 14 days predicting and 1 day ahead as well as 1-week prediction and 1-week ahead	Strong evidence of momentum, which is unaffected by market and size factors. Unlike traditional stock markets, there is no evidence of long-term reversal in cryptocurrencies
Nguyen et al. (2020)	100 largest cryptocurrencies as of 5 Sep 2019	April 2013 to September 2019	Past 3-, 7-, days, and 1 month predicting 1-day ahead	Evidence for significant short-term momentum effect for 3- and 7- days but not for 1-month prediction period after controlling for size
Zaremba et al. (2021)	Up to 2,500 assets at any one time or a total of 3607 over complete sample form CoinMarketCap with minimum history 20 weeks and reported MCap	Daily, winsorized at ln 2 return January 2015 to March 2021	momentum with current daily predicting 1 day ahead returns	Positive and significant returns on the majority of long-short momentum portfolios
Momentum with Intraday Data				
Author	**Crypto-Asset**	**Data-Period**	**Strategies**	**Results**
Shen et al. (2022)	Bitcoin	Intraday, January 2013 to December 2020	intraday momentum with first and the second-to-last trading sessions used to predict last half-hour return	Strong evidence for intraday momentum and stronger on days where the first trading sessions have higher trading volume and higher volatility
Wen et al. (2022)	Bitcoin, Ethereum, Litecoin, Ripple from Bitcoincharts	Intraday, April 2013 to May 2021	hour prediction–hour ahead: 3-5, 3-15, 3-17, 8-22, 10-11, 12-13, 22-23 Half-hour prediction – halve hour ahead: 1-8, 1-12, 1-47, 2-18, 3-10, 3-28, 3-30, 4-35, 4-40	Cryptocurrency market exhibits intraday return predictability, with both positive momentum and negative reversal effects observed

Table 2: Constituents and descriptive statistics for Small, Mid and Large cryptocurrency size categories

The table shows the average market capitalization (Mcap) if available at the beginning of each quarter over all cryptocurrencies included in the respective size category in million USD, the average daily trading volume (Vol) if available in thousand USD and the number of cryptocurrencies per quarter in each size category.

	Large			Mid			Small		
Year / QTR	Mcap	Vol	Count	Mcap	Vol	Count	Mcap	Vol	Count
2013/2	569	n/a	2	5.0	n/a	2	1.168	n/a	5
2013/3	528	33,547	3	2.6	n/a	2	0.660	n/a	4
2013/4	342	82,312	6	2.6	n/a	23	0.564	n/a	3
2014/1	1,227	4,544	9	1.6	n/a	111	0.010	n/a	2
2014/2	932	6,862	7	1.5	820	107	0.060	21.9	79
2014/3	873	7,665	10	0.8	116	173	0.023	10.3	49
2014/4	311	1,659	18	0.3	898	166	0.001	26.8	3
2015/1	292	612	16	0.4	6,386	123	0.001	120.7	11
2015/2	183	1,241	20	0.3	2,672	94	0.001	67.1	17
2015/3	272	2,486	15	0.6	3,636	104	0.001	54.3	10
2015/4	251	1,542	15	0.5	1,814	102	0.001	47.3	9
2016/1	299	1,677	24	0.4	2,190	106	0.000	37.5	7
2016/2	243	1,846	36	0.5	2,238	126	0.008	15.3	7
2016/3	463	6,986	27	0.8	1,871	157	0.001	33.2	18
2016/4	326	9,099	41	0.7	276	155	0.001	60.9	17
2017/1	406	4,222	46	0.5	1,546	193	0.000	33.9	19
2017/2	972	17,706	30	3.5	3,133	319	0.011	38.9	49
2017/3	2,092	288,625	43	12.3	3,122	466	0.020	139.6	65
2017/4	3,147	49,517	46	15.2	15,157	687	0.020	219.2	74
2018/1	11,432	2,556,180	44	52.7	12,998	992	0.044	88.7	82
2018/2	3,587	415,500	66	15.0	5,306	1,119	0.005	3.9	65
2018/3	4,411	541,085	51	15.8	5,475	1,311	0.021	420.3	91
2018/4	3,142	547,477	60	8.4	2,267	1,406	0.010	319.1	82
2019/1	1,683	386,002	64	4.5	1,433	1,370	0.006	146.4	88
2019/2	1,421	376,510	96	5.3	1,958	1,416	0.001	51.8	59
2019/3	2,454	591,206	128	5.8	1,633	1,437	0.000	102.7	51
2019/4	1,071	227,639	206	2.8	938	1,364	0.000	10.1	61
2020/1	1,269	310,989	151	3.3	951	1,395	0.001	39.9	91
2020/2	962	415,546	197	2.5	1,256	1,456	0.000	17.3	120
2020/3	1,053	169,385	282	3.5	1,467	1,823	0.000	12.2	191
2020/4	2,481	674,674	133	15.9	2,544	2,306	0.000	54.1	292
2021/1	3,559	480,476	227	7.4	2,614	2,540	0.001	25.5	359
2021/2	5,099	608,972	402	19.4	6,572	3,098	0.000	17.0	436

