Salience theory in Cryptocurrency returns and trading volume: Empirical evidence

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Abstract

In our research focusing on the cryptocurrency market, we find that the Salience theory (ST) effect based on returns and trading volume exhibits negative predictive power in forecasting return trends in the cryptocurrency market. Unlike studies in the stock market, in the cryptocurrency market the ST effect exhibits a greater negative effect and stronger persistence. Further, our findings highlight the critical role of trading volume, which has often been overlooked in previous studies of cryptocurrency asset pricing. We find that investors in the cryptocurrency market are more sensitive to fluctuations in trading volume, causing the volume-based ST effect to exhibit a stronger effect compared to the return-based ST effect. When factors such as market capitalization size, lottery preferences, reversal effects, investor sentiment, and investor attention are taken into account, the ST effect changes significantly differently than in the stock market. The unique dynamics of asset pricing in cryptocurrency markets are such that the ST effect will show the strongest negative effect in the mid-cap group.

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1. Introduction

Asset pricing in the cryptocurrency market represents a highly challenging arena. Due to the unique and rapidly evolving nature of this market, valuing assets becomes complex and highly uncertain. Unlike traditional investment assets such as stocks, cryptocurrencies are fundamentally based on a series of underlying technologies (Yuan & Wang (2018)), which is why they are considered alternative assets, lacking traditional fundamental support. This means that traditional financial analysis models have limited applicability in this field. However, the rapid development of the cryptocurrency market, coupled with increasing investor participation, makes it an unavoidable subject of interest. Compared to the mature data systems in the stock market, the data available for reference in the cryptocurrency market is relatively limited. This data typically includes historical returns, trading volumes, market capitalization, and circulating supply. In the absence of traditional fundamental data, these market-driven data points become key factors in influencing investor decision-making. Furthermore, the process of price discovery in cryptocurrencies is also unique. Unlike traditional assets, whose value is typically determined by a company's financial performance and the market's economic environment, the value of cryptocurrencies is heavily

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influenced by market sentiment, technological innovation, regulatory policies, and global macroeconomic conditions (Makarov & Schoar (2020)). For instance, the introduction of new technology or a change in regulatory policies by a major country can significantly impact the price of a specific cryptocurrency. In such a dynamic and evolving market, investors and analysts need to adopt more flexible and innovative approaches to evaluate the value of cryptocurrencies. As the market matures and its participants diversify, the cryptocurrency asset pricing mechanism continues to evolve. The increasing incorporation of cryptocurrencies into investment portfolios raises a new question: how to price cryptocurrencies and discover their true value?

In the field of behavioral finance, there exists the salience theory. Researchers such as Bordalo et al. (2012) argue that investors are irrational and tend to overemphasize salient features, such as potential high returns or high risks, when making investment choices, rather than basing their decisions on a comprehensive risk-reward assessment. This leads them to focus excessively on assets with extreme returns or volatility, while neglecting assets with average performance. This behavior is particularly evident in the cryptocurrency market. In this rapidly changing and highly uncertain market, irrational investors tend to give excessive attention to cryptocurrencies with the potential for extreme returns or volatility, while overlooking the potential risks associated with them. This decision-making bias based on salience leads to subjectivity in the objective decision weights. Assets with strong salience in the cryptocurrency market often attract a large number of buyers in the short term, but this may also increase the risk of future price declines. Conversely, assets with weaker salience, although potentially undervalued and overlooked in the short term, may exhibit an upward trend in the long run due to their intrinsic value. Therefore, for participants in cryptocurrency market investment, understanding and identifying this behavioral pattern is crucial for formulating more robust and effective investment strategies.

The salience effect has indeed been preliminarily observed in the stock market. Cosemans & Frehen (2021) first demonstrates the existence of the salience effect in the U.S. stock market. Subsequently, Cakici & Zaremba (2022) confirms its presence in a broader market context. Furthermore, Cakici & Zaremba (2022) finds that markets with less available information tend to exhibit a stronger salience effect because investors have limited information available, leading them to assign higher weights to information such as past returns. This indirectly enhances the salience effect. Compared to the traditional stock market, the cryptocurrency market often lacks sufficient transparency and standardized information disclosure mechanisms. This information asymmetry and limitation may cause investors to rely more on available salient information, such as historical price performance and trading volume, thereby enhancing the salience effect. Therefore, we believe that the salience effect in the cryptocurrency market is likely to be more pronounced than in the stock market. While Cai & Zhao (2023) have made preliminary findings regarding the salience effect in the cryptocurrency market, our experiment, although not built upon their work, further supports their findings. Additionally, by expanding the precision of the experiment and conducting further research, we can discover more.

