Investor Sentiment and Cryptocurrency Returns *

Zeyun Bei† Jian Chen‡ Yinggang Zhou§

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†Department of Economics and Finance, City University of Hong Kong and Wang Yanan Institute for Studies in Economics, Xiamen University; e-mail: zeyun.bei@my.cityu.edu.hk

‡Department of Finance, School of Economics, Xiamen University; e-mail: jchenl@xmu.edu.cn

§Center for Macroeconomic Research and Department of Finance at School of Economics, Wang Yanan Institute for Studies in Economics, Xiamen University; e-mail: ygzhou@xmu.edu.cn

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Abstract

Little is known about how investor sentiment predicts individual cryptocurrency returns. Utilizing coin-level sentiment measures, we show that sentiment predicts subsequent cryptocurrency returns positively in the short run but negatively in the long run. Further analysis reveals that, in cryptocurrencies preferred by short-term traders, high sentiment initially boosts prices but eventually crowds out investor participation, suppressing long-term prices. Conversely, in cryptocurrencies favored by long-term holders, high sentiment persistently attracts investor adoption and maintains its positive return predictability. This sentiment-based mechanism primarily explains momentum and reversal anomalies in cryptocurrency markets. Additionally, sentiment mainly arises from extrapolating past returns and user participation.

JEL classifications: C22, C53, G11, G12, G17

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1. Introduction

Forecasting asset returns has been a fundamental and long-standing focus in the field of asset pricing. A stream of research maintains attention on the return predictability of various asset classes, such as individual stocks (Fama and French, 1992, 1993), bonds (Elton, Gruber, Agrawal and Mann, 2001; Bai, Bali and Wen, 2019), currencies (Lustig, Roussanov and Verdelhan, 2011), and commodities (Bakshi, Gao and Rossi, 2019), typically evaluating the significance of predictor coefficients (through Fama-MacBeth or panel regression models) to determine whether returns on individual assets are predictable on average. Cryptocurrency, a burgeoning asset class based on blockchain technology, has witnessed remarkable growth with global user adoption soaring into the tens of millions. The return predictability of individual cryptocurrencies has emerged as a novel and general research topic.

There is growing research on the predictability of cryptocurrency returns, yet this field remains incomplete. Cryptocurrency does not provide the fundamental accounting information as individual stocks do, and its values are not backed by any government credit as sovereign currencies do, suggesting that its pricing mechanisms are distinct from traditional financial assets (Liu and Tsyvinski, 2021). Theoretical frameworks are increasingly focusing on the valuation of cryptocurrencies, such as Pagnotta and Buraschi (2018), Cong, Li and Wang (2021), and Biais, Bisiere, Bouvard, Casamatta and Menkveld (2023). These theoretical predictions link the dynamics of cryptocurrency pricing to investor adoptions and their network effects. Following these theories, Liu and Tsyvinski (2021) and Liu, Tsyvinski and Wu (2022) empirically analyze the determinants of cryptocurrency returns, with a particular emphasis on the unique predictive power of the momentum factor. Sockin and Xiong (2023a) propose a theoretical model that highlights the salient

connection between sentiment, investor adoption, and cryptocurrency pricing, providing a rational explanation for the momentum factor.

Considering the fundamental dependence of cryptocurrency valuation on investor behavior and the well-documented influence of investor sentiment on traditional assets, such as stocks, bonds, and commodities(see, e.g., De Long, Shleifer, Summers and Waldmann, 1990; Baker and Wurgler, 2006; Stambaugh, Yu and Yuan, 2012; Da, Engelberg and Gao, 2015; Da, Tang, Tao and Yang, 2024), it is posited that investor sentiment should play an even more pivotal role in predicting cryptocurrency prices. Although the theoretical model proposed by Sockin and Xiong (2023a,b) provides a rich set of theoretical predictions, little empirical research investigates the predictive power of investor sentiment on individual cryptocurrency returns and its underlying mechanisms in pricing dynamics. This paper aims to shed light on this gap.

Our paper is the first comprehensive analysis evaluating the predictive power of investor sentiment on individual cryptocurrency returns. We employ the MarketPsych index (TRMI) from Thomson Reuters as our sentiment gauge. This advanced linguistic index, based on the expanded dictionary method of Loughran and McDonald (2011), analyzes real-time news and social media content to generate sentiment scores for 264 actively traded cryptocurrencies. In contrast to recent research focusing on aggregated cryptocurrency sentiment indices and market returns (Chen, Guo and Renault, 2019a; Liu and Tsyvinski, 2021), our extensive dataset of individual cryptocurrencies not only facilitates a more generalized observation of the predictability of cryptocurrency returns but also provides deeper insights into the heterogeneity and underlying mechanisms.

First, we confirm the sentiment-driven predictability of individual cryptocurrency returns by employing a panel regression of future cryptocurrency returns on current sentiment while partic-

ularly controlling for four categories of predictors— momentum, size, volume, and volatility— as documented by Liu et al. (2022). Specifically, we find that high investor sentiment predicts high cryptocurrency returns in the subsequent periods from one-week to 48-week (approximately a year) horizons; the regression slope on sentiment (β) is 1.232 with a t-statistic of 2.418 at the one-week horizon and increases to 6.961 at the 48-week horizon. Thereafter, the relationship inverts, with the coefficient turning negative and statistically significant since the 84-week horizon, indicating a price reversal over longer horizons. In contrast to the negative predictive power of investor sentiment on traditional asset returns, which indicates biased belief and overreaction stories, we find distinct patterns that momentum and long-term reversal occur when investor sentiment predicts cryptocurrency returns.

Second, we further investigate how cryptocurrency investors form their sentiments. Following the studies on the equity market (Greenwood and Shleifer, 2014; Barberis, Greenwood, Jin and Shleifer, 2015; Cassella and Gulen, 2018; Da, Huang and Jin, 2021), we exploit whether investors extrapolate past cryptocurrency returns into the future and then form biased expectations. Through a linear regression of current sentiment on past returns, we observe persistently positive and significant slopes across the lagged periods, suggesting that high sentiment follows the past high returns. To parsimoniously capture the extrapolation pattern, we further employ an exponential decay function as the weighting scheme on past returns to test the weight investors put on distant past returns relative to recent past returns when forming beliefs. Results show that consistent with the linear model, current sentiment is positively correlated with past returns, and more recent returns have larger decay parameters, indicating that investors are more likely to extrapolate the recent returns. We separate the positive and negative returns in the non-linear model and find

asymmetric evidence: positive past returns have a more significant and persistent effect on forming investors' expectations compared to negative returns.

In addition to return extrapolation, we also examine whether investors extrapolate fundamentals. In the equity market, investors hold extrapolative expectations from firms' fundamentals (Barberis, Greenwood, Jin and Shleifer, 2018; Frydman and Stillwagon, 2018; Huang, Zhang, Zhou and Zhu, 2023). As documented by both empirical and theoretical research, the fundamental of cryptocurrency closely relates to investor adoptions (Cong, Li and Wang, 2021; Cong, Karolyi, Tang and Zhao, 2022; Sockin and Xiong, 2023a). We regress current sentiment on the lagged number of new addresses and find that the regression slopes are all positive and statistically significant across the lag periods, indicating a sentiment boost following an increase in new entrants in the past period. Thus, cryptocurrency investors extrapolate past user participation to form their expectations.

Third and most interestingly, we delve into the underlying economic mechanisms responsible for return predictability. We empirically elucidate the crucial link between sentiment, investor adoption, and cryptocurrency pricing, which provides a well-founded basis for the observed momentum and long-term reversal effects. Our empirical tests are designed following the theoretical framework proposed by Sockin and Xiong (2023a), who introduce two types of cryptocurrency investors: user and speculator, predicting that users' optimism, by raising their expectations of the token's resale value, increases user participation and subsequently raises cryptocurrency price. Conversely, speculators' sentiment raises the token price and meanwhile crowds out user participation, which, in turn, lowers the equilibrium valuation. Confronted with data constraints, it is difficult to distinctly decompose our investor sentiment index into user and speculator sentiment.

Using the ownership data from *IntoTheBlock*, we distinguish between short-term traders, likely acting as speculators who actively engage in short-term benefits, and long-term holders, more apt to be users who hold the balance for transaction needs (Bayer et al., 2020; DeFusco et al., 2022; Sockin and Xiong, 2023a). Following the approach of Han and Kumar (2013), who investigate the behaviors of retail investors via the stocks with high retail trading proportion, we approximately explore the behaviors of speculators and users by observing the evidence from the coins dominated by the participation of short-term traders and long-term holders, respectively. Our findings show that the sentiment-driven long-term reversal is more pronounced in coins with higher participation of short-term traders. Specifically, for coins with more short-term traders, the coin returns initially rise in subsequent periods from one to 12 weeks following high current sentiment and decline in the long run. Whereas, for cryptocurrencies with more long-term holders participating, our findings reveal a distinct pattern: positive sentiment is a significant predictor of future returns in the short term and remains its positive forecasting power in the long run.

Moreover, our additional findings reveal that the distinct predictability of individual cryptocurrency returns primarily stems from the interplay between investor sentiment and investor participation. In cryptocurrencies favored by short-term traders, we observe an initial positive correlation between sentiment and investor adoptions in the short run, which inversely turns significantly negative over time, revealing a crowding-out effect in prolonged scenarios. On the other hand, in the case of cryptocurrencies with a longer-term investor base, high sentiment persistently promotes investor participants to the platform. Overall, our further analysis reveals that in both segments of cryptocurrencies— those preferred by short-term traders and those by long-term holders— high sentiment positively attracts investor adoption at the initial stages, subsequently fostering short-

term momentum. However, in coins favored by short-term traders, increased sentiment results in long-term crowding out of investor participation, thereby triggering long-term price reversal. Compared to the stock market, where investors can correct sentiment-induced pricing errors based on fundamental values, our empirical results confirm a significant relationship between investor sentiment and cryptocurrency valuations, contributing to the distinct predictability of cryptocurrency returns by investor sentiment.

Lastly, to further substantiate whether investor sentiment is the primary driver of momentum and long-term reversal effects in the cryptocurrency market, we utilize a decomposition method proposed by Hou and Loh (2016). This method allows us to assess and quantify the contribution of candidate explanatory factors to explain market anomalies. Specifically, we decompose the momentum and long-term reversal betas, which are obtained by regressing the future return on the recent and distant past returns, respectively, to dissect the proportion of these betas explained by the candidate explanatory factor. After comparing with a broad array of competing candidate factors, investor sentiment emerges as a dominant explanatory factor, elucidating 83.294% of the momentum beta. Furthermore, investor sentiment is notably effective in explaining the long-term reversal effect in coins that are predominantly held by short-term traders, accounting for 56.429% of the reversal beta, ranking first among all candidate variables. Our analysis offers robust corroboration that investor sentiment serves as the primary impetus behind the momentum and long-term reversal phenomena evident in the cryptocurrency market.

Relate Literature. Our paper contributes to the literature on cryptocurrency pricing. There exist several models that explore the fundamental values of cryptocurrency, including the martingale process of Schilling and Uhlig (2019), the users' adoption and demand of Cong, Li and Wang

(2021), and transaction costs and benefits of Biais, Bisiere, Bouvard, Casamatta and Menkveld (2023). Empirically, Liu and Tsyvinski (2021) and Liu, Tsyvinski and Wu (2022) provide evidence on the time-series and cross-sectional predictability. In addition to investigating the fundamentals, the model of Sockin and Xiong (2023a) highlights the role of investor sentiment. Notably, our study is the first to utilize coin-level sentiment data to examine the predictability of individual cryptocurrency returns rather than the relationship between aggregated cryptocurrency sentiment and market returns (Chen, Guo and Renault, 2019a; Liu and Tsyvinski, 2021). By doing so, we uncover underlying mechanisms and demonstrate heterogeneity in the predictive power of sentiment across coins distinguished by various investor participations.

Our paper is also related to the sentiment literature. Prior studies mainly focus on the impact of sentiment on the equity market (Baker and Wurgler, 2006; Stambaugh, Yu and Yuan, 2012; Baker, Wurgler and Yuan, 2012; Cen, Lu and Yang, 2013; Da, Engelberg and Gao, 2015). This group of papers demonstrates that sentiment has a negative predictive power for future stock returns because stock prices can be overpriced due to investor sentiment and corrected towards fundamentals subsequently. Additionally, the literature shows that investors are more likely to extrapolate past performances of stocks into the future and form biased expectations (Greenwood and Shleifer, 2014; Barberis, Greenwood, Jin and Shleifer, 2015; Cassella and Gulen, 2018; Da, Huang and Jin, 2021).

The rest of this paper is organized as follows: Section 2 describes the data. Section 3 shows the empirical evidence. Section 4 presents the results of the potential economic mechanism. Section 5 concludes.

2. Data and Variables

2.1. Cryptocurrency Sentiment

The sentiment measure used by this study is the MarketPsych index (TRMI), obtained from Thomson Reuters. The dataset includes 264 actively traded cryptocurrencies for the period from January 2016 to December 2020. TRMI is an advanced linguistic index that analyzes news and social media in real time using natural language processing techniques to convert the volume and variety of professional news and online information into manageable score series. Powered by a complex grammar framework that includes traits specific to different text sources, MarketPsych's textual analytics boast customized lexicons, superior disambiguation, and optimized grammatical structures.