2021/3	5,381	585,060	255	14.8	3,867	3,633	0.000	16.8	847
2021/4	7,690	674,465	290	19.8	4,771	5,284	0.001	22.9	1,205
2022/1	7,217	454,375	318	20.1	5,396	5,424	0.000	25.6	2,103
2022/2	6,599	636,930	306	18.0	6,190	5,069	0.000	26.9	2,279
2022/3	3,103	383,918	239	9.1	3,824	4,179	0.000	14.1	2,319
2022/4	4,981	362,590	161	14.2	5,865	4,063	0.001	11.2	1,843
2023/1	4,074	200,759	168	10.9	4,439	3,935	0.000	9.3	1,418
2023/2	4,762	272,023	225	13.6	4,334	4,484	0.001	10.4	2,021
2023/3	4,613	254,479	230	10.1	4,601	3,456	0.000	10.6	1,725

Table 3: Distribution characteristics of daily cryptocurrency log returns

The table shows the non missing return observation (N), average daily log returns (Mean and Median), the daily standard deviation (Std Dev), the skewness (skew), excess-kurtosis (kurt), the 5%-percentile (5th Pctl), the 25%-percentile (lower Quartile), 75%-percentile (upper Quartile) as well as the 95%-percentile (95th Pctl) for Bitcoin, Ethereum, Ripple, Dash, Litecoin, MaidSafeCoin, Monero (Top 7), Small (S), Mid (M) and Large (L) cryptocurrencies. Note, Top 7 cryptocurrencies represent the cryptocurrencies which have been appearing in related research most frequently if the dataset was focussing on selected cryptocurrencies only (see e.g. Chu et al. (2020)).

Size	N	Mean	Median	Std Dev	Skew	Kurt	5th Pctl	25th Pctl	75th Pctl	95th Pctl
All	6,427,578	-0.65%	-0.31%	18.89%	-4.0	2472.3	-17.4%	-4.3%	2.9%	15.9%
Top 7	24,059	0.13%	0.02%	6.13%	0.7	16.9	-8.6%	-2.3%	2.5%	9.2%
L	398,202	-0.24%	-0.12%	10.27%	-4.9	651.3	-11.1%	-3.2%	2.7%	10.7%
M	4,994,948	-0.62%	-0.34%	18.39%	-4.3	2556.9	-17.7%	-4.4%	3.0%	16.4%
S	1,034,428	-0.95%	-0.26%	23.29%	-2.7	1832.4	-18.4%	-3.9%	2.3%	15.3%

Table 4: Distribution characteristics of normalized payoffs in estimation period

	Monthly (monthly rolling window)			Weekly (weekly rolling window)		
	Small	**Mid**	**Large**	**Small**	**Mid**	**Large**
N	27,895	153,948	12,869	143,208	694,827	56,224
$\boldsymbol{\mu_x}$	1.13	1.08	1.01	1.04	1.03	1.00
$\boldsymbol{\sigma_x}$	5.78	3.87	0.47	2.45	2.02	0.25
$\boldsymbol{\mu_s}$	1.22	1.18	1.05	1.19	1.04	1.01
$\boldsymbol{s_{90}}$	1.45	1.55	1.51	1.21	1.25	1.20
	Monthly (daily rolling window)			**Weekly (daily rolling window)**		
	Small	**Mid**	**Large**	**Small**	**Mid**	**Large**
N	723,169	4,335,871	381,385	938,897	4,809,122	393,322
$\boldsymbol{\mu_x}$	1.13	1.08	1.05	1.04	1.03	1.00
$\boldsymbol{\sigma_x}$	5.02	3.05	1.18	2.52	1.82	0.22
$\boldsymbol{\mu_s}$	1.21	1.17	1.08	1.07	1.05	1.01
$\boldsymbol{s_{90}}$	1.45	1.55	1.52	1.20	1.23	1.18

Table 5: Linear regression of the initial return on the subsequent return

This table shows the linear regression slope estimation of subsequent return dependent on the initial return, with bucket size 0.025 and signals up to 1.75 for all strategies and sub-samples. %M (%R) indicates how often we observe statistically significant momentum (reversal) effects at the 10% level. (**) [***] indicate statistical significance at the 1% (5%) [10%] level respectively.