Trading volume is an important indicator for measuring market activity. High trading volume typically indicates an active market with a large number of buying and selling transactions taking place. This activity can attract more investors and increase market liquidity. Trading volume is also an important measure of market liquidity. A market with high liquidity makes buying and selling easier, reducing transaction costs and price fluctuations. Moreover, the information conveyed by trading volume in the cryptocurrency market may be more relevant to investors. King & Koutmos (2021) argue that investors in the cryptocurrency market are significantly influenced by high trading volumes. Considering the potential criminal activities such as money laundering that may exist in the cryptocurrency market (Trozze et al. (2022)), *trading volume may be a more important indicator* for investors than returns, as significant trading volume implies greater security. Furthermore, regarding the salience effect, it is worth noting that high trading volume can contribute to the salience of a cryptocurrency. When a cryptocurrency experiences a surge in trading volume, it becomes more noticeable to market participants, potentially leading to increased attention and investor interest. This heightened salience can impact the price dynamics of the cryptocurrency, as investors may be more inclined to buy or sell based on the increased visibility and perceived significance of the asset. Meanwhile, as far as the ST effect is concerned, it is also possible to construct an ST indicator based on volume fluctuations. Sun et al. (2023) construct a volume-based ST indicator in the Chinese stock market. We believe that a volume-based ST indicator can also be constructed in the cryptocurrency market using a proxy variable for volume.

In this study, we delve into the intriguing dynamics of the cryptocurrency market, examining the full developmental cycle from ascent to decline. We have utilized comprehensive data from CryptoCompare, covering the period from 2013 to 2023, and have included over 4000 cryptocurrencies each with a market capitalization exceeding 1 million. Our analysis is centered around two specially constructed indicators: the Salience Theory based on daily returns (STR) and another based on daily volume volatility (STV).

Our empirical results unfold in two segments. The first part pertains to the empirical validation of the ST effect. Initial univariate analyses, involving the computation of average returns and multifactor ALPHA values across various ST groups, reveal a decrement in returns with increasing ST values, indicating a negative ST effect in the cryptocurrency market. Remarkably, this effect is more pronounced than what Cakici & Zaremba (2022) observes in global stock markets, with a significant spread of -8.6% in high-low returns in extreme ST groups. Contrary to the findings of Cai & Zhao (2023), our results show minor fluctuations in the extreme positive segments of ST, suggesting the influence of other similar effects and necessitating further experiments. In the subsequent bivariate sorting experiments, the most critical finding is the non-substitutability of STR and STV when cross-examined, underscoring the necessity to independently examine returns and volume.

Interestingly, different from Cosemans & Frehen (2021) in stock markets, our study finds that extreme ST groups in cryptocurrency markets often exhibit lower average prices, higher specific volatilities, and nearly constant market capitalizations across groups. This suggests that the ST effect in cryptocurrency markets might not be confined to small-cap segments as in stock markets. Our Fama-Macbeth regressions reveal a strong negative impact of both STR and STV on future one-month returns of cryptocurrencies. The influence of both indicators persists negatively, albeit weakened, even with the inclusion of control variables. Notably, compared to STR, STV exerts a stronger impact on future returns, possibly due to higher liquidity and reduced likelihood of fraudulent activities in cryptocurrencies with higher STV.

The second part of our study focuses on robustness tests, assessing whether the ST effect is encompassed within other established market phenomena. Calculating the ST effect across different market cap groups, we find the STR (STV) effect to be prevalent but most pronounced in the mid-cap group, deviating from the micro-cap prominence observed in stock markets. This suggests that a robust ST effect in cryptocurrency markets might not necessarily correlate with smaller market caps. Tests with arbitrage constraints indicate that smaller market caps, lower liquidity levels, and higher volatilities often intensified the STR (STV) effect. Our experiments also confirm that in the cryptocurrency market, the STV indicator does not substitute for abnormal turnover(ABTURN). Based on our Fama-Macbeth regression outcomes, we explore the 'Lottery preference' as a potential alternative effect for ST. Inspired by Kumar et al. (2016), the experiments conducted by our constructed Lottery Preference Index (LIDX index) consistently show that the STR (STV) effect is negative in different lottery preference environments and increases with the increase of lottery preference.

Further, examining the potential substitution relationship between the Reversal effect and the salience effect over various time frames, we find persistent negative differentials between high and low ST groups, devoid of reversal signs even over extended periods. The incorporation of the emotional index, FNG, reveals that STR (STV) displays significant negative effects across different emotional periods, with amplified impacts during high-emotion phases. Although considering the attention effect slightly weakens the ST effect, its negative significance remains, aligning with our expectations given the nuanced differences between the two effects. Finally, by observing price trends before and after ST effect occurrences, we identify positive and negative price pressures induced by the ST effect, potentially elucidating the operational mechanisms behind the ST effects manifestation, where the salience-induced mispricing persists over the following six months, particularly evident in STV's durability.

The primary contributions of our study are manifold and significant in advancing the understanding of asset pricing in the cryptocurrency market. We have introduced two pivotal factors: STR and STV, which, considering their exceptional predictive power for returns, emerge as potent explicators of earnings in the cryptocurrency domain. Our research, through its expanded scope and multidimensional approach, has unearthed distinctive characteristics of the ST effect in the cryptocurrency market, distinguishing it markedly from its manifestation in stock markets. Furthermore, this effect consistently presents a significant negative impact and stands independent of other established effects.