TRMI is distinguished by its expansive coverage, surpassing alternative datasets cited in the literature (Audrino and Tetereva, 2019). TRMI integrates a triad of content categories: news, social media, and combined, based on articles and posts in English. TRMI covers more than 2,000 news sources, including leading professional financial news presses such as *The Wall Street Journal*, *The Financial Times*, and *The New York Times*, as well as other less influential news collected by Thomson Reuters News Feed Direct, such as *Factiva News* and *Google News*. TRMI also claws and scrapes the top 30% of over two million blogs, microblogs, stock message boards, and other financial social media content for daily estimation, including *StockTwits*, *Twitter*, *Facebook*, *Yahoo! Finance*, and *SeekingAlpha*. In contrast, most existing sentiment measures based on press releases rely on a singular or a constrained set of information sources, such as *The Wall Street Journal* (Antweiler and Frank, 2004; Tetlock, 2007; Engelberg, Reed and Ringgenberg, 2012),

The New York Times (García, 2013), *Yahoo Finance* (Das and Chen, 2007), *Facebook* (Siganos, Vagenas-Nanos and Verwijmeren, 2014), *StockTwits* (Chen, Guo and Renault, 2019a), *Google* (Da, Engelberg and Gao, 2015), and *SeekingAlpha* (Chen, De, Hu and Hwang, 2014a; Farrell, Green, Jame and Markov, 2022). In addition, directional expressions of emotions in news and social media vary to some extent. Social media discourse, for instance, may feature a complex array of text or graphic emotions (e.g., ": -(" expresses sadness) and acronyms (e.g., "LOL" is an abbreviation of "laugh out loud"). TRMI incorporates specialized models for both news and social media content, enhancing accuracy through text analytics that is fine-tuned to the nuances of each media type. Consequently, owing to its extensive coverage and precision-engineered analytic models, TRMI has gained widespread adoption as a tool for the quantification of investor sentiment (Audrino and Tetereva, 2019; Michaelides et al., 2015, 2019).

The TRMI scoring algorithm is an extension of the dictionary method suggested by Loughran and McDonald (2011). Specifically, the algorithm starts with identifying entity characteristics (e.g., the word "Bitcoin" in the sentence "Bitcoin just suffered a bearish monthly close" will be identified as the associated coin ticker "BITCOIN"). MarketPsych searches for keywords associated with an entity of interest. These keywords are then mapped to various coin-related topic variables (e.g., the word "close" in the sentence "Bitcoin just suffered a bearish monthly close" will be mapped to the price-related topic variable like "priceDirection"). Next, the algorithm searches for positive and negative words associated with the keywords and assigns a numerical value that accounts for emotion, intensity, and other multipliers to the keyword (e.g., the word "bearish" in the above example can also be identified as a down-word with a negative value based on the emotional intensity, whereas an up-word is assigned a positive value). Keywords referring to the

same topic variable are then aggregated to a numerical variable score. Finally, a coin-level overall sentiment score is derived as a weighted average of the score of references in news or social media to each topic variable with the weight of the number of references. The overall sentiment index of each coin is derived from 52 topic subindexes based on prices, risks, emotions, and other market performance aspects. The overall sentiment index ranges from -1 to 1. Negative (positive) values represent pessimism (optimism), with a higher absolute value of the score indicating a higher degree of the specific emotion. To comprehensively measure investor emotions and expectations about cryptocurrency performance, we use the overall sentiment indexes for all 264 cryptocurrencies. In our empirical analysis, we compute weekly indexes, the average of daily sentiment indexes within each week.

2.2. Cryptocurrency Returns

We obtain cryptocurrency trading data from *Coinmarketcap.com*, a widely used data source for cryptocurrency price and volume (Liu, Tsyvinski and Wu, 2022). It provides information about the opening, closing, high, and low prices, as well as the volume and market capitalization for most cryptocurrencies from over 200 major platforms worldwide. For each cryptocurrency, its price is calculated by taking the volume-weighted average of all prices reported by each platform. We follow Liu, Tsyvinski and Wu (2022) and employ the cryptocurrency that meets a list of criteria, such as being traded on at least one public exchange and having a non-zero trading volume on at least one exchange to enable a valid price determination. To avoid the weekend effect, we compute the Wednesday-to-Wednesday log returns (Gutierrez Jr and Kelley, 2008). [1] Because the cryptocurrency market opens 24 hours, the weekly interval begins or ends at 23:59 UTC on each

[1] If the price on Wednesday is missing, we use the closing price on Tuesday.

Wednesday. Our results are robust to weekend-to-weekend returns.

We merge the cryptocurrencies provided by Coinmarketcap.com with those of MarketPhych and exclude the cryptocurrencies that have low media coverage, say less than 35 references in each week (equivalent to an average of five references in each day).[2] This cutoff helps mitigate concerns that sentiment indices of cryptocurrencies with low media coverage may not accurately reflect market sentiments. The merged sample contains 195 actively traded cryptocurrencies and spans from January 2016 to December 2020.

2.3. Other Variables

Following Liu, Tsyvinski and Wu (2022), we use four categories of cryptocurrency characteristics as control variables, including size, momentum, volume, and volatility. In each category, we only focus on those variables that can significantly affect cryptocurrency returns suggested by Liu, Tsyvinski and Wu (2022). Thus, size-related characteristics include market capitalization, price, and maximum price; momentum variables are past one-, two-, three-, and four-week returns; volume refers to price volume; and volatility is the standard deviation of price volume. The construction is described as follows,

- Market capitalization (MCAP), defined as the logarithm of the market capitalization on Wednesday of each week.
- Weekly price (PRC), the logarithm of the closing price on Wednesday of each week.
- Maximum price (MAXDPRC), the logarithm of the maximum price within each week.

[2]TRMIs are constructed using text contents sourced from news and social media that appear and are collected within a specific time interval, the sentiment index that consists of a limited number of references may be not informative and representative. We find our results robust to the cutoff of media coverage, e.g., 20, 30, or 40.

- Past one-, two-, three-, and four-week returns, denoted as $R_{1,0}$, $R_{2,0}$, $R_{3,0}$, $R_{4,0}$, respectively, are the cumulative returns over the past one, two, three, and four weeks.
- Volume, constructed as the logarithm of the average daily trading volume within each week.
- Volatility (Vol), defined as the logarithm of the standard deviation of daily trading volume within each week.

Therefore, we use a total of 9 control variables in our empirical analysis and investigate whether the impact of sentiment on cryptocurrency returns can be explained by them.

2.4. Summary Statistics

Table 1 presents the summary statistics of the main variables and characteristics. As indicated by the table, the average sentiment on the cryptocurrency market (S) is 0.143 with a standard deviation of 0.219, indicating relatively optimistic beliefs of cryptocurrency investors. The weekly return on cryptocurrency (R) averages at -0.064%, pointing to a negative performance over the observed period. The substantial return volatility observed, along with the wide range of maximum and minimum values, may indicate the presence of price bubbles and crashes within the cryptocurrency market. Moreover, the market capitalization (MCAP) for cryptocurrency demonstrates an average logarithmic value of 17.680, which corresponds to a nominal amount of approximately \$59 million, pointing to a large market capitalization. In terms of trading activity, the average weekly logarithm of trading volume (Volume) stands at 14.247, with the volatility of trading volume (Vol) averaged at 13.204. These figures highlight intense and volatile trading activity within the cryptocurrency markets.

[Insert Table 1 about here]

3. Empirical Results

In this section, we present several stylized facts to provide a comprehensive overview of the relationship between sentiment and cryptocurrency market dynamics. First, we conduct panel regressions to examine whether investor sentiment successfully predicts individual cryptocurrency returns after controlling for the comprehensive list of predictors documented by Liu, Tsyvinski and Wu (2022). Second, following the methodology outlined by Da, Huang and Jin (2021), we employ both linear and non-linear models to investigate how cryptocurrency investors shape their sentiments, aiming to gain a deeper understanding of the sentiment dynamics in the cryptocurrency market. Third, we tend to exploit how sentiment predicts cryptocurrency returns by influencing trading activities. Lastly, we conduct robustness tests to confirm whether the predictive power of investor sentiment remains robust across various coins with different sizes and trading volumes.

3.1. Forecasting Cryptocurrency Returns

In this subsection, we analyze how investor sentiment predicts individual cryptocurrency returns by using a standard predictive regression model as follows:

$$R_{i,t+h} = \alpha + \beta S_{i,t} + \psi \mathbf{X}_{i,t} + \varepsilon_{i,t} \ , \tag{1}$$

where $R_{i,t+h}$ is cumulative excess returns of cryptocurrency i over the prediction horizon h, h =1, 4, 12, 48, 72, 84, 88, and 92 weeks; $S_{i,t}$ is the investor sentiment on cryptocurrency i at time t;

and $\mathbf{X}_{i,t}$ contains a comprehensive list of control variables, including four categories of significant predictors documented by Liu, Tsyvinski and Wu (2022), as detailed in Section 2.3. To account for potential omitted variables, we include time and cryptocurrency fixed effects, capturing idiosyncratic factors related to temporal variations and time-invariant characteristics of individual cryptocurrencies, such as the technology backing each coin. Following Chen, Gao, He, Jiang and Xiong (2019b), we adopt robust standard errors clustered by time in all panel regressions to control for the correlation and heteroscedasticity among coins caused by common shocks. Our primary coefficient of interest, β, measures the impact of sentiment $S_{i,t}$ on future returns $R_{i,t+h}$. We expect a non-zero β under the alternative hypothesis, indicating the predictive power of sentiment over future returns.

[Insert Table 2 about here]

Table 2 reports the estimation results of regression (1). The significant predictive power of investor sentiment has been preserved under controlling for the comprehensive set of predictors. Specifically, we observe that high investor sentiment predicts high cryptocurrency returns in the subsequent periods from one-week to 48-week (proximately a year) horizons; the regression slope on sentiment (β) is 1.232 with a t-statistic of 2.418 at the one-week horizon and increases to 6.961 at the 48-week horizon. Thereafter, the coefficient exhibits shrinkage and becomes negative. Since the 84-week horizon, it becomes statistically significant at the 10% level at least. Thus, there exists a price reversal over the longer horizons. Our results are partially consistent with Liu and Tsyvinski (2021), who find that investor sentiment, measured as the log ratio between the number of positive and negative phrases associated with "Bitcoin" in Google searches, positively predicts future cryptocurrency market returns. Our evidence of price reversal is similar to the "value" factor

documented by Cong, Karolyi, Tang and Zhao (2022).

Table 2 reveals a discernible divergence in the influence of investor sentiment on future returns between the cryptocurrency market and the traditional asset markets. In the latter, the literature suggests that biased beliefs about future returns are typically corrected in subsequent periods— e.g., within one month as shown by Baker and Wurgler (2006) and Huang, Jiang, Tu and Zhou (2015), one week as demonstrated by Da, Huang and Jin (2021), or even one trading day (Da, Engelberg and Gao, 2015; Da, Tang, Tao and Yang, 2024). By contrast, the reversal in predicting cryptocurrency returns occurs in the long run. The model proposed by Sockin and Xiong (2023a) offers a theoretical underpinning for this discrepancy, distinguishing between two types of investors in the cryptocurrency market: users and speculators. According to their model, user optimism boosts participation by heightening users' expectations of the token's resale value, thus pushing prices upward. Speculator sentiment also inflates token prices, but, in turn, it crowds out user participation, eventually leading to a subsequent decline in value. Following this theoretical framework, we empirically test the interplay between sentiment, investor adoption, and cryptocurrency pricing in Section 4, aiming to elucidate the mechanisms behind observed momentum and long-term reversal when sentiment predicts individual cryptocurrency returns.

Moreover, we separate the investor sentiment measure into news sentiment (S^{News}) and social media sentiment (S^{Social}) based on the sources of content, and we show their forecasting abilities in Tables IA 1 and IA 2 of the internet appendix. We find that both S^{News} and S^{Social} predict the cryptocurrency returns positively in the subsequent periods, and their regression slopes become negative at the longer horizons, consistent with our findings for the aggregate sentiment index S in Table 2. When evaluating the comparative predictive strength of S^{News} versus S^{Social}, it becomes

apparent that S^{Social} possesses a more pronounced ability to forecast cryptocurrency returns, as evidenced by the more substantial regression coefficients associated with S^{Social}. This is consistent with Chen, Guo and Renault (2019a), who measure the sentiment by using the messages containing a hashtag referring to a cryptocurrency from *StockTwits* and find that it can predict the cryptocurrency market returns.

In summary, investor sentiment exhibits significant predictive power for future cryptocurrency returns, with a pattern of short-run price momentum and long-run mean-reverting. This evidence is consistent with the recent theoretical studies on the cryptocurrency market but differs from the negative predictive power of investor sentiment observed in the traditional asset markets.

3.2. Extrapolative Beliefs

The inquiry into how cryptocurrency investors shape their expectations is a fascinating topic. In the stock market, investors have a propensity to extrapolate past superior performances of stocks into the future, harboring an optimistic view that such trends will persist (Greenwood and Shleifer, 2014; Barberis, Greenwood, Jin and Shleifer, 2015; Cassella and Gulen, 2018; Da, Huang and Jin, 2021). In this subsection, we explore whether cryptocurrency investors hold such extrapolative beliefs.

3.2.1. Extrapolating Past Returns

Following Da, Huang and Jin (2021), we first investigate whether cryptocurrency investors extrapolate past returns to form their expectations by considering both linear and non-linear models of the relationship between sentiment and cryptocurrency past returns.

The linear model is,

$$S_{i,t} = \alpha + \beta R_{i,t-L} + \psi \mathbf{Z}_{i,t-L} + \varepsilon_{i,t} \ , \tag{2}$$

where $S_{i,t}$ is the aggregated sentiment index of cryptocurrency i at time t, $R_{i,t-L}$ is the past accumulated returns of coin i from $t-L$ to t, and $L = 1$, 2, 3, 4, 8, and 12 weeks, $\mathbf{Z}_{i,t-L}$ is a vector of control variables that include the market capitalization (MCAP), the weekly price (PRC), the maximum price (MAXDPRC) in a week, the average daily trading volume (Volume) in a week, and the volatility of trading volume (Vol) in a week.

[Insert Table 3 about here]

Table 3 reports the estimation results of regression (2). We observe that the slopes on $R_{i,t-L}$ are all positive and statistically significant across the lagged periods L, indicating that high sentiment follows the past high returns. Thus, like stock investors, cryptocurrency investors also extrapolate the past performance of cryptocurrency in shaping their forward-looking optimism. Together with the results of Table 2, these biased expectations would be corrected in the long run, generating a price reversal.