	Winner				Winner and Loser			
Est.	30 days	7 days	1 month	1 week	30 days	7 days	1 month	1 week
Inv.	30 days	7 days	1 month	1 week	30 days	7 days	1 month	1 week
Rolling	daily	daily	monthly	weekly	daily	daily	monthly	weekly
BTC	0.065	0.16	n/a	n/a	-0.077	0.025	n/a	n/a
BTC&ETH	0.34***	0.173**	n/a	n/a	0.353***	0.221***	n/a	n/a
Top 7	0.062	0.119***	n/a	0.332*	0.079***	0.028	n/a	0.41**
Large	0.036***	-0.043**	0.099	0.039**	0.08***	-0.102***	0.109**	-0.058**
Mid	-0.278***	-0.322***	-0.118***	-0.215***	-0.256***	-0.19***	0.085***	-0.166***
Small	-0.18***	-0.314***	-0.538**	-0.189***	-0.103***	-0.134***	0.134*	-0.105***

Figure 1: Market price for Abel-finance and "inactive" cryptocurrency detection

The figure shows the observed price development of *abel-finance* since Jan 22, 2023, which is still available on CoinMarketCap. *abel-finance*'s daily trading volume fell below USD 10,000 for more than 30 consecutive trading days after 9 June 2023 (black line) and was thereafter excluded from our dataset.

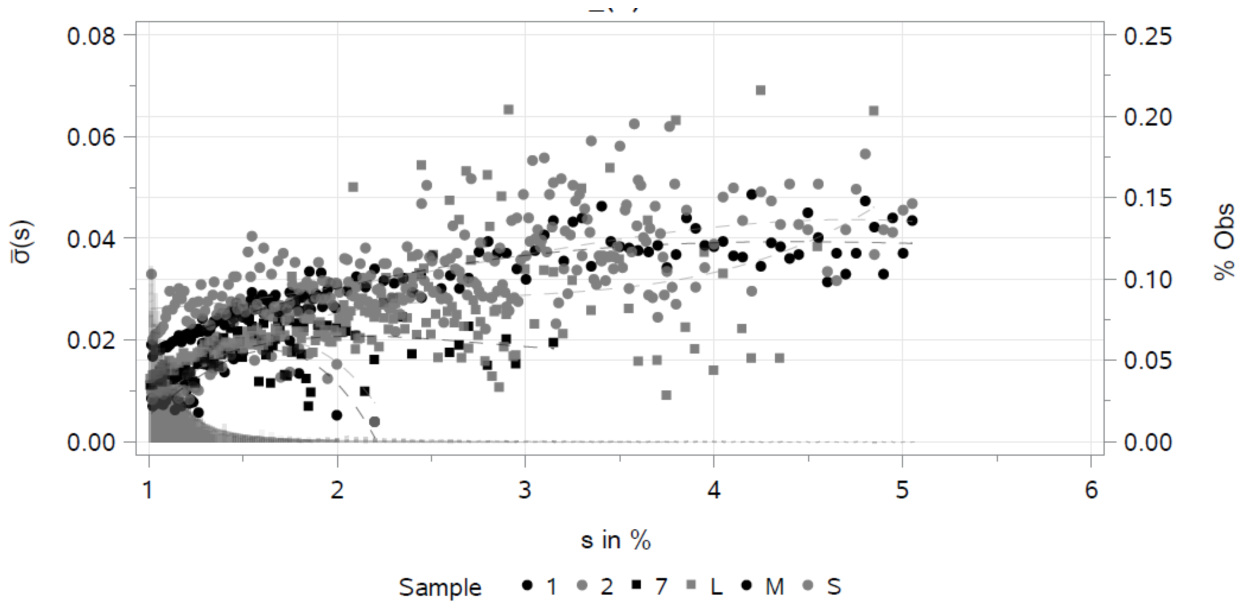
Figure 2: Market price and MC for Gains Network and observation bias

The upper graph shows the observed price development of *gains network* since Nov 3, 2021. The lower graph shows the observed MC development including when CoinMarketCap started reporting MC since March 1, 2023. *gains network* has been actively traded ever since it first appeared on CoinMarketCap November 3, 2021 with a daily trading volume greater 2 Mio. USD initially, illustrating observation bias if *gains network* would only be included if MC is available on CoinMarketCap.