On the other hand, our findings accentuate the influential role of volume volatility in shaping investor behavior within the cryptocurrency landscape. Particularly regarding the ST effect, its volume-based variant exerts a more pronounced influence. A critical observation is the prolonged duration of mispricing induced by the ST effect in the cryptocurrency market, suggesting a more sustained impact compared to traditional markets. Thus, the ST effect in cryptocurrencies is not a mere replication of its stock market counterpart but is characterized by distinct features. Moreover, the study of volume movements assumes a greater significance in the realm of cryptocurrencies, potentially offering deeper insights into market dynamics and investor behavior.

In summary, our research contributes two effective influencing factors to the empirical asset pricing in the cryptocurrency market, thereby expanding the literature in this field. Our study not only substantiates the research on the ST effect but also broadens its application scope and methodologies. This work not only enriches the understanding of asset dynamics in the evolving landscape of cryptocurrencies but also paves the way for future explorations into the nuanced mechanisms driving market behavior in this domain.

Related Literature.—Our research primarily relates to three types of academic literature and contributes in these three aspects. The first aspect pertains to the measurement of the traditional salience theory. Bordalo et al. (2012) argue that investors have limited capacity to process information when making portfolio choices. This limited processing ability leads investors to focus on more salient risky assets, giving rise to the salience theory (ST). Furthermore, Bordalo et al. (2013) describe the application of ST theory in asset pricing, including stock trading. Building upon this, Cosemans & Frehen (2021) are the first to construct salience variables based on ST theory in the US stock market. They capture the temporal and spatial salience of individual stock returns using cross-sectional and time-series approaches. They design experiments to validate the effectiveness of salience indicators in asset pricing models. Moreover, Cakici & Zaremba (2022) extend previous research by demonstrating the effectiveness of ST in the context of international stock markets. While the overall effect strength is generally not as strong as in the US stock market, it is still consistently effective. Similar to previous studies, we also provide evidence that the salience effect is widely present in different cryptocurrencies across various exchanges.

The second aspect relates to the impact of trading volume volatility on investment behavior choices. The preference for high trading volume in cryptocurrencies is evident among investors (Makarov & Schoar (2020)). In the case of investment-grade financial assets, high trading volume not only signifies high liquidity and low risk but also has a significant impact on future returns. Numerous studies have been conducted on the trading volume of risky assets (Karpoff (1986); Karpoff (1987); Easley et al. (1996); Tkac (1999); Lee & Swaminathan (2000); Lo & Wang (2000)). Additionally, modern investment decision-making relies more on high-frequency trading, and trading volume has become a criterion for modern investment decision-making (Ohara (2015)). In cryptocurrency trading, trading volume still contains valuable information for decision-making. Cong et al. (2023) argues that trading decisions in cryptocurrencies depend on trading volume, although this may lead to the exaggeration of trading on exchanges. Furthermore, trading volume volatility may capture liquidity effects and the convenience yield of assets, making it an effective factor influencing cryptocurrency pricing (Cong et al. (2021); Prat et al. (2021); Sockin & Xiong (2023)). Furthermore, Bianchi et al. (2022) conducts a study on the relationship between trading volume, liquidity, and cryptocurrencies. They discover that cryptocurrencies demonstrate diverse feedback on investors' expected returns, depending on their levels of trading volume and liquidity. Considering the possibility of false trading affecting actual trading volume in cryptocurrency exchanges (Cong et al. (2023)), we use turnover rate as a proxy variable for trading volume to filter out the potential impact of false trading. The use of turnover rate as a proxy variable for trading volume is also inspired by Sun et al. (2023), who validates the existence of salience effects based on trading volume in the stock market. Notably, we are the first to examine the volume-based ST effect in the cryptocurrency market.

The third aspect pertains to the research on empirical asset pricing in the cryptocurrency domain. While there is a wealth of risk factor explanations for excess returns in stock markets (Fama & French (1996); Feng et al. (2020); Chen & Zimmermann (2020)), there are relatively fewer risk factor explanations for excess returns of cryptocurrencies in the cryptocurrency market. We primarily follow the approach of Liu et al. (2022) in constructing a multi-factor model for empirical asset pricing. Their study lays the foundation for empirical asset pricing in the cryptocurrency domain. Their findings suggest that, similar to the stock market, market, size, and momentum are the most important risk factors in the cryptocurrency market. Additionally, Cai & Zhao (2023) also conducts research on the salience effect in the cryptocurrency market, demonstrating the presence of a negative salience effect in this context. In the cryptocurrency market, we construct a multi-factor model to examine and analyze the salience effect. Our findings illustrate that the ST factor captures future return information that cannot be captured by traditional multi-factor models.