Additionally, the results show that the economic magnitude of the coefficient estimate β declines with the lag L; it is 0.036 when L equals one week and decreases to 0.014 when $L = 4$ weeks and keeps a similar value from 8 to 12 weeks. Our results are supported by Kogan, Makarov, Niessner and Schoar (2024), who observe that investors tend to increase their investments in cryptocurrencies following a price increase, with this tendency diminishing over longer lagged periods. The evidence indicates that the extrapolation decays with the lagged period of past return. Investors are more likely to extrapolate the most recent past returns. Given this evidence, we follow

Da, Huang and Jin (2021) and test the non-linear relationship between sentiment and past returns, in which the weights placed on historical returns feature a geometric decay function.

The non-linear model is specified as,

$$\begin{aligned} S_{i,t} &= \alpha + \beta \sum_{s=0}^{L} w_s R_{i,t-s,t-s-1} + \varepsilon_{i,t} \ , \\ w_s &= \frac{\lambda^s}{\sum_{j=0}^{L} \lambda^j} \ , \quad 0 < \lambda \leq 1 \ , \end{aligned} \tag{3}$$

where $S_{i,t}$ is the aggregated investor sentiment index of cryptocurrency i; $R_{i,t-s,t-s-1}$ is the past return of coin i realized between weeks $t-s$ and $t-s-1$. The term $\sum_{s=0}^{L} w_s R_{i,t-s,t-s-1}$ is the sum of the past returns from $t-L$ to t with the weights of an exponential decay function $w_s = \frac{\lambda^s}{\sum_{j=0}^{L} \lambda^j}$, and $L = 1$, 2, 3, 4, 8, and 12 weeks.

To investigate the relationship between sentiment and past returns, we focus on the parameters β and λ. While β captures the overall impact of past returns from $t-L$ to t on current investor sentiment, λ determines the weights on past returns in various lagged periods. A lower (higher) λ suggests that investors place more weights on recent (distant) returns. When λ equals one, there are equal weights on all past returns, and Equation (3) reduces to the linear model (2).

[Insert Table 4 about here]

Panel A of Table 4 details the estimation results of non-linear regression (3). We find that all the β estimates are positive and statistically significant across the lags; the coefficients increase from 0.109 for the one-week lag to 0.129 for the 12-week lag, with t-statistics ranging from 7.867 to 10.439. This finding confirms the evidence shown by the linear model (2) that investors are more

likely to extrapolate past cryptocurrency returns. Additionally, we observe that the λ estimates are significantly positive, ranging from 0.404 to 0.444, much smaller than one, indicating more weights allocated on the recent returns rather than the distant returns.

Furthermore, we investigate the heterogeneous impacts of positive and negative returns on sentiment formation. We extend the regression (3) by separately estimating β and λ for past positive and negative returns. The model is as follows,

$$\begin{aligned} S_{i,t} &= \alpha + \beta_p \sum_{s=0}^{L} w_{s,p} 1_{\{R_{i,t-s,t-s-1} \geq 0\}} R_{i,t-s,t-s-1} \\ &\quad + \beta_n \sum_{s=0}^{L} w_{s,n} 1_{\{R_{i,t-s,t-s-1} < 0\}} R_{i,t-s,t-s-1} + \varepsilon_{i,t} \ , \qquad (4) \\ \text{where} \quad w_{s,p} &= \frac{\lambda_p^s}{\sum_{j=0}^{L} \lambda_p^j} \ , \quad w_{s,n} = \frac{\lambda_n^s}{\sum_{j=0}^{L} \lambda_n^j} \ , \quad 0 < \lambda_p, \ \lambda_n \leq 1 \ . \end{aligned}$$

Similar to in regression (3), while β_p and β_n, respectively, capture the heterogeneous impacts of past positive and negative returns on investor sentiment, λ_p and λ_n govern the weights on positive and negative past returns, respectively.

Panel B of Table 4 reports the estimated results of regression (4). First, we observe that the return extrapolation is robust to both positive and negative past returns, as the β_p and β_n estimates are positive and statistically significant across the board. Second, the return extrapolation seems to be asymmetric. Specifically, positive past returns are likely to play a more important role in the sentiment formation than negative past returns do; the magnitude of β_p (ranging from 0.111 to 0.191) is systematically larger than that of β_n (ranging from 0.107 to 0.137). A similar finding is present for λ; the magnitude of λ_p, ranging from 0.522 to 0.765, is closer to one, whereas λ_n,

ranging from 0.253 to 0.295, is much smaller than one. These magnitudes suggest that positive past returns exert a more significant and enduring influence on shaping investors' expectations than do negative returns.

Our results, which show that positive past returns dominate negative returns in forming investors' beliefs, are inconsistent with the literature on stock sentiment. Da, Huang and Jin (2021) find that investors put more weights on negative stock returns because negative news can be rather salient to investors. We then examine whether the salience theory can explain the return predictability by cryptocurrency sentiment. Following Cosemans and Frehen (2021) and Cakici and Zaremba (2022), we construct a salience theory measure (ST) on cryptocurrency. Table IA 3 reports the results of regressing coin returns on sentiment and ST. We observe that ST can predict subsequent cryptocurrency returns significantly and negatively, which is consistent with the evidence on the stock market. Importantly, after controlling for ST, sentiment still has strong forecasting power, indicating that the economic source of cryptocurrency sentiment is unlikely to be the salience theory. We interpret the economic mechanism of cryptocurrency sentiment in Section 4.

In summary, our findings reveal that investors are more likely to extrapolate past recent returns into the future. In particular, positive past returns dominate negative past returns in forming investors' expectations. This evidence is distinct from that of the stock market.

3.2.2. Extrapolating User Participation

In addition to the return extrapolation, equity market investors are likely to hold extrapolative expectations from firms' fundamentals (Barberis, Greenwood, Jin and Shleifer, 2018). It is of great interest whether cryptocurrency investors extrapolate user participation, the fundamental value of

cryptocurrency (Cong, Li and Wang, 2021; Sockin and Xiong, 2023a). Unlike the equity market, cryptocurrency is a transparent platform where each investor can observe transactions originating from others. This makes the participation extrapolation more accessible relative to the equity market (Pan, Su, Wang and Yu, 2023).

Following Cong, Karolyi, Tang and Zhao (2022), we obtain the number of new addresses, defined as newly created addresses that receive their first deposit in cryptocurrency, from *Intothe-block*. Next, we regress the logarithm of one plus the number of new addresses in the past period on the current sentiment,

$$S_{i,t} = \alpha + \beta NA_{i,t-L} + \psi \mathbf{Z}_{i,t-L} + \varepsilon_{i,t} \ , \tag{5}$$

where $NA_{i,t+h}$ is the logarithm of one plus the number of new addresses participating in cryptocurrency i in the past period L, $L = 1$, 2, 3, 4, 8, and 12 weeks; $S_{i,t}$ is the investor sentiment on cryptocurrency i at time t; and $\mathbf{Z}_{i,t}$ is a vector of control variables, including past returns and other control variables described in Section 2.3., and time and cryptocurrency fixed effects.

[Insert Table 5 about here]

Table 5 reports the estimation results of regression (5). We find evidence that slopes on the number of new addresses are all positive and statistically significant across the periods L after controlling the return extrapolation, indicating that an increase in new entrants in the past period generates high sentiment. Thus, cryptocurrency investors indeed extrapolate past user participation to form their expectations, consistent with the evidence from the equity market (Pan, Su, Wang and Yu, 2023). This may also help interpret the short-term momentum shown in Table 2; user participation raises investor sentiment and, meanwhile, increases cryptocurrency's fundamental

values, generating a positive relationship between sentiment and returns in the short run. Our findings are robust to alternative measures of market participation, such as the number of active addresses and transactions (Cong, Karolyi, Tang and Zhao, 2022), shown in Tables IA 4 and IA 5.

3.3. Sentiment and Trading Activity

In this subsection, we tend to exploit how sentiment affects cryptocurrency returns through trading activities. Ben-Rephael, Kandel and Wohl (2011, 2012) find that stock sentiment significantly induces fund net buying flows, indicating that a positive sentiment should lead investors to be optimistic and thus buy stocks or funds. We are interested in whether such evidence is present in the cryptocurrency market.

We obtain daily inflows and outflows from *Intotheblock*, which are amounts (in USD) of tokens entering exchange deposit wallets and leaving exchange withdrawal wallets, respectively. For each coin, we calculate the average daily inflows and outflows within a week and construct net flows as the log difference between weekly inflows and outflows. A panel regression of the relationship between net flows and investor sentiment is

$$Net\ Flows_{i,t+h} = \alpha + \beta S_{i,t} + \psi \mathbf{X}_{i,t} + \varepsilon_{i,t}\ , \tag{6}$$

where $Net\ Flows_{i,t+h}$ is the weekly net flows of cryptocurrency i over the horizon h, and $h = 0$, 1, 8, 12, 48, 72, 84, and 88 weeks; $S_{i,t}$ is the investor sentiment on cryptocurrency i at time t; and $\mathbf{X}_{i,t}$ is a vector of control variables, including market capitalization (MCAP), price (PRC), maximum price (MAXDPRC), past one-week return ($R_{1,0}$), past two-week return ($R_{2,0}$), past three-week return ($R_{3,0}$), past four-week return ($R_{4,0}$), trading volume (Volume), and volatility of daily trading

volume (Vol). We also include time and cryptocurrency fixed effects. "$h = 0$" refers to a contemporaneous regression of the relationship between net flows and sentiment.

[Insert Table 6 about here]

Table 6 reports the estimation results of regression (6). We find evidence that investor sentiment positively correlates with contemporaneous net flows; the regression slope is 0.221 with a t-statistic of 3.211. This positive and significant relationship persists for up to 12 weeks. Thus, investors' optimistic beliefs induce the contemporaneous buying pressure, pushing up the coin price. This pressure is persistent and causes a short-term price momentum. Compared with the equity market, the duration of the buying pressure induced by sentiment on the cryptocurrency market is longer-lasting. As documented by equity research, the temporary pressure lasts for no more than one trading week (Tetlock, 2007). In the long run, the buying pressure diminishes, leading the sign of the regression slopes to flip. The slope coefficient turns negative, reaching -0.042 over the 48-week horizon as shown in column (5), and becomes significantly negative since the 80-week horizon, suggesting that investors are likely to net sell coins in the long run.

Our evidence from Table 6 may help explain the short-term price momentum and long-term reversal after investor optimism. In the presence of optimistic expectations, investors are likely to purchase coins and push up the prices in the short run. Subsequently, the net buying activity decelerates and may eventually shift to net selling, resulting in a reversal in price.

3.4. Robust Checks

To verify the robustness of our results regarding return predictability, we extend our analysis to examine whether these results are consistent across cryptocurrencies with varying market sizes and levels of trading activity. We categorize cryptocurrencies into two distinct groups by sorting the coins according to their average market capitalization and trading volume. Coins in the top quartile of market capitalization (or trading volume) are designated as the "Large" ("High") group, while those in the bottom quartile are categorized as the "Small" ("Low") group. We again estimate the panel predictive regression (1) within each group.

[Insert Table 7 about here]

Table 7 reports the estimation results. Our evidence supports the robustness of investor sentiment as a predictive tool for cryptocurrency returns across diverse groups of cryptocurrencies characterized by their size and trading activity. Moreover, We find that the forecasting power of investor sentiment is more pronounced for large-cap cryptocurrencies and those with higher trading volumes. Specifically, as shown in Panel A, the economic magnitude of the regression slopes for large coins ranges from 3.348 to 16.337 in the first 48 weeks and from -11.074 to -5.711 in the subsequent horizons, much larger than those of small coins in absolute values. Similar results exist in Panel B. The return predictability is stronger for high-volume coins than for low-volume coins. One possible explanation might be attributed to investor attention. Begenau, Farboodi and Veldkamp (2018) find that the information of larger firms is more visible to investors than smaller firms. Gervais, Kaniel and Mingelgrin (2001) shows that attention, as captured by trading volume, is positively related to a stock's visibility. Similarly, large and active-traded coins may attract more

media attention and be more accessible to investors than small and less active-traded coins. Indeed, some leading cryptocurrency platforms, such as *coinmarketcap.com* and *coinbase.com*, only present information about large and active-traded cryptocurrencies on their homepages.

4. Economic Explanation

So far, we have confirmed the predictability of individual cryptocurrency returns by investor sentiment, which indicates distinct patterns that momentum and long-term reversal occur when investor sentiment predicts cryptocurrency returns. Unlike individual stocks, whose fundamentals rely on accounting information, the fundamental valuation of cryptocurrencies is documented to be closely related to investor adoption (Cong, Li and Wang, 2021; Biais, Bisiere, Bouvard, Casamatta and Menkveld, 2023; Sockin and Xiong, 2023a). Particularly, the model of Sockin and Xiong (2023a) reveals the interplay among sentiment, user adoptions, and equilibrium price by introducing two types of cryptocurrency investors: user and speculator. Users' optimism increases user participation by raising their expectations of the token's resale value, which in turn raises cryptocurrency prices, whereas speculators' optimism may initially elevate prices and meanwhile crowd out user participation, which, in turn, lowers the equilibrium price. Following the theoretical framework, this section conducts additional tests to digest the mechanism underlying the predictability of cryptocurrency returns driven by sentiment.

4.1. Heterogeneity in Cryptocurrency

Motivated by the theoretical predictions of Sockin and Xiong (2023a), we construct our first test to show whether the long-term reversal is primarily driven by heightened speculator sentiment.

Confronted with data constraints, it is challenging to clearly separate our investor sentiment index into components of user and speculator sentiment. Following the approach of Han and Kumar (2013), who investigate the behaviors of retail investors via the stocks with high retail trading proportion, we explore the behaviors of speculators and users by observing the evidence from the coins dominated by the participation of user-like and speculator-like investors, respectively.