Figure 3: Conditional standard deviation for different signal strength

The figure shows the observed conditional standard deviation $\overline{\sigma}(s)$ approximated by the standard deviation of realized returns after receiving the signal s. Signals are iterated in steps of 0.05 for small signals (usually smaller than 3) and in steps of 0.2 for large signals. We require at least four observations in each signal bracket. Panel A shows the 1-month (30 days) prediction period with 1-month (30 days) ahead returns (realized returns); Panel B shows 1-week (7 days) with 1-week (7 days) ahead returns. The bar charts indicate the percentage-number of observations in each bucket.

Panel A



Panel B

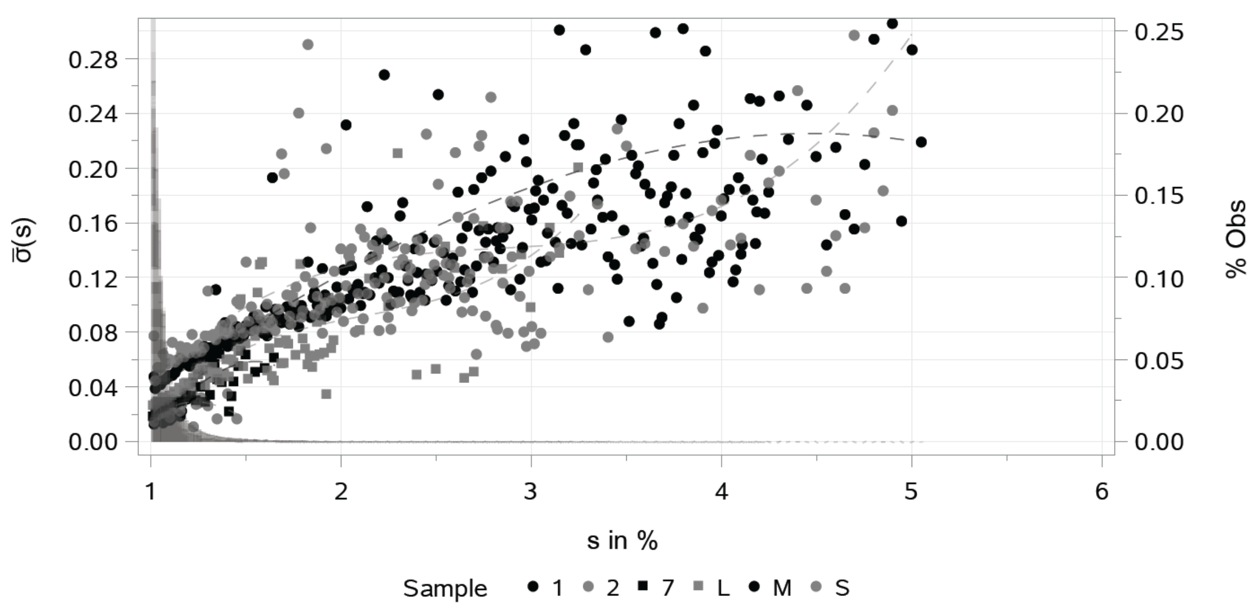
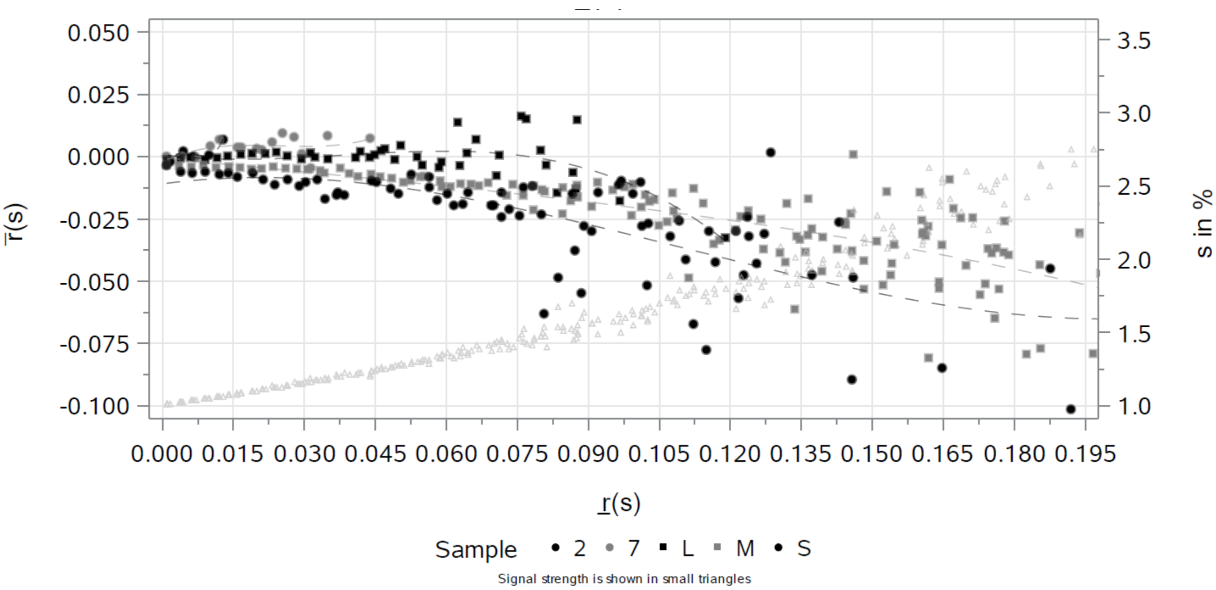