Our research builds upon the work of Cosemans & Frehen (2021), Sun et al. (2023), and Cai & Zhao (2023). We extend and deepen their studies by conducting further experiments. In addition to examining the negative effect of volume-based salience in the cryptocurrency market, we also expand their research on the duration of the effects. Furthermore, we further investigate and eliminate potential similar phenomena that may exist in the stock market. Unlike Cosemans & Frehen (2021), we expand the experimental analysis based on Sun et al. (2023) to explore how long the negative impact persists. Similar to the experiments conducted by Sun et al. (2023), we demonstrate the manifestation of the salience effect based on trading volume. Building upon the experiments conducted by Cai & Zhao (2023), we enlarge the sample size, study a broader range of market capitalizations and a longer period, and include more cryptocurrencies. Additionally, we improve the experimental precision by using more granular intervals to analyze the salience effect. This enhances the accuracy of our experiments. Since salience theory is derived from prospect theory (Tversky & Kahneman (1992)) and argues that investors assign subjective perceptions to past returns and distort objective probabilities based on these perceptions, its manifestations appear similar to other behavioral finance theories (Barber & Odean (2008); Barber et al. (2022); Antoniou et al. (2016); Bali et al. (2011); Bali et al. (2017)). Unlike Cai & Zhao (2023), we consider potential similar correlational effects in the stock market and robustly compare different effects in our sensitivity tests, providing further evidence of the robustness of the salience effect in the cryptocurrency market. Our research extends the robustness of price-based salience effects in the cryptocurrency market, complements the experiments on the extension and sustainability of the salience effect, and is the first study to explore the salience effect of trading volume information in the cryptocurrency market. We contribute to the empirical asset pricing literature in the cryptocurrency field by examining the salience effect. Our research not only expands the understanding of the salience effect's duration and robustness in the cryptocurrency market but also investigates the salience effect based on trading volume, filling a gap in the literature.

2. Data and Methodology

2.1. Data source

Drawing from the works of Liu et al. (2022) and Bianchi et al. (2022), we conduct our research by integrating data from multiple databases to ensure comprehensive coverage of the cryptocurrency market and enhance the dataset's availability. We source market capitalization, OHLC (Open, High, Low, Close) prices, and trading volume data from reputable platforms such as cryptocompare.com and Coinmarketcap.com. Our data collection spans from May 2013 to March 2023, encompassing nearly a decade of cryptocurrency trading activity. By including data from over 250 global exchanges, our chosen data providers, cryptocompare and Coinmarketcap, minimize the risk of survivorship bias.

To ensure data quality and account for liquidity concerns highlighted in Liu et al. (2022), we exclude cryptocurrencies with market capitalization below one million US dollars during the portfolio construction process. This approach aims to mitigate potential return errors associated with cryptocurrencies characterized by inadequate liquidity. The selected research period, while relatively short, effectively captures essential phases of the cryptocurrency market's life cycle. Throughout this timeframe, the market experiences significant events such as European debt crisis, the COVID-19 pandemic, and the Russia-Ukraine conflict. From a cryptocurrency trend perspective, we witness the market's evolution from obscurity to frenzy, followed by the introduction of regulatory policies that contribute to a restoration of calm. Consequently, the chosen time interval allows for a comprehensive examination of the cryptocurrency market's trading dynamics and various trends.

2.2. Salience theory value

Building upon the findings of Bordalo et al. (2013) and Cosemans & Frehen (2021) among others, we assume that investors' cryptocurrency choices are influenced by differences in the average selection set. Salient thinkers infer future return states based on past state spaces. We posit that the state space, denoted as S is formed based on daily returns over the past month. By utilizing the daily return of cryptocurrency$i$ denoted as $r_{i,s}$ and the average market return at that time denoted as $\bar{r}_s$ we can calculate the salience value of cryptocurrency i as follows:

$$\sigma\left(r_{i,s}, \bar{r}_s\right) = \frac{\left|r_{i,s} - \bar{r}_s\right|}{\left|r_{i,s}\right| + \left|\bar{r}_s\right| + \theta}, \tag{1}$$

where, θ is a constant used to avoid extreme salience levels. Referring to the experiments conducted by Cosemans & Frehen (2021), we set θ to 0.1.

Based on the salience levels, we can determine the salience ranking k_{iS} of each cryptocurrency within the state space. The ranking varies from 1 (most salient) to S (least salient), where S represents the capacity of the state space. In an objective scenario, the probabilities of each state occurring within the state space are equal and denoted as π_s with the condition that $\sum \pi_S = 1$. However, in reality, investors assign different weights to different states within the state space. Objective weights are distorted by irrational thinking, resulting in subjective weights as follows:

$$\tilde{\pi}_{iS} = \pi_S \cdot \frac{\delta^{k_{iS}}}{\sum_{S'} \delta^{k_{iS'}} \cdot \pi_{S'}}. \tag{2}$$

In the above equation, δ is a constant that captures the degree of probability distortion by investors and typically ranges between 0 and 1. As a result, with increasing insignificance k, the overall value decreases, indicating that investors tend to disregard insignificant return states and assign higher weights to salient return states. Consistent with the studies by Cosemans & Frehen (2021) and Cakici & Zaremba (2022) in the stock market, we set δ to 0.7.