The definition of users and speculators is based on the theoretical framework of Sockin and Xiong (2023a). Users are defined as those who share a certain demand to transact goods with each other and need to purchase and hold the tokens to participate in the platform. In contrast, speculators, who provide liquidity by buying and selling tokens with noisy information, seek capital gains from higher next-period token prices. Users are generally incentivized to maintain a positive position to facilitate transactional convenience. Conversely, speculators with a short-term focus are more likely to engage in short-term buying and selling strategies to capitalize on recent market movements.

Therefore, we follow the above definition from the theoretical framework of Sockin and Xiong (2023a) and empirical approach of Bayer, Geissler, Mangum and Roberts (2020) and DeFusco, Nathanson and Zwick (2022), who also classify speculators as those likely holding positions for short time periods for speculative investment purposes. We similarly categorize short-term traders as speculator-like investors and long-term holders as user-like investors who maintain a positive balance for transactional needs. Our classification of investors is based on ownership data sourced from *IntoTheBlock*, which categorizes crypto-asset addresses into three groups— short-term traders, medium-term cruisers, and long-term holders— by the duration they have held the specific crypto-asset. This duration is defined as the period from the establishment of the po-

sition to its ultimate closure, at which point the balance reaches zero. Specifically, short-term traders, medium-term cruisers, and long-term holders are defined as the addresses that have held the coin for less than one month, between one and twelve months, and over one year, respectively. *IntoTheBlock* provides coin-level information on the number of addresses with categories of short-, medium-, and long-term holding periods.

Following the approach of Han and Kumar (2013), we separate the coins in terms of the proportions of short-term traders and long-term holders. Specifically, we sort coins based on the averaged proportion of short-term traders (long-term users), defined as the number of short-term traders (long-term holders) divided by the total number of addresses, and then select the upper quartile of cryptocurrencies as those with higher participation of short-term traders (long-term users). We approximately explore the behaviors of speculators and users by analyzing evidence from coins predominantly traded by short-term traders and long-term holders, respectively.

For the two distinct coin groups— those favored by short-term traders and long-term holders— we revisit the predictive regression (1). Following the theoretical prediction of Sockin and Xiong (2023a), we anticipate that the sentiment-driven long-term reversal is more pronounced in coins with higher participation of short-term traders.

[Insert Table 8 about here]

The estimation results are presented in Table 8, with Panel A detailing results for coins with a higher proportion of short-term traders and Panel B for those with more long-term holders. As depicted in Panel A, in coins preferred by short-term traders, high investor sentiment initially predicts high coin returns in subsequent periods from one-week to 12-week (a quarter) horizons; the

regression slope is 3.806 with a t-statistic of 2.694 at the one-week horizon and increases to 25.633 at the 12-week horizon. Subsequently, a significant price reversal is observed over the longer term; the coefficient begins to shrink after the 48-week horizon and turns significantly negative between the 84- to 92-week horizons, ranging from -14.672 to -18.222. Thus, for coins that more short-term traders participate in, the magnitude of the long-run reversal exceeds the initial price run-up, ultimately leading to a decline in the long-term equilibrium price of the cryptocurrency.

In coins favored by long-term users, as shown in Panel B, investor sentiment consistently predicts coin returns positively across all examined horizons; the regression slope peaks between 12- and 48-week horizons with magnitudes ranging from 11.760 to 15.072. Thereafter, the coefficient begins to diminish but remains positive, indicating that high investor sentiment ultimately raises the equilibrium price of cryptocurrency with more long-term holders participating.

In summary, results from Table 8 show distinct predictability patterns on coins in which more short-term traders and long-term holders participate. For the former, sentiment predicts that the coin returns positively in the short run but negatively in the long run. In contrast, for the latter, the forecasting power of sentiment is positive across horizons. The dynamics of long-run reversal are much more pronounced in coins with higher speculative activities. Our finding is consistent with the theoretical prediction of Sockin and Xiong (2023a).

4.2. Sentiment and Cryptocurrency Participants

Previous findings reveal distinct patterns of return predictability across cryptocurrencies, segmented by the dominance of short-term traders and long-term holders. Evidence indicates that the sentiment-driven long-term reversals are more pronounced in coins with heightened speculative

activities. Sockin and Xiong (2023a) theoretically illustrate that increased speculator sentiment reduces transaction demands for coins and eventually crowds out user adoptions, resulting in a decline in equilibrium prices. Therefore, our second test seeks to determine whether, in coins preferred by short-term traders, high sentiment adversely predicts long-term cryptocurrency returns by crowding out investor adoptions in the long run.

Similar to the approach described above, we regress future investor adoptions— measured by the number of new addresses, defined as newly created addresses that receive their first deposit in cryptocurrency— on the current investor sentiment across coins dominated by long-term holders and short-term traders. Table 9 presents the estimation results; Panel A details the results for coins predominantly traded by short-term traders, while Panel B focuses on those held by a greater proportion of long-term holders.

[Insert Table 9 about here]

As demonstrated in Panel B, for coins preferred by short-term traders, high investor sentiment initially predicts higher investor adoptions from one to 12 weeks; the regression slope starts at 0.384 with a t-statistic of 2.946 at the one-week horizon and declines to 0.064 at the 12-week horizon. Subsequently, the slope turns negative and becomes statistically significant starting from the 72-week horizon. The results indicate that while investor sentiment initially boosts adoptions, it eventually crowds out long-term investor participation.

For coins favored by long-term users, as shown in Panel B, the regression slope starts at 0.259 with a t-statistic of 5.072 at the one-week horizon, peaking at 0.316 with a t-statistic of 5.501 at the 12-week horizon. Thereafter, the coefficients, though insignificant, remain positive, indicating that

high sentiment persistently encourages new participants to engage with the platform over periods extending from one week to 92 weeks.

In addition, we revisit the test using alternative measures of investor adoption— the number of active addresses and transactions— to confirm the robustness of our results (Cong, Karolyi, Tang and Zhao, 2022). Table IA 6 and Table IA 7 present the robust result, showing identical patterns across both alternative investor adoption measures.

Overall, our research shows that in both categories of coins— those favored by short-term traders and long-term holders— sentiment initially has a positive influence on investor adoption, which triggers short-term momentum in cryptocurrencies. However, in coins preferred by short-term traders, increased sentiment tends to crowd out participants in the long run, ultimately leading to price reversals over the long term. This finding corroborates the theoretical predictions proposed by Sockin and Xiong (2023a).

4.3. Explaining Momentum and Long-term Reversal

So far, our analysis indicates that investor sentiment serves a dual role by promoting both momentum and long-term price reversals in the cryptocurrency market. An interesting question arises regarding whether this sentiment-driven mechanism is the primary driving force behind the momentum and long-term reversal observed in the digital asset markets. Besides, explaining momentum and reversal anomalies remains a fundamental topic in the field of asset pricing (Guo, Li and Li, 2022). Therefore, we conduct our third test to quantify the proportions of momentum and long-term reversal anomalies explained by investor sentiment and compare them with other competing explanations.

4.3.1. Decompose Momentum

Building upon the decomposition technique proposed by Hou and Loh (2016), we first scrutinize the influence of various candidate determinants on momentum phenomena. Previous empirical studies, such as Cong, Karolyi, Tang and Zhao (2022) and Liu, Tsyvinski and Wu (2022), have documented a pronounced momentum effect in cryptocurrency markets, with a duration of approximately one month. In stage one, we regress the future one-month returns of individual coins on their past one-week returns as follows:

$$R_{i,t+4} = \alpha_t + \beta_t R_{i,t-1} + \varepsilon_{i,t} \ , \tag{7}$$

where $R_{i,t+4}$ is the cumulative future returns of coins i over the prediction horizon of 4 weeks; $R_{i,t-1}$ is the past one-week returns of coins i. β_t is the momentum beta, which measures the relationship between $R_{i,t-1}$ and $R_{i,t+4}$.

In stage 2, we add a candidate explanatory variable to Equation (7) as follows:

$$R_{i,t+4} = \tilde{\alpha}_t + \beta_t^{\tilde{R}} R_{i,t-1} + \beta_t^{\tilde{C}} Candidiate_{i,t-1} + \varepsilon_{i,t}. \tag{8}$$

Regression (8) is designed to evaluate if the inclusion of the candidate variable markedly diminishes the explanatory significance traditionally attributed to the momentum anomaly.

In stage 3, we regress past return on a candidate explanatory variable as follows:

$$R_{i,t-1} = \mu_{t-1} + \delta_{t-1} Candidiate_{i,t-1} + \varphi_{i,t-1} \ . \tag{9}$$

Equation (9) helps examine the interplay between past returns and the candidate variable, as any candidate variable that can serve as a potential driver of momentum must be correlated with the past return. Therefore, we can decompose the past return into two mutually exclusive components: a related candidate component ($\delta_{t-1}Candidate_{i,t-1}$) and an unrelated residual component ($\mu_{t-1} + \varphi_{i,t-1}$).

In stage 4, the linearity of covariance is used to decompose the momentum beta (β_t) from Equation(7) into two components: a related candidate beta (β_t^C) and an unrelated residual beta (β_t^R). Specifically,

$$\begin{aligned}\beta_t &= \frac{\mathrm{Cov}\left[R_{i,t+4}, R_{i,t-1}\right]}{\mathrm{Var}\left[R_{i,t-1}\right]} = \frac{\mathrm{Cov}\left[R_{i,t+4}\,,\,(\mu_{t-1} + \delta_{t-1}Candidate_{i,t-1} + \varphi_{i,t-1})\right]}{\mathrm{Var}\left[R_{i,t-1}\right]} \\ &= \frac{\mathrm{Cov}\left[R_{i,t+4}\,,\,\delta_{t-1}Candidate_{i,t-1}\right]}{\mathrm{Var}\left[R_{i,t-1}\right]} + \frac{\mathrm{Cov}\left[R_{i,t+4}\,,\,(\mu_{t-1} + \varphi_{i,t-1})\right]}{\mathrm{Var}\left[R_{i,t-1}\right]} \\ &= \beta_t^C + \beta_t^R\,,\end{aligned} \tag{10}$$

where the ratio β_t^C/β_t quantifies the portion of the momentum explained by the candidate variable in week t, and β_t^R/β_t represents the portion of the anomaly that remains unexplained by the candidate variable in week t. Drawing from Equation (10), the relative contribution of a candidate variable depends on two dimensions: the correlation between the candidate variable and the past return (δ) and the return predictability by the candidate variable ($\mathrm{Cov}\left[R_{i,t+4}\,,\,Candidate_{i,t-1}\right]$). The time-series average of β_t^C divided by the time-series average of β_t measures the average fraction of the anomaly attributable to the candidate variable. Similarly, the time-series average of β_t^R divided by the time-series average of β_t measures the average fraction of the anomaly left unexplained by

the candidate variable. Specifically,

$$\hat{E}\left(\frac{\beta_t^C}{\beta_t}\right) \approx \frac{\overline{\beta_t^C}}{\overline{\beta_t}}, \quad \hat{E}\left(\frac{\beta_t^R}{\beta_t}\right) \approx \frac{\overline{\beta_t^R}}{\overline{\beta_t}}. \tag{11}$$

The corresponding estimated variances of the fractions are based on the respective time series of β_t^C, β_t^R, and β_t estimates (over T weeks):

$$\begin{aligned}
\widehat{\text{Var}}\left(\frac{\overline{\beta_t^C}}{\overline{\beta_t}}\right) &\approx \frac{1}{T}\left(\frac{\overline{\beta_t^C}}{\overline{\beta_t}}\right)^2\left(\frac{SD(\beta_t^C)^2}{\overline{\beta_t^C}^2}+\frac{SD(\beta_t)^2}{\overline{\beta_t}^2}-2\frac{\hat{\rho}(\beta_t^C,\beta_t)SD(\beta_t^C)SD(\beta_t)}{\overline{\beta_t^C}\,\overline{\beta_t}}\right), \\
\widehat{\text{Var}}\left(\frac{\overline{\beta_t^R}}{\overline{\beta_t}}\right) &\approx \frac{1}{T}\left(\frac{\overline{\beta_t^R}}{\overline{\beta_t}}\right)^2\left(\frac{SD(\beta_t^R)^2}{\overline{\beta_t^R}^2}+\frac{SD(\beta_t)^2}{\overline{\beta_t}^2}-2\frac{\hat{\rho}(\beta_t^R,\beta_t)SD(\beta_t^R)SD(\beta_t)}{\overline{\beta_t^R}\,\overline{\beta_t}}\right),
\end{aligned} \tag{12}$$

where $SD(\cdot)$ and $\hat{\rho}(\cdot)$ denote the functions of standard deviation and correlation coefficient, respectively.

Building on the foundational research of momentum in conventional asset classes and considering the distinct data landscape of the cryptocurrency market, we endeavor to curate an exhaustive set of candidate indicators. First, investor sentiment (S) is posited as a focal point. Guo, Li and Li (2022) suggest an amplified momentum effect during periods of elevated sentiment in the equity market. The second group of candidate variables is attributed to fundamental factors. The research on the stock market documented that firms' profit performance, such as earnings and revenue, drives the price momentum (Chan, Jegadeesh and Lakonishok, 1996; Chordia and Shivakumar, 2006; Chen, Chen, Hsin and Lee, 2014b; Cen, Wei and Yang, 2017). To adapt these insights to the cryptocurrency domain, we follow empirical and theoretical findings (Liu and Tsyvinski, 2021; Cong, Karolyi, Tang and Zhao, 2022; Sockin and Xiong, 2023a) and select the number of

new addresses (NA), active addresses (AA), and on-chain transactions (TRAN) as proxies for the fundamental value of cryptocurrencies.