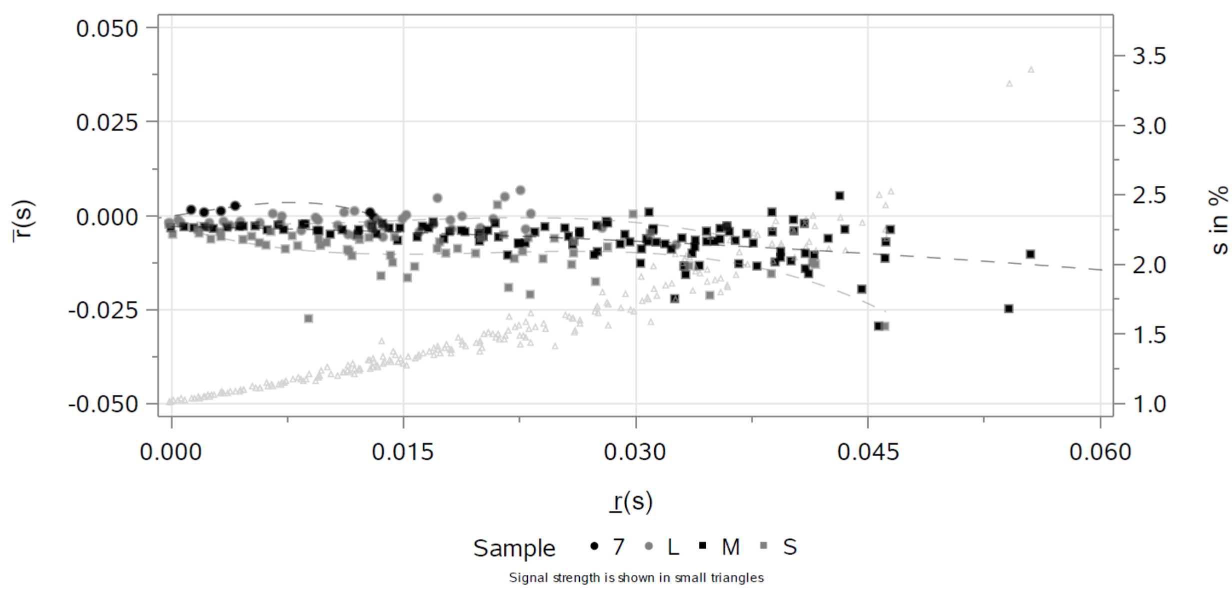
Figure 4: Conditional subsequent return depending on initial return and signal

The figure illustrates how the subsequent return $\overline{r}(s)$ relates to the initial return $\underline{r}(s)$ conditional to the observed signal s. Signals are iterated in steps of 0.05 for small signals (usually smaller than 3) and in steps of 0.2 for large signals. We require at least 25 observations in each signal bracket. A positive initial return followed by a positive (negative) subsequent refers to momentum (contrarian) effects. Panel A shows the 1-month (30 days) prediction period with 1-month (30 days) ahead returns (realized returns); Panel B shows 1-week (7 days) with 1-week (7 days) ahead returns.