Furthermore, we can construct a salience indicator, STR, which captures the phenomenon of subjective weight distortion, for portfolio analysis:

$$STR_{it} = \operatorname{cov}\left[\frac{\tilde{\pi}_{iS,t}}{\pi_{S,t}}, r_{iS,t}\right]. \tag{3}$$

Following the approach of Sun et al. (2023), we believe that the cryptocurrency market exhibits a salience-through-volume (STV) effect. Investors tend to invest in cryptocurrencies with higher trading volumes while ignoring those with lower volumes, leading to overvaluation of high-volume cryptocurrencies and undervaluation of low-volume ones, resulting in reversals in the future. Therefore, we construct the STV indicator, which is similar to STR but replaces return variation in the state space with volume variation.

Similarly, we can obtain the salience level based on volume for cryptocurrency i as:

$$\sigma_v\left(v_{i,s}, \bar{v}_s\right) = \frac{\left|v_{i,s} - \bar{v}_s\right|}{\left|v_{i,s}\right| + \left|\bar{v}_s\right| + \theta} \tag{4}$$

And the subjective weight based on volume:

$$\tilde{\pi}^{v}_{iS} = \pi_S \cdot \frac{\delta^{k_{iS}}}{\sum_{S'} \delta^{k_{iS'}} \cdot \pi_{S'}} \tag{5}$$

Finally, we derive the salience indicator based on volume, STV, as:

$$STV_{it} = \operatorname{cov}\left[\frac{\tilde{\pi}^{v}_{iS,t}}{\pi_{S,t}}, v_{iS,t}\right] \tag{6}$$

We set the parameters θ and δ to 0.1 and 0.7, respectively. Although constructed in a similar manner, trading volume may exhibit different properties compared to returns, thus warranting further investigation.

2.3. *Control variables*

Drawing on the multifactorial research in both the cryptocurrency market and the traditional stock market, we have established a series of characteristic variables for cryptocurrencies, which are universally acknowledged as effective factors in cross-sectional regression analysis. Initially, following Liu et al. (2022), we construct a three-factor model for the cryptocurrency market encompassing CMKT, SIZE, and MOM. Concurrently, we have developed traditional asset pricing characteristic variables in line with the literature.

For the cryptocurrency market capitalization metric (ME), we utilize the log of the cryptocurrency's market value. According to Amihud (2002), we construct the illiquidity indicator (ILLIQ), calculated as the average of the absolute daily return rate of a cryptocurrency divided by its average daily dollar trading volume over a month. The reversal indicator (REV) is formulated by using the previous month's cryptocurrency return rate.

We also consider indices that measure different types of risks. The market beta (BETA) is derived by regressing the monthly cryptocurrency returns against market returns, yielding the coefficient value of the market returns. Idiosyncratic volatility (IVOL) refers to the standard deviation of the residuals from the aforementioned regression. Following Ang et al. (2006), we construct the Downside beta (DBETA) by considering only the days when the daily market returns were below the annual average in the past year. The beta coefficient obtained by regressing cryptocurrency returns against these downward market returns is the DBETA.

Referring to Bali et al. (2011), we establish metrics for the maximum (MAX) and minimum (MIN) daily returns over the past month. Based on the methodology of Barberis et al. (2016), we construct the Prospect Theory Value (TK). Due to the shorter existence period of cryptocurrencies compared to the stock market, instead of a five-year window, we use a two-year window for calculations. Skewness (SKEW) is the daily return skewness of cryptocurrencies. Idiosyncratic skewness (ISKEW), based on Boyer et al. (2010), is the skewness of the residuals from the three-factor model. Additionally, following Kumar et al. (2016), we construct the Lottery Preference Index (LIDX). The calculation method is as follows: each month, we first calculate the IVOL, ISKEW, and the negative of the monthly closing price (P) for each cryptocurrency. We then rank each cryptocurrency based on these three values from low to high, assigning scores from 1 to 20. We sum these scores for each cryptocurrency monthly, and then compute LIDX = (Score - 3) / (60 - 3). Thus, the LIDX fluctuates between 0 and 1, with values closer to 1 indicating a stronger lottery-like attribute of the cryptocurrency. Finally, we source the Fear and Greed Index (FNG) for cryptocurrencies from CoinMarketCap, with higher values indicating greater investor greed and lower values indicating more fear. All indicators are tail-trimmed to the 1%-99% range for analysis.