The third group of variables primarily includes coin-specific characteristics. George and Hwang (2004) punctuate the significance of the 52-week high price (52W) as a critical determinant of momentum profits. Grinblatt and Han (2005) suggest that prospect theory and mental accounting, proxied by capital gain overhang (CGO), can largely capture the forecasting power of past returns on future returns. Hong, Lim and Stein (2000) find that momentum profits are more significant with low analyst coverage (COV). Lee and Swaminathan (2000) suggest that trading volume— via turnover ratio (TURN)— determines momentum profits. Other stream of literature points out that volatility and uncertainty, proxied by idiosyncratic volatility, return volatility, and revenue volatility, enhance stock momentum strategies (Zhang, 2006; Sagi and Seasholes, 2007; Arena, Haggard and Yan, 2008). As Liu, Tsyvinski and Wu (2022) show that the volatility of trading volume dominates idiosyncratic volatility, return volatility, and other volatility-based characteristics in forecasting cryptocurrency future returns, we choose the volatility of trading volume (TVOL) to proxy volatility characteristics. Following these strands of literature, this study considers S, AA, NA, TRAN, CGO, 52W, COV, TURN, and TVOL as our candidate variables. For detailed definitions and methodological constructs of these variables, please refer to Appendix A.

[Insert Table 10 about here]

Table 10 shows the results for decomposing the momentum effect. To conserve space, we only report the results of stage 4. The analysis reveals that while various candidate variables contribute to some degree in explaining the momentum effect, investor sentiment emerges as the most significant factor. It alone accounts for a substantial 83.294% of the momentum anomaly,

relegating the remainder to a mere 16.706%. When examining fundamental factors (NA, AA, TRAN), we observe that they explain a smaller, yet noteworthy, proportion of the momentum effect, with contributions ranging from 24.522% to 32.456%. In contrast, other variables of coin-specific characteristics demonstrate a more modest explanatory power, ranging from -10.293% to 17.523%, indicating a potential limitation or even a reverse predictive effect on future returns.

Contrary to previous studies in the stock market that firm fundamentals are highlighted as the main explanatory factors for momentum (Guo, Li and Li, 2022), our results indicate that investor sentiment accounts for most of the momentum effect in cryptocurrencies.

4.3.2. Decompose Long-term Reversal

Recognizing the pivotal influence of investor sentiment on momentum, we extend our discussion to its impact on the long-term reversal. Both our aforementioned evidence and the theoretical model by Sockin and Xiong (2023a) show that user and speculator sentiment play distinct roles in driving the long-term reversal, suggesting that speculators' sentiment, rather than users' sentiment, is primarily responsible for triggering a price reversal over the long run. In this subsection, we delve into the contributions of sentiment to these long-term reversal phenomena in coins with more short-term traders participating through the decomposition methodology introduced by Hou and Loh (2016).

Specifically, in stage 1, as documented in the previous literature, there is a pronounced reversal effect observed over long-term periods, peaking at around 80 weeks (Liu, Tsyvinski and Wu, 2022). As a proxy for this long-term reversal, we focus on the distant past returns ranging from

48 to 90 weeks prior.[3] To dissect this phenomenon, we regress individual cryptocurrencies' future one-month returns on their distant past returns to scrutinize the dynamics of the long-term reversal effect. The regression is formalized as follows:

$$R_{i,t+4} = \alpha_t + \beta_t R48,90_{i,t} + \varepsilon_{i,t} \ , \tag{13}$$

where $R_{i,t+4}$ is the cumulative future returns of coins i over the prediction horizon of 4 weeks; $R48,90_{i,t}$ is the past 48-to-90-week returns of coins i. β_t is the reversal beta, which measures the relationship between distant past return $R48,90_{i,t}$ and future return $R_{i,t+4}$.

In stage 2, we add a distant past candidate explanatory variable to Equation (13) as follows:

$$R_{i,t+4} = \tilde{\alpha}_t + \beta_t^{\tilde{R}} R48,90_{i,t} + \beta_t^{\tilde{C}} Candidiate_{i,t-48} + \varepsilon_{i,t} \ , \tag{14}$$

where $Candidiate_{i,t-48}$ is a candidate variable of cryptocurrency i at the past period of 48 weeks. This regression helps assess how much the candidate variables predict distant future returns and whether they significantly subsume the explanatory power of the reversal anomaly.

In stage 3, we regress distant past return on a distant past candidate variable as follows:

$$R48,90_{i,t} = \mu_t + \delta_t Candidiate_{i,t-48} + \varphi_{i,t}, \tag{15}$$

where the distant past return can be decomposed into two orthogonal components: a related candidate component ($\delta_t Candidate_{i,t-48}$) and an unrelated residual component ($\mu_t + \varphi_{i,t}$).

[3] Robustness checks confirm that our results are consistent when considering a narrower window of past returns spanning from 60 to 90 weeks.

Similarly, in stage 4, the coefficient β_t in Equation (13) is decomposed as $\beta_t = \frac{\mathrm{Cov}\left[R_{i,t+4}, R48,90_{i,t}\right]}{\mathrm{Var}\left[R48,90_{i,t}\right]} = \frac{\mathrm{Cov}\left[R_{i,t+4}, \delta_t Candidate_{i,t-48}\right]}{\mathrm{Var}\left[R48,90_{i,t}\right]} + \frac{\mathrm{Cov}\left[R_{i,t+4}, \left(\mu_t + \varphi_{i,t}\right)\right]}{\mathrm{Var}\left[R48,90_{i,t}\right]} = \beta_t^C + \beta_t^R$. The time-series average of β_t^C (β_t^R) divided by the time-series average of β_t measures the fraction of candidate (residual) contribution.

Regarding candidate variables, previous literature in stock and bond markets also highlights the important role of fundamental (De Bondt and Thaler, 1985, 1987), liquidity (Avramov, Chordia and Goyal, 2006; Nagel, 2012) and volatility factors (McLean, 2010) in driving the reversal effect. Moreover, prominent theoretical research in the area of behavioral finance, such as Barberis, Shleifer and Vishny (1998), Daniel, Hirshleifer and Subrahmanyam (1998), and Hong and Stein (1999), treats short-term momentum and long-term reversals as inseparable phenomena. It is reasonable to continue using the comprehensive set of candidate variables in the decomposition of the momentum phenomenon. To verify the explanatory power of speculator sentiment on the long-term reversal effect, we narrow our sample to encompass coins with a higher proportion of short-term traders (top 50%). Table 11 shows the results. To conserve space, we only report the results of stage 4.

[Insert Table 11 about here]

Table 11 illustrates that, in coins dominated by short-term traders, investor sentiment explains 56.429% of the long-term reversal effect, ranking first among all candidate variables, which underscores the strong connection between sentiment and price reversals in markets dominated by speculative trading. The liquidity (TURN) and volatility (TVOL) factors also contribute significantly to the explanation of the reversal effect, elucidating 45.729% and 29.398% of the effect, respectively. This result is consistent with the evidence in the stock market that liquidity and volatility

can explain a sizable fraction of reversal effect (Avramov, Chordia and Goyal, 2006; Nagel, 2012; McLean, 2010).

In summary, after comparing with other competing explanations, our empirical evidence highlights investor sentiment as the most crucial factor driving both momentum and long-term reversal effects in cryptocurrency markets.

5. Conclusion

In this study, we comprehensively investigate the predictive power of investor sentiment on individual cryptocurrency returns. First, using a panel predictive regression, we find that investor sentiment positively predicts future returns over a relatively short horizon of approximately one year, followed by a return reversal over longer horizons.

Second, using both linear and nonlinear models, we find compelling evidence that investors are likely to extrapolate past returns of cryptocurrency. In particular, this extrapolation is asymmetric, with investors giving more weight to positive returns than negative returns. In addition to return extrapolation, investors also extrapolate the cryptocurrency participation, proxied by the number of new addresses.

To interpret the return predictability, we find evidence that the sentiment-driven long-run reversal is more pronounced in cryptocurrencies with higher speculative activities. Further analysis of the mechanism demonstrates that across both segments of cryptocurrencies— those preferred by short-term traders and those by long-term holders— sentiment positively affects investor adoption at the early stages, subsequently generating short-term momentum. However, in segments pre-

dominantly influenced by short-term traders, increased sentiment ultimately crowds out investor participation in the long run, eventually causing long-term price reversals. Our results are consistent with Sockin and Xiong (2023a).

Lastly, employing a decomposition method proposed by Hou and Loh (2016), we provide compelling evidence that the sentiment-driven mechanism is the predominant driver of the momentum and long-term reversal effects observed in the cryptocurrency market. Future research can extend our study by testing the interaction between cryptocurrency sentiment and stock sentiment and assessing its impact on both cryptocurrency and stock markets.

Appendix

A Candidate Variables

- The number of new addresses (NA), defined as the logarithm of one plus the number of newly created addresses that receive their first deposit in cryptocurrency within each week, sourced from *Intotheblock*.
- The number of active addresses (AA), defined as the logarithms of one plus the number of active addresses that made at least one transaction within each week, sourced from *Intotheblock*.
- The number of transactions (TRAN), defined as the logarithms of one plus the number of on-chain transactions within each week, sourced from *Intotheblock*.
- 52-week high price (52W), defined as the highest price during the past 52 weeks, sourced

from *CoinMarketcap*.

- The turnover ratio (TURN), as the weekly trading volume divided by the market capitalization, sourced from *CoinMarketcap*.

- The capital gains overhang variable (CGO), following Grinblatt and Han (2005):

$$CGO_t = \frac{P_{t-2} - RP_{t-1}}{P_{t-2}},$$

where P_t is the cryptocurrency price in week t; RP_t is the reference price, as follows

$$RP_t = \frac{1}{K} \sum_{n=1}^{N=12} \left(V_{t-n} \prod_{\tau}^{n-1} (1 - V_{t-n+\tau}) \right) P_{t-1-n}$$

where V_t is the cryptocurrency turnover ratio in week t; K is a constant that makes the weights on past prices sum to one. The weight $\left(V_{t-n} \prod_{\tau}^{n-1} (1 - V_{t-n+\tau})\right)$ is the probability that the stock was last bought at week $t-n$ and has not been traded since.

- The media coverage (COV), defined as the logarithms of one plus the number of relevant references feeding into the Thomson Reuters within each week, sourced from *Thomson Reuters*.

- Volatility (TVOL), defined as the logarithm of the standard deviation of daily trading volume within each week, sourced from *CoinMarketcap*.

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Table 1. Summary Statistics

This table reports the mean, median, standard deviation (Std. Dev.), minimum (Min), maximum (Max), the 25% (Q25) and 75% (Q75) quartiles, and the number of observations of variables that include the investor sentiment (S), the market capitalization (MCAP), the weekly price (PRC) in a week, the maximum price (MAXDPRC) in a week, the weekly return (R), the past one-week return ($R_{1,0}$), the past two-week return ($R_{2,0}$), the past three-week return ($R_{3,0}$), the past four-week return ($R_{4,0}$), the average daily volume (Volume) in a week, and the volatility of daily trading volume (Vol) in a week.

	Mean	Std. Dev.	Min	Q25	Median	Q75	Max	# of Obs.
S	0.143	0.219	−1.000	0.044	0.145	0.256	1.000	32630
MCAP	17.680	2.487	4.716	16.389	17.726	19.064	27.007	35602
PRC	−1.544	3.582	−12.975	−3.634	−1.478	0.509	10.270	36293
MAXDPRC	−1.447	3.573	−12.658	−3.542	−1.387	0.612	10.270	36309
$R(\%)$	−0.064	22.574	−438.492	−10.603	−0.672	8.646	529.219	36080
$R_{1,0}(\%)$	−0.170	31.902	−462.220	−15.732	−1.197	12.532	658.958	35871
$R_{2,0}(\%)$	−0.208	39.713	−445.921	−20.642	−1.735	15.798	699.144	35671
$R_{3,0}(\%)$	−0.281	46.400	−455.982	−24.642	−2.066	18.561	731.716	35473
$R_{4,0}(\%)$	−0.339	52.248	−569.042	−28.827	−2.311	21.355	745.135	35275
Volume	14.247	3.586	−9.588	12.271	14.548	16.388	25.072	36266
Vol	13.204	3.350	−8.615	11.285	13.428	15.325	23.746	36228