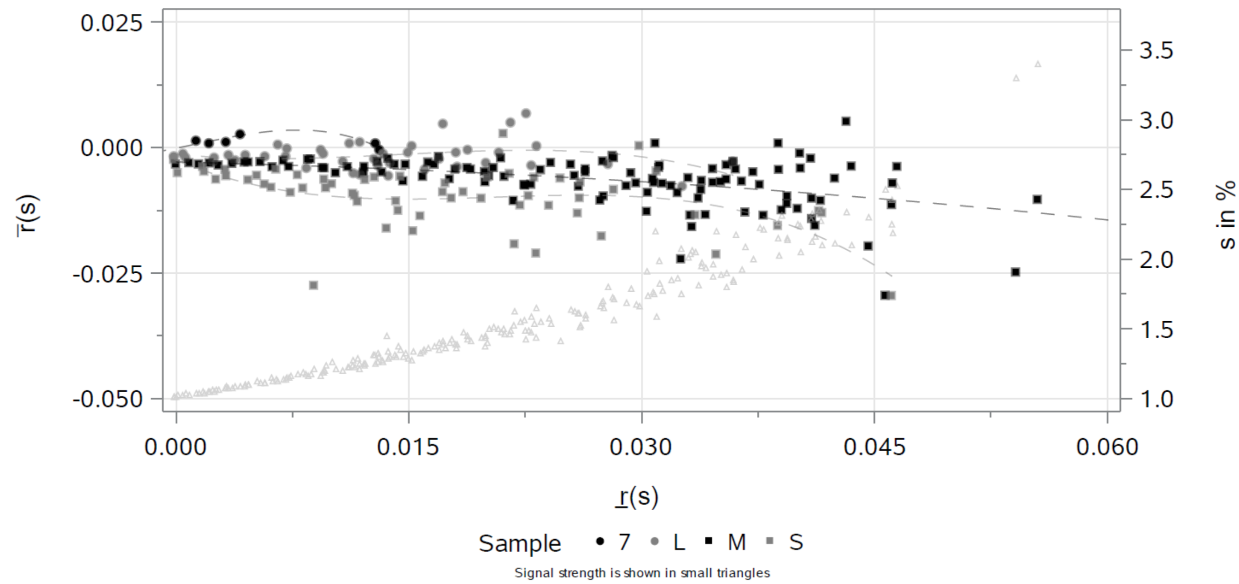
Panel A-1



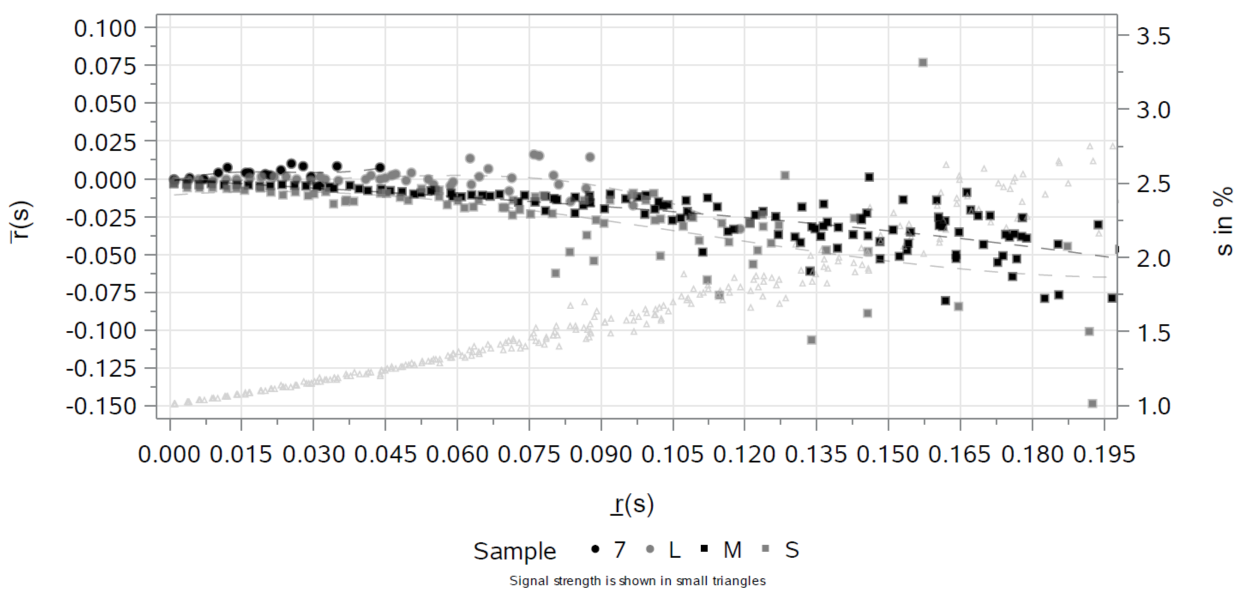
Panel A-2



Panel B-1



Panel B-2

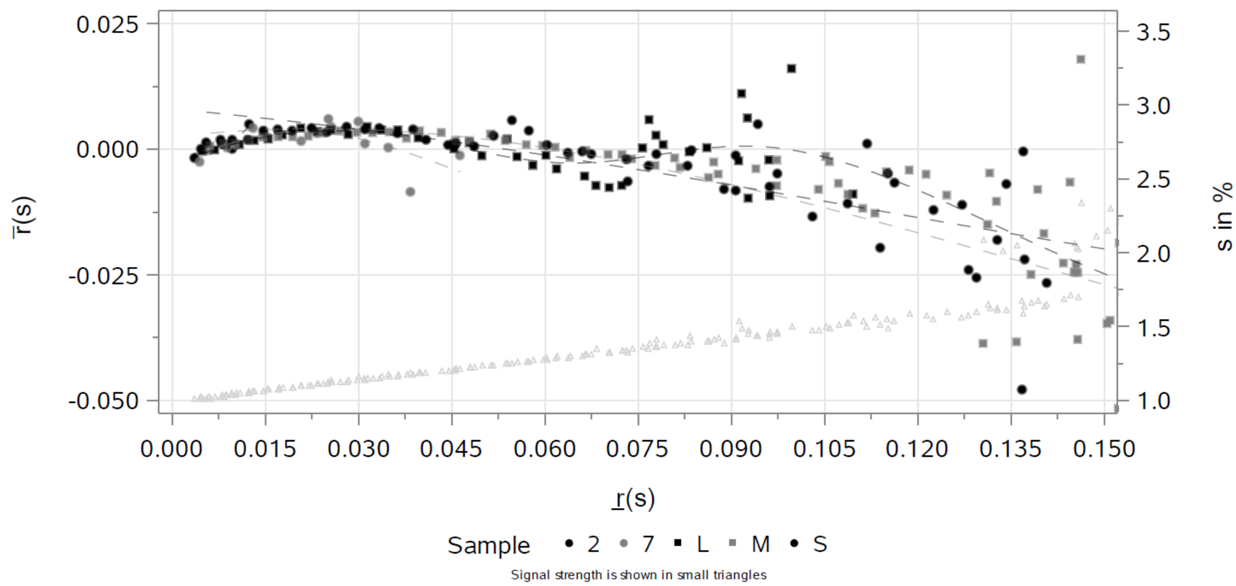


Appendix

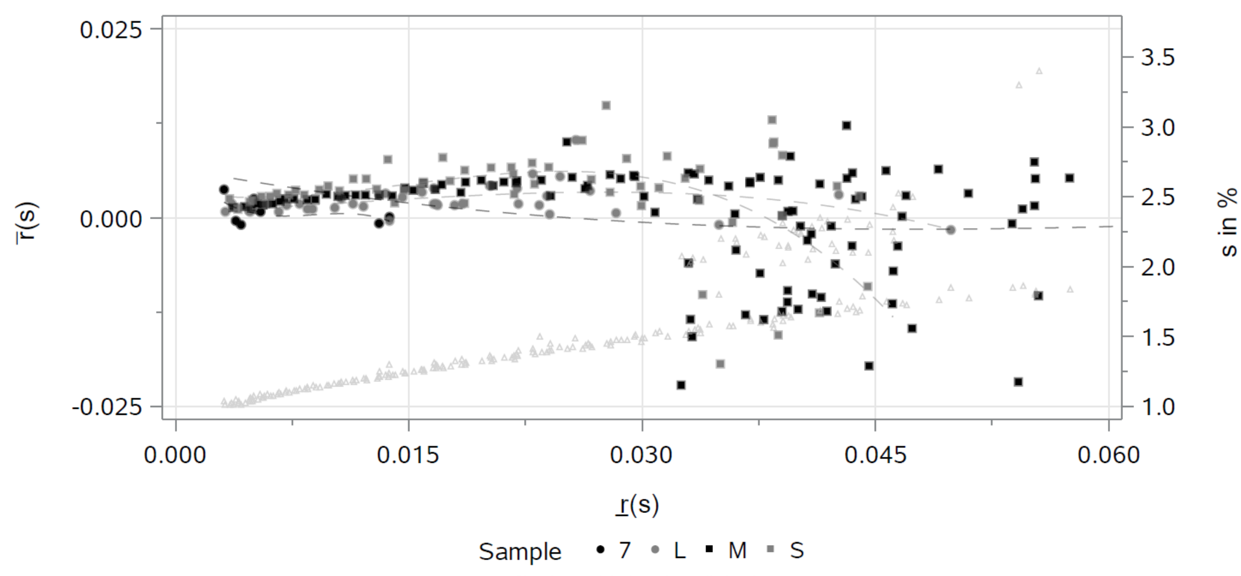
Figure 1A: Conditional subsequent return depending on initial return and signal

The figure illustrates how the subsequent return $\overline{r}(s)$ relates to the initial return $\underline{r}(s)$ conditional to the observed signal s. Signals are iterated in steps of 0.05 for small signals (usually smaller than 3) and in steps of 0.2 for large signals. We require at least 25 observations in each signal bracket. A positive initial return followed by a positive (negative) subsequent refers to momentum (contrarian) effects. Panel A1 shows 2-month (61 days) and Panel A2 shows 6-month (182 days) prediction period with 1-month (30 days) ahead returns, Panel B1 shows 2-weeks (14 days) and Panel B2 4-weeks (28 days) prediction period with 1-week (7 days) ahead returns.

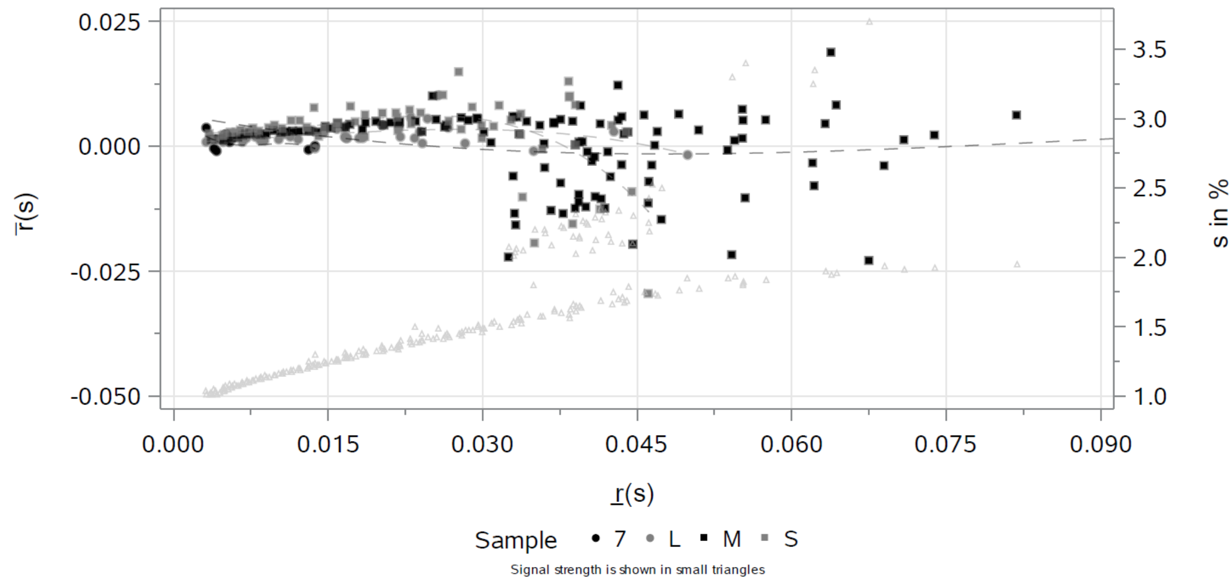
<u>Panel A-1</u>



<u>Panel A-2</u>



Panel B-1



Panel B-2