2.4. *Summary statistics*

Table 1 presents the time series average values of cross-sectional statistics for each variable, including the mean, median, and standard deviation. Furthermore, the table below illustrates the correlation coefficients among the variables. It is observed that STR (Short-Term Reversal) demonstrates a positive correlation with STV (Short-Term Volatility) with a correlation coefficient of 0.189. This finding is coherent since both variables represent the ST effect, reflecting it in terms of trading volume and price, respectively. Additionally, the positive correlation coefficients between STR and REV (Returns), as well as between STV and REV, are 0.081 and 0.205, respectively, indicating a relatively weak relationship. This can be explained by the fact that when calculating the STR (STV) effect, the focus lies on comparing the daily returns (trading volumes) of a specific cryptocurrency with those of the broader market during the same period. Although the time series may exhibit some influence, the emphasis is primarily on whether the cryptocurrency's performance stands out compared to the market's performance. Consequently, the positive correlations are present but not strongly significant. Moreover, a study conducted by Cosemans & Frehen (2021) also mentions that severe price fluctuations have a more pronounced impact on the monthly ST values compared to moderate price changes. This further supports our research findings. Therefore, it is not surprising to observe a similar relationship between MAX (ISKEW) and STR (STV) compared to REV and STR (STV).

3. Results of empirical tests

3.1. Univariate portfolio analysis

In this empirical asset pricing study focusing on the cryptocurrency domain, our aim is to examine the factors influencing the pricing of cryptocurrencies. We employ a portfolio-based approach, where portfolios are constructed based on the salience indicators, STR (salience-based return) and STV (salience-based trading volume). These indicators allow us to capture the relative importance and attention assigned to different cryptocurrencies.In the first step of our empirical analysis, we conduct a univariate examination. At the end of each month, all cryptocurrencies are divided into ten investment portfolios based on their STR (STV) values, ranked in ascending order. We calculate the average monthly returns of each portfolio for the following month and recompute the composition of each portfolio at the beginning of the next month. The time series averages of all portfolios are computed and reported in the table. We apply both equal-weighting (EW) and value-weighting (VW) schemes to weight the portfolios. Furthermore, we calculate the three-factor ALPHA values for different portfolios, with the corresponding t-values in parentheses, following the methodology of NEWEY & WEST (1987).

Table 3 presents the returns of single-factor investment portfolios for STV and STR, under equal-weighted and value-weighted schemes, along with their corresponding three-factor ALPHA returns. The average returns exhibit a generally decreasing trend as the STR (STV) deciles decrease, indicating a monotonic decline. Moreover, the three-factor ALPHA returns are statistically significant. The return differential between the highest and lowest STR deciles is -14.7%, with a t-value of -5.181, significant at the 1% level, and the average return difference is noticeably pronounced. Similarly, under the equal-weighted scheme, the decreasing pattern in returns becomes more evident. However, even under the value-weighted scheme, the return differentials between the high and low STR and STV deciles remain significant. For instance, the return differential for STR is -2.5% with a t-value of -2.467, and for STV, it is -8.6% with a t-value of -4.066.

In addition, we also observe a slight reversal in the returns of the STR (STV) single-factor portfolios at extreme STR (STV) deciles compared to the adjacent deciles. This phenomenon can be attributed to the overall upward trend in the cryptocurrency market, which might overshadow the negative ST effect in the extreme positive STR (STV) deciles. However, from a broader perspective, we can still discern the presence of the overall ST effect in the cryptocurrency market, as the significant disparity between the highest and lowest STR (STV) deciles remains evident.

Additionally, we can observe that the three-factor alphas associated with the return differentials between high and low STR (STV) portfolios are economically and statistically significant, indicating that the significant differences arising from the STR (STV) values cannot be explained by market, momentum, or size factors. In the equal-weighted portfolios, the three-factor alpha for the return differential of STR (STV) is -2.5% (-15.9%), with t-values of -2.467 (-2.455), which is economically and statistically significant. Similarly, in the value-weighted portfolios, the three-factor alpha for the return differential of STR (STV) is -4.9% (-9.3%), with t-values of -2.543 (-3.333), both of which are statistically significant. However, both at the significance level and economic level, these values experience a decline when compared to the equal-weighted portfolios. This finding aligns with the results of Cosemans & Frehen (2021), suggesting that the ST effect might be influenced by market capitalization, which will be further discussed in subsequent sections. Unlike the stock market, in the cryptocurrency market, due to the continuous trading of cryptocurrencies 24/7 and its higher volatility, as well as the relative immaturity of the entire market compared to the stock market, the return differentials resulting from STR (STV) are much larger.

The results of our experiment reveal that, despite the overall decline in the cryptocurrency market, the ST effect persists, although with reduced magnitude compared to the findings of Cai & Zhao (2023). This indicates that salience, as measured by the salience indicators, continues to influence the pricing dynamics of cryptocurrencies. While the effect may not be as prominent during a market downturn, it remains statistically significant and provides further support for previous research in the field.

Moreover, by expanding the number of experimental groups, We find that the yield trend is not strictly decreasing. However, the variation in the effect's magnitude remains significant. This suggests that in groups where the ST effect is not extremely pronounced, it may be masked by other similar effects. This finding emphasizes the need for further experimental exploration to better understand the interplay and relative significance of various effects.