Table 2. Results of Forecasting Coin Returns

This table presents results of the predictive regressions,

$$R_{i,t+h} = \alpha + \beta S_{i,t} + \psi \mathbf{X}_{i,t} + \varepsilon_{i,t} \ ,$$

where $R_{i,t+h}$ is the weekly excess return of cryptocurrency i over the prediction horizon h and $h = 1$, 4, 12, 48, 72, 84, 88, and 92 weeks; $S_{i,t}$ is the investor sentiment on cryptocurrency i at time t; and $\mathbf{X}_{i,t}$ is a vector of control variables, including the market capitalization (MCAP), the weekly price (PRC), the maximum price (MAXDPRC) in a week, the past one-week return ($R_{1,0}$), the past two-week return ($R_{2,0}$), the past three-week return ($R_{3,0}$), the past four-week return ($R_{4,0}$), the average daily volume (Volume) in a week, and the volatility of daily trading volume (Vol) in a week. Standard errors are clustered by time. Reported are the regression slopes, t-statistics in the parentheses, and R^2s. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	(1) 1 week	(2) 4 weeks	(3) 12 weeks	(4) 48 weeks	(5) 72 weeks	(6) 84 weeks	(7) 88 weeks	(8) 92 weeks
S	1.232**	2.926***	6.216***	6.961***	−1.663	−5.052**	−4.484**	−3.387*
	(2.418)	(3.054)	(4.055)	(3.173)	(−0.767)	(−2.371)	(−2.145)	(−1.650)
MCAP	−0.310	−2.432***	−4.457***	−2.406	−0.286	−1.629	−1.272	−0.482
	(−0.948)	(−3.891)	(−4.353)	(−1.515)	(−0.170)	(−0.936)	(−0.736)	(−0.281)
PRC	−5.484***	−6.065**	−18.607***	−81.060***	−96.042***	−105.745***	−113.955***	−116.441***
	(−4.215)	(−2.544)	(−5.197)	(−16.452)	(−19.668)	(−21.387)	(−23.484)	(−23.991)
MAXDPRC	3.271***	−1.975	−4.212	5.623	2.198	9.268**	16.383***	17.929***
	(2.599)	(−0.860)	(−1.231)	(1.212)	(0.482)	(2.009)	(3.618)	(3.948)
$R_{1,0}$	0.019**	0.012	0.009	0.005	0.026	0.026	0.031	0.023
	(2.287)	(0.814)	(0.451)	(0.184)	(1.103)	(1.110)	(1.343)	(0.999)
$R_{2,0}$	−0.003	−0.022	−0.008	−0.010	−0.002	0.000	−0.004	−0.001
	(−0.314)	(−1.406)	(−0.368)	(−0.362)	(−0.080)	(0.013)	(−0.162)	(−0.057)
$R_{3,0}$	−0.015*	−0.003	−0.024	−0.005	−0.011	−0.007	−0.007	−0.007
	(−1.743)	(−0.188)	(−1.091)	(−0.183)	(−0.443)	(−0.275)	(−0.292)	(−0.268)
$R_{4,0}$	−0.005	−0.024**	−0.049***	−0.008	0.007	0.013	0.002	0.018
	(−0.751)	(−2.200)	(−3.047)	(−0.419)	(0.370)	(0.721)	(0.100)	(1.003)
Volume	0.617***	2.056***	3.378***	8.534***	8.291***	5.898***	4.963***	3.231***
	(3.532)	(6.239)	(6.739)	(12.276)	(10.905)	(7.416)	(6.185)	(3.958)
Vol	−0.678***	−1.541***	−2.420***	−3.943***	−3.681***	−2.455***	−1.932***	−1.003
	(−4.392)	(−5.298)	(−5.481)	(−6.645)	(−5.934)	(−3.864)	(−3.028)	(−1.553)
Coin FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.017	0.059	0.159	0.450	0.575	0.619	0.637	0.652

Table 3. Results of Linear Regressions of Sentiment on Past Returns

This table presents results of the following regressions,

$$S_{i,t} = \alpha + \beta R_{i,t-L} + \psi \mathbf{Z}_{i,t-L} + \varepsilon_{i,t} \ ,$$

where $S_{i,t}$ is the investor sentiment on cryptocurrency i at time t; $R_{i,t-L}$ is the past accumulated returns of coin i from $t-L$ to t, and $L = 1$, 2, 3, 4, 8, and 12 weeks; $\mathbf{Z}_{i,t-L}$ is the control variables that include the market capitalization (MCAP), the weekly price (PRC), the maximum price (MAXDPRC) in a week, the average daily volume (Volume) in a week, and the volatility of daily trading volume (Vol) in a week. Standard errors are clustered by time. Reported are the regression slopes, t-statistics in the parentheses, and R^2s. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
$L =$	1 week	2 weeks	3 weeks	4 weeks	8 weeks	12 weeks
$R_{i,t-L}$	0.036***	0.026***	0.019***	0.014***	0.012***	0.011***
	(6.946)	(6.126)	(5.359)	(4.294)	(4.598)	(4.346)
MCAP	−0.004	−0.003	−0.003	−0.003	−0.005	−0.005
	(−0.835)	(−0.699)	(−0.701)	(−0.676)	(−0.982)	(−0.969)
PRC	0.029*	−0.006	0.019	0.011	0.015	0.028**
	(1.906)	(−0.401)	(1.351)	(0.764)	(1.077)	(1.972)
MAXDPRC	−0.016	0.018	−0.007	0.003	−0.001	−0.014
	(−1.084)	(1.304)	(−0.483)	(0.211)	(−0.092)	(−1.053)
Volume	0.005**	0.005**	0.004**	0.003	0.002	0.001
	(2.368)	(2.263)	(1.981)	(1.644)	(0.907)	(0.583)
Vol	−0.006***	−0.005***	−0.005**	−0.005***	−0.002	−0.001
	(−3.244)	(−2.901)	(−2.535)	(−2.659)	(−1.364)	(−0.743)
Coin FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.003	0.002	0.002	0.002	0.002	0.002

Table 4. Results of Non-Linear Regressions of Sentiment on Past Returns

Panel A presents results of the exponential decay model,

$$S_{i,t} = \alpha + \beta \sum_{s=0}^{L} w_s R_{i,t-s,t-s-1} + \varepsilon_{i,t} \ , \quad \text{and} \quad w_s = \frac{\lambda^s}{\sum_{j=0}^{L} \lambda^j} \ ,$$

where $S_{i,t}$ is the investor sentiment on cryptocurrency i; $R_{i,t-s,t-s-1}$ is the past return of coin i realized between weeks $t-s$ and $t-s-1$. The weights on past returns sum to one, with lower λ indicating more weights on recent data. β captures the overall impact of all past returns of coin i from t to $t-L$ on current investor sentiment $S_{i,t}$. Panel B reports the results of the following regressions,

$$S_{i,t} = \alpha + \beta_p \sum_{s=0}^{L} w_{s,p} 1_{\{R_{i,t-s,t-s-1} \geq 0\}} R_{i,t-s,t-s-1} + \beta_n \sum_{s=0}^{L} w_{s,n} 1_{\{R_{i,t-s,t-s-1} < 0\}} R_{i,t-s,t-s-1} + \varepsilon_{i,t} \ ,$$

$$\text{and} \quad w_{s,p} = \frac{\lambda_p^s}{\sum_{j=0}^{L} \lambda_p^j} \ , \quad w_{s,n} = \frac{\lambda_n^s}{\sum_{j=0}^{L} \lambda_n^j} \ ,$$

where $1_{\{R_{i,t-s,t-s-1} \geq 0\}}$ and $1_{\{R_{i,t-s,t-s-1} < 0\}}$ are indicator variables that allow coefficients λ and β to differ across positive (p) and negative (n) returns. Lower λ_p (λ_n) indicates more weights on recent positive (negative) returns. β_p (β_n) captures the overall impact of all past positive (negative) returns of coin i from weeks t to $t-L$ on current investor sentiment $S_{i,t}$. Reported are the regression slopes, t-statistics in the parentheses, and R^2s. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
L =	1 week	2 weeks	3 weeks	4 weeks	8 weeks	12 weeks
Panel A: Results of the exponential decay model						
β	0.109***	0.118***	0.125***	0.125***	0.129***	0.129***
	(10.439)	(9.506)	(9.106)	(8.618)	(8.111)	(7.867)
λ	0.444***	0.404***	0.414***	0.410***	0.420***	0.431***
	(4.048)	(4.756)	(5.379)	(5.402)	(5.617)	(5.665)
R^2	0.004	0.004	0.004	0.004	0.004	0.004
Panel B: Results for heterogeneous impacts						
β_p	0.111***	0.124***	0.142***	0.151***	0.184***	0.191***
	(6.222)	(6.074)	(6.328)	(6.218)	(6.133)	(5.601)
β_n	0.107***	0.112***	0.116***	0.117***	0.134***	0.137***
	(5.897)	(5.426)	(5.361)	(5.318)	(5.745)	(5.612)
λ_p	0.623**	0.522***	0.612***	0.634***	0.759***	0.765***
	(2.400)	(3.201)	(4.657)	(5.516)	(9.537)	(10.421)
λ_n	0.295	0.291*	0.253*	0.249*	0.261**	0.284**
	(1.586)	(1.908)	(1.838)	(1.859)	(2.258)	(2.445)
R^2	0.004	0.004	0.004	0.004	0.004	0.004

Table 5. Results of Regressions of Sentiment on Past Participation

This table presents results of the following regressions,

$$S_{i,t} = \alpha + \beta NA_{i,t-L} + \psi \mathbf{Z}_{i,t-L} + \varepsilon_{i,t} \ ,$$

where $S_{i,t}$ is the investor sentiment on cryptocurrency i at time t; $NA_{i,t-L}$ is the logarithm of one plus the number of new addresses of coin i at time $t-L$, and $L = 1$, 2, 3, 4, 8, and 12 weeks; $\mathbf{Z}_{i,t-L}$ is the control variables that include the past accumulated returns ($R_{L,0}$), the market capitalization (MCAP), the weekly price (PRC), the maximum price (MAXDPRC) in a week, the average daily volume (Volume) in a week, and the volatility of daily trading volume (Vol) in a week. Standard errors are clustered by time. Reported are the regression slopes, t-statistics in the parentheses, and R^2s. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
$L =$	1 week	2 weeks	3 weeks	4 weeks	8 weeks	12 weeks
NA	0.007***	0.007***	0.006***	0.006***	0.007***	0.004**
	(3.453)	(3.295)	(3.026)	(3.166)	(3.317)	(2.087)
$R_{L,0}$	0.044***	0.036***	0.030***	0.020***	0.014***	0.012***
	(6.090)	(6.251)	(6.172)	(4.555)	(3.918)	(3.596)
MCAP	−0.008	−0.007	−0.008	−0.009	−0.011*	−0.013**
	(−1.410)	(−1.230)	(−1.493)	(−1.587)	(−1.956)	(−2.097)
PRC	0.035*	0.008	−0.006	−0.005	−0.023	0.005
	(1.769)	(0.417)	(−0.268)	(−0.251)	(−1.262)	(0.246)
MAXDPRC	−0.031	−0.005	0.011	0.013	0.034*	0.007
	(−1.601)	(−0.273)	(0.552)	(0.679)	(1.935)	(0.395)
Volume	0.010***	0.008***	0.010***	0.009***	0.009***	0.008***
	(3.498)	(2.788)	(3.344)	(3.176)	(2.944)	(2.752)
Vol	−0.006**	−0.004	−0.006**	−0.008***	−0.006**	−0.004
	(−2.336)	(−1.510)	(−2.436)	(−3.097)	(−2.308)	(−1.563)
Coin FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.006	0.005	0.005	0.003	0.003	0.003

Table 6. Relation with the Net Flows

This table presents results of the following regressions,

$$Net\ Flows_{i,t+h} = \alpha + \beta S_{i,t} + \psi \mathbf{X}_{i,t} + \varepsilon_{i,t}\ ,$$

where $Net\ Flows_{i,t+h}$ is the weekly net flows of cryptocurrency i, defined as the log difference between the amount (in USD) of tokens incoming exchanges and those outgoing exchanges over the horizon h, and $h = 0$, 1, 8, 12, 48, 72, 84, and 88 weeks; $S_{i,t}$ is the investor sentiment on cryptocurrency i at time t; and $\mathbf{X}_{i,t}$ is a vector of control variables, including the market capitalization (MCAP), the weekly price (PRC), the maximum price (MAXDPRC) in a week, the past one-week return ($R_{1,0}$), the past two-week return ($R_{2,0}$), the past three-week return ($R_{3,0}$), the past four-week return ($R_{4,0}$), the average daily volume (Volume) in a week, and the volatility of daily trading volume (Vol) in a week. In column (1), $h = 0$ week means a contemporaneous regression between net flows and sentiment. Standard errors are clustered by time. Reported are the regression slopes, t-statistics in the parentheses, and R^2s. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	(1) 0 week	(2) 1 week	(3) 8 weeks	(4) 12 weeks	(5) 48 weeks	(6) 80 weeks	(7) 84 weeks	(8) 88 weeks
S	0.221***	0.262***	0.266***	0.195***	−0.042	−0.197**	−0.171*	−0.250**
	(3.211)	(3.770)	(3.826)	(2.774)	(−0.490)	(−2.043)	(−1.731)	(−2.431)
MCAP	0.399***	0.418***	0.436***	0.361***	−0.003	−0.107**	−0.036	−0.046
	(9.124)	(9.455)	(9.259)	(7.292)	(−0.059)	(−2.284)	(−0.755)	(−0.918)
PRC	−0.739***	−0.612***	−0.479***	−0.084	−0.163	0.030	0.034	0.039
	(−4.584)	(−3.720)	(−2.885)	(−0.504)	(−0.882)	(0.167)	(0.181)	(0.185)
MAXDPRC	0.376**	0.244	0.087	−0.226	0.236	0.052	−0.001	0.031
	(2.411)	(1.536)	(0.543)	(−1.400)	(1.319)	(0.298)	(−0.006)	(0.149)
$R_{1,0}$	0.000	0.000	0.001	−0.000	−0.002*	−0.000	0.000	−0.001
	(0.082)	(0.511)	(0.638)	(−0.026)	(−1.871)	(−0.003)	(0.391)	(−1.249)
$R_{2,0}$	−0.000	0.001	−0.000	0.000	0.001	0.000	−0.000	0.002
	(−0.035)	(0.665)	(−0.070)	(0.278)	(0.648)	(0.344)	(−0.361)	(1.274)
$R_{3,0}$	0.001	−0.001	−0.002*	−0.000	0.001	0.001	−0.000	−0.001
	(0.747)	(−1.284)	(−1.952)	(−0.264)	(1.146)	(0.615)	(−0.160)	(−1.014)
$R_{4,0}$	−0.001	0.001	0.002**	0.000	−0.001*	0.000	0.000	0.001
	(−0.896)	(1.007)	(2.283)	(0.448)	(−1.839)	(0.417)	(0.175)	(0.895)
Volume	0.029	0.060**	0.017	−0.038	−0.033	−0.038	−0.056	−0.055
	(1.243)	(2.540)	(0.709)	(−1.603)	(−1.186)	(−1.066)	(−1.531)	(−1.429)
Vol	−0.008	−0.066***	−0.020	0.028	0.031	−0.057**	−0.041	−0.026
	(−0.416)	(−3.260)	(−0.972)	(1.343)	(1.329)	(−2.082)	(−1.439)	(−0.867)
Coin FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.017	0.018	0.017	0.010	0.003	0.013	0.011	0.008