In summary, our empirical asset pricing study in the cryptocurrency domain extends the research conducted by Cai & Zhao (2023). By expanding the number of experimental groups and extending the sample period, we observe a diminished ST effect compared to previous findings. However, the ST effect remains consistent on a broader scale, providing additional support for research in the relevant field.

Additionally, our expansion of the experimental groups reveals that the ST effect does not strictly decrease, although its magnitude varies significantly. This highlights the potential masking of the ST effect by other similar effects in groups where it is not extremely pronounced, necessitating further experimentation.

Our study contributes to the existing literature on salience-based asset pricing in the context of cryptocurrencies, particularly during market downturns. The findings deepen our understanding of the ST effect and its relative significance, paving the way for future research in this area.

3.2. Bivariate Analysis

In our empirical asset pricing study focusing on the cryptocurrency domain, we aim to examine the relationship between ST values and future returns after controlling for relevant market characteristics. To achieve this, we employ a bivariate sorting analysis. This analysis allows us to investigate how the ST values, which indicate the salience of cryptocurrencies, interact with other market factors to influence future returns. To control for confounding variables, we integrate the findings from the experiments conducted by Cosemans & Frehen (2021) and Cai & Zhao (2023). These experiments provide insights into the salience-based framework and offer variables that capture both general market characteristics and specific characteristics of cryptocurrencies. By incorporating these control variables, we ensure a comprehensive analysis that accounts for relevant factors influencing the relationship between ST values and future returns. By conducting the bivariate sorting analysis and controlling for relevant variables, we aim to better understand the role of salience in asset pricing within the cryptocurrency domain. The results will contribute to our understanding of the conditional relationship between ST values and future returns, shedding light on the unique dynamics of the cryptocurrency market.

The following table 4 presents the monthly high-low ST return differentials of dual-classification investment portfolios based on a control variable and a stock's STR (STV) values. Firstly, the stocks are categorized into decile portfolios based on one of the 14 control variables. Subsequently, within each decile portfolio, the stocks are further classified into deciles based on their ST values, resulting in a total of 100 investment portfolios. All portfolios are rebalanced at the end of each month, and their realized returns are recorded. For each decile of the control variable, we report the average monthly return differential between the high ST and low ST sub-deciles. The first two tables represent the return differentials in equal-weighted portfolios, while the latter two tables represent the return differentials in market-value-weighted portfolios. This methodology allows us to assess whether the ST effect is widely present across various portfolio conditions or if it only manifests under specific conditions.

The panel analysis reveals that even after controlling for these features, STR (STV) remains statistically significant in equal-weighted portfolios. However, controlling for these variables has varying degrees of impact on the high-low STR (STV) differential. Specifically, in the case of equal-weighted portfolios, the minimum average high-low differential for STV (three-factor alpha) is -10% (-13%), while the maximum is -31% (-37%). For STR, the minimum average high-low differential (three-factor alpha) is -11% (-9%), while the maximum is -52% (-52%). However, when considering market-value-weighted portfolios, the situation changes, and the overall high-low differentials decrease. The minimum average high-low differential for STV (three-factor alpha) is -6% (-7%), while the maximum is -15% (-23%). For STR, the minimum average high-low differential (three-factor alpha) is -4% (-4%), while the maximum is -12% (-14%). These findings suggest that the ST effect, whether from a price or trading volume perspective, may be influenced by market value. We will further discuss this in subsequent sections. Nevertheless, in all experimental groups, STR (STV) exhibits a significant negative impact on the future trends of cryptocurrencies. Moreover, in the cross-experiment of STV and STR, neither can explain the negative effects of the other, emphasizing the necessity of studying STV and STR separately.

3.3. Characteristics of STR(STV) deciles

In our study, we employ a monthly methodology to construct ten portfolios by sorting all cryptocurrencies in ascending order based on their STR (STV) values. Within each portfolio, we calculate the equal-weighted average of the feature values for the cryptocurrencies it contains. Furthermore, we adjust the composition of each portfolio on a monthly basis according to the STR (STV) values. By doing so, we obtain the time series average values for each portfolio, as presented in table 5.

Panel A represents the average feature values of ten portfolios formed based on STR as the percentile criterion, while Panel B corresponds to portfolios formed using STV as the percentile criterion. It can be observed that STR and STV generally exhibit a positive correlation and tend to move in the same direction. Both tables show that cryptocurrencies in the extreme ends of the ST values have lower average prices. However, unlike the findings of Cosemans & Frehen (2021), there is no clear trend in the size of cryptocurrencies within the extreme groups. Additionally, both tables demonstrate a positive correlation between SKEW values and ST. Furthermore, the extreme ST groups are more likely to exhibit higher past returns (mom, rev), greater upside potential (MAX, IKEW), higher risk (BETA, IVOL), and lower liquidity (ILLIQ). In contrast to the results for STR, STV exhibits lower BETA values (0.6 compared to the STR group's 1.95) in the extreme groups. The highest STR group shows smaller ISKEW values and lower upside potential, while the STR group exhibits a positive correlation with REV.