Table 7. Robust Results of Forecasting Coin Returns

Panel A reports results of forecasting the top 25% large and the bottom 25% small market size coins, respectively. In each subsample, we regress the h-week cryptocurrency returns on current investor sentiment and control variables that include the market capitalization (MCAP), the weekly price (PRC), the maximum price (MAXDPRC) in a week, the past one-week return ($R_{1,0}$), the past two-week return ($R_{2,0}$), the past three-week return ($R_{3,0}$), the past four-week return ($R_{4,0}$), the average daily volume (Volume) in a week, and the volatility of daily trading volume (Vol) in a week. Panel B shows the results for the top 25% high volume and the bottom 25% low volume coins, respectively. Standard errors are clustered by time. To save space, we only present the regression slope on investor sentiment and corresponding t-statistics in the parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	Panel A: Size		Panel B: Volume	
	Large	Small	High	Low
1 week	4.260***	0.516	4.077***	1.075
	(3.155)	(0.507)	(3.531)	(1.126)
4 weeks	12.447***	2.731	10.227***	2.794
	(4.532)	(1.516)	(4.194)	(1.587)
12 weeks	16.337***	7.937***	16.033***	6.103**
	(3.789)	(2.757)	(4.249)	(2.189)
48 weeks	3.348	10.227***	−6.835	10.440***
	(0.657)	(2.761)	(−1.398)	(2.977)
72 weeks	−9.752**	1.325	−16.745***	−2.237
	(−2.076)	(0.388)	(−3.583)	(−0.675)
84 weeks	−11.074***	−6.112*	−11.255***	−10.827***
	(−2.593)	(−1.821)	(−2.671)	(−3.339)
88 weeks	−9.240**	−5.634*	−5.247	−9.733***
	(−2.212)	(−1.716)	(−1.232)	(−3.028)
92 weeks	−5.711	−2.577	−6.288	−7.285**
	(−1.426)	(−0.793)	(−1.512)	(−2.304)

Table 8. Forecasting Results for Heterogeneous Coins

In panel A, we sort coins according to the proportions of short-term traders (their holding periods are less than one month) and select the top 25% coins. We regress the h-week returns of these cryptocurrencies on their sentiment (S) and controls. Standard errors are clustered by time. To save space, we only report the regression slopes and t-statistics in the parentheses for S. The regression R^2s are also reported. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. In panel B, we sort coins according to the proportions of long-term holders (their holding periods are more than one year) and select the top 25% coins. We then analyze the return predictability for these coins.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$h=$	1 week	4 weeks	12 weeks	48 weeks	72 weeks	84 weeks	88 weeks	92 weeks
Panel A: Results for coins that have a large proportion of short-term traders								
S	3.806***	12.342***	25.633***	1.412	−12.590	−14.672**	−14.738**	−18.222**
	(2.694)	(4.270)	(5.305)	(0.199)	(−1.579)	(−2.099)	(−2.143)	(−2.543)
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Coin FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.022	0.066	0.152	0.461	0.621	0.701	0.702	0.709
Panel B: Results for coins that have a large proportion of long-term holders								
S	0.761	4.850**	15.072***	11.760**	2.003	5.688	6.442	0.591
	(0.631)	(2.100)	(4.556)	(2.277)	(0.360)	(1.015)	(1.149)	(0.106)
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Coin FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.030	0.099	0.223	0.433	0.564	0.514	0.533	0.550

Table 9. Results for the Analysis of Underlying Mechanism

In panel A, we sort coins according to the proportions of short-term traders (their holding periods are less than one month) and select the top 25% coins. For these cryptocurrencies, we regress the number of new addresses on sentiment (S) and control variables over the h period. In panel B, we sort coins according to the proportions of long-term holders (their holding periods are more than one year) and select the top 25% coins. For these cryptocurrencies, we regress the number of new addresses on sentiment (S) and control variables over the h period. Standard errors are clustered by time. To save space, we only report the regression slopes and t-statistics in the parentheses for S. The regression R^2s are also reported. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$h =$	1 week	4 weeks	12 weeks	48 weeks	72 weeks	84 weeks	88 weeks	92 weeks
Panel A: Results for coins that have a large proportion of short-term traders								
S	0.384***	0.306**	0.064	−0.037	−0.877***	−0.410***	−0.277**	−0.178
	(2.757)	(2.119)	(0.421)	(−0.211)	(−5.040)	(−2.845)	(−2.007)	(−1.321)
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Coin FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.250	0.225	0.214	0.253	0.400	0.472	0.508	0.499
Panel B: Results for coins that have a large proportion of long-term holders								
S	0.259***	0.294***	0.316***	0.062	0.034	0.185**	0.120	0.023
	(5.072)	(5.554)	(5.501)	(0.923)	(0.446)	(2.178)	(1.468)	(0.280)
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Coin FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.155	0.105	0.063	0.002	0.008	0.018	0.029	0.016

Table 10. Results for Decomposing the Momentum Effect

With the decomposition method proposed by Hou and Loh (2016), the momentum effect is decomposed into a component that is related to a candidate variable and a residual component. The table reports the slopes of decomposed components and fractions of each candidate. The time-series average of β_t^C (β_t^R) divided by the time-series average of β_t measures the fraction of candidate (residual) contribution. Time-series averages of estimated coefficients are reported with t-statistics in parentheses. Candidate variables include investor sentiment (S), the number of new addresses (NA), the number of active addresses (AA), the number of transactions (TRAN), the capital gains overhang variable (CGO), the 52-week high price (52W), trading volume volatility (TVOL), the turnover ratio (TURN), and the media coverage (COV). Appendix A provides detailed variable definitions and constructions. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Variable	S	NA	AA	TRAN	CGO	52W	TVOL	TURN	COV
Candidate component	83.294%***	32.456%***	24.522%***	25.552%***	16.102%***	17.523%***	−0.947%	−0.193%	−10.293%***
	(35.376)	(23.859)	(20.801)	(25.560)	(6.971)	(12.954)	(−0.748)	(−0.119)	(−10.931)
Residual component	16.706%***	67.544%***	75.478%***	74.448%***	83.898%***	82.477%***	100.947%***	100.193%***	110.293%***
	(7.095)	(49.652)	(64.023)	(74.473)	(36.322)	(60.971)	(79.712)	(61.704)	(117.136)

Table 11. Results for Decomposing the Long-term Reversal Effect

This table reports results for decomposing long-term reversal effect in coins with more short-term traders participating. We sort coins according to the proportions of short-term traders (their holding periods are less than one month) and select the top 50% coins. The time-series average of β_t^C (β_t^R) divided by the time-series average of β_t measures the fraction of candidate (residual) contribution. The t-statistics are in parentheses. Candidate variables include investor sentiment (S), the number of new addresses (NA), the number of active addresses (AA), the number of transactions (TRAN), the capital gains overhang variable (CGO), the 52-week high price (52W), trading volume volatility (TVOL), the turnover ratio (TURN), and the media coverage (COV). Appendix A provides detailed variable definitions and constructions. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Variable	S	NA	AA	TRAN	CGO	52W	TVOL	TURN	COV
Candidate component	56.429%***	21.268%***	7.691%***	−9.557%***	39.905%***	33.189%***	29.398%***	45.729%***	9.177%***
	(37.409)	(29.156)	(12.042)	(−9.037)	(25.821)	(31.318)	(30.954)	(38.312)	(14.204)
Residual component	43.571%***	78.732%***	92.309%***	109.557%***	60.095%***	66.811%***	70.602%***	54.271%***	90.823%***
	(28.885)	(107.932)	(144.535)	(103.604)	(38.886)	(63.045)	(74.337)	(45.470)	(140.582)

Internet Appendix for

Investor Sentiment and Cryptocurrency Returns

September 12, 2024

This Internet Appendix reports the results of supplementary and robustness tests:

Table IA 1: Forecasting Results for News Sentiment

Table IA 2: Forecasting Results for Social Media Sentiment

Table IA 3. Forecasting Results under Control of Salience Theory

Table IA 4. Robust Results for Regressions of Sentiment on Past Participation (Number of Active Addresses)

Table IA 5. Robust Results for Regressions of Sentiment on Past Participation (Number of Transactions)

Table IA 6. Robust Results for the Analysis of Underlying Mechanism (Number of Active Addresses)

Table IA 7. Robust Results for the Analysis of Underlying Mechanism (Number of Transactions)

Table IA 1. Forecasting Results for News Sentiment

This table presents results of the predictive regressions,

$$R_{i,t+h} = \alpha + \beta\, S_{i,t}^{News} + \psi \mathbf{X}_{i,t} + \varepsilon_{i,t}\ ,$$

where $R_{i,t+h}$ is the weekly excess return of cryptocurrency i over the prediction horizon h and $h = 1$, 4, 12, 48, 72, 84, 88, and 92 weeks; $S_{i,t}^{News}$ is the news sentiment on cryptocurrency i at time t; and $\mathbf{X}_{i,t}$ is a vector of control variables, including the market capitalization (MCAP), the weekly price (PRC), the maximum price (MAXDPRC) in a week, the past one-week return ($R_{1,0}$), the past two-week return ($R_{2,0}$), the past three-week return ($R_{3,0}$), the past four-week return ($R_{4,0}$), the average daily volume (Volume) in a week, and the volatility of daily trading volume (Vol) in a week. Standard errors are clustered by time. Reported are the regression slopes, t-statistics in the parentheses, and R^2s. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	(1) 1 week	(2) 4 weeks	(3) 12 weeks	(4) 48 weeks	(5) 72 weeks	(6) 84 weeks	(7) 88 weeks	(8) 92 weeks
S^{News}	0.838**	0.537	1.507	−3.060**	−2.531*	−2.396*	−3.056**	−3.060**
	(2.498)	(0.845)	(1.595)	(−2.295)	(−1.818)	(−1.706)	(−2.185)	(−2.181)
MCAP	−0.127	−1.880***	−3.922***	−2.630	−0.252	−1.091	−0.842	0.330
	(−0.378)	(−2.891)	(−3.713)	(−1.558)	(−0.138)	(−0.578)	(−0.447)	(0.177)
PRC	−6.819***	−14.641***	−27.203***	−83.486***	−94.999***	−105.717***	−114.438***	−117.719***
	(−5.174)	(−5.740)	(−7.277)	(−16.345)	(−18.198)	(−20.013)	(−22.192)	(−22.860)
MAXDPRC	4.198***	4.656*	2.214	5.271	−0.909	7.386	15.476***	17.755***
	(3.305)	(1.896)	(0.621)	(1.100)	(−0.188)	(1.506)	(3.239)	(3.711)
$R_{1,0}$	0.003	−0.002	−0.007	0.000	0.001	0.024	0.028	0.022
	(0.380)	(−0.132)	(−0.337)	(0.015)	(0.025)	(0.965)	(1.109)	(0.862)
$R_{2,0}$	0.017*	0.014	0.018	0.012	0.017	0.006	0.010	0.007
	(1.830)	(0.827)	(0.768)	(0.398)	(0.607)	(0.233)	(0.362)	(0.268)
$R_{3,0}$	−0.013	−0.016	−0.033	−0.018	−0.014	−0.012	−0.018	−0.011
	(−1.401)	(−1.006)	(−1.426)	(−0.620)	(−0.497)	(−0.441)	(−0.687)	(−0.441)
$R_{4,0}$	−0.010	−0.022*	−0.064***	−0.007	0.021	0.017	0.003	0.018
	(−1.480)	(−1.858)	(−3.798)	(−0.324)	(1.082)	(0.878)	(0.171)	(0.951)
Volume	0.747***	2.708***	4.321***	10.457***	10.663***	8.049***	7.292***	5.569***
	(4.003)	(7.755)	(8.321)	(14.432)	(13.421)	(9.759)	(8.771)	(6.568)
Vol	−0.847***	−2.146***	−3.108***	−4.392***	−4.662***	−3.504***	−3.117***	−2.351***
	(−5.248)	(−7.087)	(−6.904)	(−7.198)	(−7.247)	(−5.354)	(−4.756)	(−3.540)
Coin FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.020	0.072	0.179	0.474	0.579	0.625	0.643	0.656

Table IA 2. Forecasting Results for Social Media Sentiment

This table presents results of the predictive regressions,

$$R_{i,t+h} = \alpha + \beta S_{i,t}^{Social} + \psi \mathbf{X}_{i,t} + \varepsilon_{i,t} \ ,$$

where $R_{i,t+h}$ is the weekly excess return of cryptocurrency i over the prediction horizon h and $h = 1$, 4, 12, 48, 72, 84, 88, and 92 weeks; S^{Social} is the social media sentiment on cryptocurrency i at time t; and $\mathbf{X}_{i,t}$ is a vector of control variables, including the market capitalization (MCAP), the weekly price (PRC), the maximum price (MAXDPRC) in a week, the past one-week return ($R_{1,0}$), the past two-week return ($R_{2,0}$), the past three-week return ($R_{3,0}$), the past four-week return ($R_{4,0}$), the average daily volume (Volume) in a week, and the volatility of daily trading volume (Vol) in a week. Standard errors are clustered by time. Reported are the regression slopes, t-statistics in the parentheses, and R^2s. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	(1) 1 week	(2) 4 weeks	(3) 12 weeks	(4) 48 weeks	(5) 72 weeks	(6) 84 weeks	(7) 88 weeks	(8) 92 weeks
S^{Social}	0.633	2.348***	5.109***	4.071**	−2.526	−5.303***	−4.042**	−3.054*
	(1.388)	(2.766)	(3.826)	(2.143)	(−1.329)	(−2.849)	(−2.192)	(−1.685)
MCAP	−0.278	−2.525***	−4.790***	−10.474***	−13.046***	−13.710***	−12.445***	−10.486***
	(−0.774)	(−3.803)	(−4.429)	(−6.247)	(−7.244)	(−7.295)	(−6.605)	(−5.570)
PRC	−5.176***	−5.663**	−17.371***	−69.339***	−80.114***	−90.838***	−100.653***	−104.081***
	(−3.819)	(−2.327)	(−4.774)	(−14.210)	(−16.358)	(−18.091)	(−20.479)	(−21.191)
MAXDPRC	2.887**	−2.541	−5.781*	2.087	−0.122	6.945	14.283***	15.175***
	(2.212)	(−1.090)	(−1.672)	(0.460)	(−0.027)	(1.496)	(3.148)	(3.341)
$R_{1,0}$	0.022**	0.013	0.010	0.004	0.020	0.019	0.027	0.016
	(2.510)	(0.910)	(0.457)	(0.146)	(0.844)	(0.807)	(1.149)	(0.664)
$R_{2,0}$	−0.006	−0.023	−0.004	0.002	0.013	0.016	0.005	0.010
	(−0.694)	(−1.465)	(−0.189)	(0.058)	(0.486)	(0.632)	(0.212)	(0.384)
$R_{3,0}$	−0.012	−0.006	−0.034	−0.021	−0.023	−0.023	−0.023	−0.018
	(−1.390)	(−0.417)	(−1.528)	(−0.767)	(−0.924)	(−0.944)	(−0.921)	(−0.753)
$R_{4,0}$	−0.005	−0.021**	−0.042**	−0.004	0.010	0.017	0.010	0.027
	(−0.883)	(−1.965)	(−2.574)	(−0.211)	(0.552)	(0.981)	(0.591)	(1.549)
Volume	0.520***	1.943***	3.513***	8.183***	7.812***	5.781***	4.845***	3.264***
	(2.946)	(5.872)	(6.995)	(11.945)	(10.372)	(7.336)	(6.060)	(4.004)
Vol	−0.629***	−1.402***	−2.418***	−3.755***	−3.569***	−2.514***	−1.857***	−0.947
Coin FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.017	0.061	0.162	0.450	0.566	0.609	0.626	0.641

Table IA 3. Forecasting Results under Control of Salience Theory

This table presents results of the predictive regressions,

$$R_{i,t+h} = \alpha + \beta\, S_{i,t} + \gamma ST_{i,t} + \psi \mathbf{X}_{i,t} + \varepsilon_{i,t}\ ,$$

where $R_{i,t+h}$ is the weekly excess return of cryptocurrency i over the prediction horizon h and $h = 1$, 4, 12, 48, 72, 84, 88, and 92 weeks; $S_{i,t}$ is the sentiment on cryptocurrency i at time t; $ST_{i,t}$ is the salience theory measure of cryptocurrency i at time t (see Cosemans and Frehen, 2021; Cakici and Zaremba, 2022, for details of the construction of the salience theory measure) ; and $\mathbf{X}_{i,t}$ is a vector of control variables, including the market capitalization (MCAP), the last day price (PRC) in a week, the maximum price (MAXDPRC) in a week, the past one-week return ($R_{1,0}$), the past two-week return ($R_{2,0}$), the past three-week return ($R_{3,0}$), the past four-week return ($R_{4,0}$), the average daily volume (Volume) in a week, and the volatility of daily trading volume (Vol) in a week. Standard errors are clustered by time. Reported are the regression slopes, t-statistics in the parentheses, and R^2s. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	(1) 1 week	(2) 4 weeks	(3) 12 weeks	(4) 48 weeks	(5) 72 weeks	(6) 84 weeks	(7) 88 weeks	(8) 92 weeks
S	1.230**	2.913***	6.171***	6.916***	−1.687	−5.073**	−4.495**	−3.400*
	(2.415)	(3.041)	(4.028)	(3.153)	(−0.778)	(−2.382)	(−2.150)	(−1.657)
ST	−0.033	−0.253**	−0.586***	−0.490**	−0.208	−0.161	−0.083	−0.108
	(−0.592)	(−2.522)	(−4.100)	(−2.521)	(−1.126)	(−0.877)	(−0.457)	(−0.587)
MCAP	−0.313	−2.460***	−4.531***	−2.475	−0.308	−1.640	−1.279	−0.487
	(−0.958)	(−3.935)	(−4.428)	(−1.559)	(−0.183)	(−0.943)	(−0.739)	(−0.284)
PRC	−5.342***	−4.979**	−15.946***	−78.896***	−94.961***	−104.998***	−113.564***	−115.932***
	(−4.117)	(−2.076)	(−4.392)	(−15.748)	(−19.141)	(−20.973)	(−23.123)	(−23.619)
MAXDPRC	3.133**	−3.033	−6.803*	3.515	1.132	8.533*	15.999***	17.426***
	(2.498)	(−1.315)	(−1.959)	(0.743)	(0.244)	(1.824)	(3.487)	(3.790)
$R_{1,0}$	0.020**	0.015	0.017	0.011	0.029	0.028	0.032	0.025
	(2.324)	(1.024)	(0.788)	(0.429)	(1.198)	(1.190)	(1.378)	(1.052)
$R_{2,0}$	−0.003	−0.021	−0.005	−0.008	−0.001	0.001	−0.004	−0.001
	(−0.296)	(−1.327)	(−0.239)	(−0.294)	(−0.053)	(0.037)	(−0.150)	(−0.042)
$R_{3,0}$	−0.015*	−0.004	−0.027	−0.007	−0.012	−0.007	−0.008	−0.007
	(−1.757)	(−0.247)	(−1.189)	(−0.250)	(−0.475)	(−0.302)	(−0.305)	(−0.288)
$R_{4,0}$	−0.005	−0.024**	−0.049***	−0.009	0.007	0.012	0.002	0.018
	(−0.752)	(−2.210)	(−3.067)	(−0.447)	(0.358)	(0.711)	(0.095)	(0.997)
Volume	0.610***	2.008***	3.272***	8.419***	8.235***	5.851***	4.939***	3.199***
	(3.497)	(6.096)	(6.524)	(12.080)	(10.804)	(7.338)	(6.138)	(3.908)
Vol	−0.669***	−1.470***	−2.250***	−3.769***	−3.596***	−2.388***	−1.897***	−0.958
Coin FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.017	0.059	0.160	0.450	0.575	0.619	0.637	0.652

Table IA 4. Robust Results for Regressions of Sentiment on Past Participation (Number of Active Addresses)

This table presents results of the following regressions,

$$S_{i,t} = \alpha + \beta AA_{i,t-L} + \psi \mathbf{Z}_{i,t-L} + \varepsilon_{i,t} \ ,$$

where $S_{i,t}$ is the investor sentiment on cryptocurrency i; $AA_{i,t-L}$ is the logarithm of one plus the number of active addresses, defined as addresses that made at least one transaction on a given day, of coin i in $t-L$, and $L = 1$, 2, 3, 4, 8, and 12 weeks; $\mathbf{Z}_{i,t-L}$ is the control variables that include the past accumulated returns ($R_{L,0}$), the market capitalization (MCAP), the weekly price (PRC), the maximum price (MAXDPRC) in a week, the average daily volume (Volume) in a week, and the volatility of daily trading volume (Vol) in a week. Standard errors are clustered by time. Reported are the regression slopes, t-statistics in the parentheses, and R^2s. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
$L =$	1 week	2 weeks	3 weeks	4 weeks	8 weeks	12 weeks
AA	0.008***	0.007***	0.007***	0.007***	0.006***	0.005***
	(3.984)	(3.651)	(3.713)	(3.532)	(3.209)	(2.787)
$R_{L,0}$	0.044***	0.036***	0.030***	0.020***	0.014***	0.012***
	(6.099)	(6.260)	(6.145)	(4.551)	(3.919)	(3.500)
MCAP	−0.008	−0.007	−0.009	−0.009	−0.011*	−0.013**
	(−1.472)	(−1.266)	(−1.574)	(−1.619)	(−1.921)	(−2.182)
PRC	0.035*	0.008	−0.005	−0.005	−0.024	0.006
	(1.776)	(0.407)	(−0.244)	(−0.259)	(−1.314)	(0.302)
MAXDPRC	−0.031	−0.005	0.011	0.014	0.035**	0.006
	(−1.602)	(−0.256)	(0.531)	(0.695)	(2.006)	(0.333)
Volume	0.010***	0.008***	0.010***	0.009***	0.009***	0.008***
	(3.515)	(2.811)	(3.340)	(3.200)	(3.004)	(2.740)
Vol	−0.006**	−0.004	−0.006**	−0.008***	−0.006**	−0.004
	(−2.298)	(−1.464)	(−2.403)	(−3.056)	(−2.251)	(−1.555)
Coin FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.006	0.005	0.005	0.003	0.003	0.003

Table IA 5. Robust Results for Regressions of Sentiment on Past Participation (Number of Transactions)

This table presents results of the following regressions,

$$S_{i,t} = \alpha + \beta TRAN_{i,t-L} + \psi \mathbf{Z}_{i,t-L} + \varepsilon_{i,t} \ ,$$

where $S_{i,t}$ is the investor sentiment on cryptocurrency i; $TRAN_{i,t-L}$ is the logarithm of one plus the number of transactions of coin i in $t-L$, and $L = 1$, 2, 3, 4, 8, and 12 weeks; $\mathbf{Z}_{i,t-L}$ is the control variables that include the past accumulated returns ($R_{L,0}$), the market capitalization (MCAP), the weekly price (PRC), the maximum price (MAXDPRC) in a week, the average daily volume (Volume) in a week, and the volatility of daily trading volume (Vol) in a week. Standard errors are clustered by time. Reported are the regression slopes, t-statistics in the parentheses, and R^2s. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
$L =$	1 week	2 weeks	3 weeks	4 weeks	8 weeks	12 weeks
TRAN	0.007***	0.007***	0.007***	0.007***	0.006***	0.005***
	(4.067)	(4.083)	(3.871)	(3.939)	(3.215)	(2.667)
$R_{L,0}$	0.043***	0.035***	0.030***	0.020***	0.014***	0.012***
	(6.061)	(6.197)	(6.106)	(4.488)	(3.897)	(3.494)
MCAP	−0.009	−0.008	−0.009	−0.010*	−0.011*	−0.013**
	(−1.521)	(−1.367)	(−1.636)	(−1.711)	(−1.954)	(−2.195)
PRC	0.036*	0.010	−0.004	−0.004	−0.023	0.006
	(1.826)	(0.493)	(−0.194)	(−0.184)	(−1.280)	(0.319)
MAXDPRC	−0.032	−0.006	0.010	0.012	0.035**	0.006
	(−1.641)	(−0.335)	(0.491)	(0.629)	(1.986)	(0.331)
Volume	0.010***	0.008***	0.010***	0.009***	0.009***	0.008***
	(3.544)	(2.817)	(3.364)	(3.209)	(3.026)	(2.766)
Vol	−0.006**	−0.004	−0.006**	−0.008***	−0.006**	−0.004
	(−2.406)	(−1.586)	(−2.511)	(−3.172)	(−2.334)	(−1.622)
Coin FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.006	0.005	0.005	0.004	0.003	0.003

Table IA 6. Robust Results for the Analysis of Underlying Mechanism (Number of Active Addresses)

In panel A, we sort coins according to the proportions of short-term traders (their holding periods are less than one month) and select the top 25% coins. For these cryptocurrencies, we regress the number of active addresses on sentiment (S) and control variables over the h period. In panel B, we sort coins according to the proportions of long-term holders (their holding periods are more than one year) and select the top 25% coins. For these cryptocurrencies, we regress the number of active addresses on sentiment (S) and control variables over the h period. The number of active addresses is defined as the logarithms of one plus the number of active addresses that made at least one transaction within each week. Standard errors are clustered by time. To save space, we only report the regression slopes and t-statistics in the parentheses for S. The regression R^2s are also reported. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$h =$	1 week	4 weeks	12 weeks	48 weeks	72 weeks	84 weeks	88 weeks	92 weeks
Panel A: Results for coins that have a large proportion of short-term traders								
S	0.456***	0.345**	0.104	−0.043	−0.936***	−0.401***	−0.319**	−0.274**
	(3.485)	(2.561)	(0.717)	(−0.241)	(−4.932)	(−2.717)	(−2.283)	(−2.088)
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Coin FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.252	0.231	0.222	0.266	0.411	0.501	0.537	0.547
Panel B: Results for coins that have a large proportion of long-term holders								
S	0.244***	0.324***	0.395***	0.125*	0.051	0.258***	0.214**	0.155*
	(4.510)	(5.774)	(6.594)	(1.872)	(0.712)	(3.141)	(2.489)	(1.954)
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Coin FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.113	0.080	0.052	0.004	0.009	0.026	0.041	0.021

Table IA 7. Robust Results for the Analysis of Underlying Mechanism (Number of Transactions)

In panel A, we sort coins according to the proportions of short-term traders (their holding periods are less than one month) and select the top 25% coins. For these cryptocurrencies, we regress the number of transactions on sentiment (S) and control variables over the h period. In panel B, we sort coins according to the proportions of long-term holders (their holding periods are more than one year) and select the top 25% coins. For these cryptocurrencies, we regress the number of transactions on sentiment (S) and control variables over the h period. The number of transactions is defined as the logarithms of one plus the number of on-chain transactions within each week. Standard errors are clustered by time. To save space, we only report the regression slopes and t-statistics in the parentheses for S. The regression R^2s are also reported. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$h=$	1 week	4 weeks	12 weeks	48 weeks	72 weeks	84 weeks	88 weeks	92 weeks
Panel A: Results for coins that have a large proportion of short-term traders								
S	0.401***	0.401***	0.105	−0.129	−0.760***	−0.276*	−0.229	−0.186
	(2.841)	(2.776)	(0.669)	(−0.682)	(−3.844)	(−1.794)	(−1.520)	(−1.288)
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Coin FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.252	0.227	0.204	0.231	0.382	0.471	0.504	0.504
Panel B: Results for coins that have a large proportion of long-term holders								
S	0.269***	0.333***	0.469***	0.175**	0.061	0.374***	0.279***	0.082
	(4.180)	(4.944)	(6.499)	(2.141)	(0.687)	(3.755)	(2.702)	(0.815)
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Coin FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.103	0.072	0.049	0.003	0.006	0.021	0.031	0.015