Compared to what Sun et al. (2023) found in the stock market, we find different results. Specifically, we observe substantial discrepancies in the characteristics between the STV group, which represents cryptocurrencies with high trading volume salience, and the STR group, which represents cryptocurrencies with high trading range salience. These differences suggest that the salience effect manifests differently depending on the specific salience indicator used.

Interestingly, despite the divergence in characteristics, the overall performance of both the STV and STR groups remains unchanged. However, the STV group stands out with a higher potential for upward movement, indicating that cryptocurrencies with high trading volume salience may possess greater growth opportunities. Additionally, it is noteworthy that the STV group exhibits a phenomenon of lower beta factor values, signifying a relatively lower sensitivity to market fluctuations.

These findings contribute to our understanding of asset pricing in the cryptocurrency domain, particularly regarding the influence of salience. The diverging characteristics between the STV and STR groups highlight the importance of considering different salience indicators and their implications for asset valuation. Moreover, the higher upward potential observed in the STV group suggests that trading volume salience may play a significant role in driving future returns in the cryptocurrency market.

3.4. Fama-MacBeth regression analysis

The previous analysis considers all cryptocurrencies as part of the overall investment portfolio, providing insights into the characteristics of cryptocurrencies across different feature value ranges. However, this approach overlooks the differences and idiosyncrasies among individual cryptocurrencies. Therefore, in order to capture the specific effects of STR (STV) while controlling for all relevant features, we employ the Fama & MacBeth (1973) regression framework.

To investigate the impact of STR (STV) effects, we construct the following regression model:

$$r_{it+1} = \lambda_{0t} + \lambda_{1t} \cdot \mathrm{ST}_{it} + \lambda_{2t} \cdot W_{it} + v_{it}. \tag{7}$$

For month t, the variable r_{it+1} represents the expected return of cryptocurrency i for the next month. The variable W_{it} denotes the control variable, while ST_{it} represents the STR (STV) value. It is important to note that when calculating the STR, we also include the STV as a control variable, and vice versa. Each regression coefficient reflects the impact of a one-standard-deviation change in the respective variable on the cryptocurrency's return in the following month.

In our analysis, we employ a regression framework to examine the relationship between the STR (STV) values and cryptocurrency returns while controlling for relevant factors represented by the variable W_{it}. The regression coefficients provide insights into the magnitude and direction of the effect that a one-standard-deviation change in the STR (STV) value has on the future returns of cryptocurrencies.

We observe robust negative impacts of both STR and STV on the future one-month returns of cryptocurrencies. Univariate regression results for the first and fifth columns reveal that the coefficient for STR is -1.13, significant at the 95% confidence level, and the coefficient for STV is -1.77, significant at the 90% confidence level. These results suggest that a one-standard-deviation decrease in STR (STV) corresponds to an increase of 113 basis points (bps) in future returns, with the impact being statistically significant.

To examine whether the negative effects of STR persist after introducing control variables, we progressively augment the regression model. The results indicate that, with the gradual introduction of variables, the coefficients for STR (STV) experience varying degrees of attenuation. In a comprehensive stepwise analysis, presented in the appendix, we observe that the influence of STR is halved upon the introduction of the variable REV. This suggests that REV partially explains the ST effect. However, even after controlling for REV, ST remains statistically significant. Furthermore, after incorporating lottery demand variables (IVOL, MAX, SKEW, ISKEW), the impact of STR decreases by approximately half. When controlling for all features, an increase of one standard deviation in STR results in a reduction of 21 bps in next month's stock returns, remaining statistically significant.

Similar results are observed for STV, and the introduction of the variable TURN leads to a relatively modest reduction in its impact. Upon controlling for all variables, the coefficient for STR is -0.194 with a t-value of -2.153 (significant at the 95% confidence level), while the coefficient for STV is -0.491 with a t-value of -2.658 (significant at the 99% confidence level).

Comparison with the literature.—Our study shows that the ST effect, while not as strong as Cai & Zhao (2023)'s results, is more significant and stable, but it does have a greater degree of impact than Cosemans & Frehen (2021)'s results in the U.S. stock market. At the same time, our findings confirm that there is an ST effect in the cryptocurrency market, with a greater impact in the STV group. The inclusion of control variables indicates that trading volume, rather than returns, may better capture the negative ST effect. Furthermore, the REV phenomenon remains significant in the cryptocurrency market, contrary to the findings of Cakici & Zaremba (2022) in the international stock market. Additionally, IVOL exhibits significant predictive power, while ILLIQ remains significant in our extended experiment. These findings enhance our understanding of asset pricing in the cryptocurrency domain and highlight the unique dynamics of the market. The stronger influence of the ST effect based on trading volume salience suggests its importance in capturing market behavior. The persistence of the REV phenomenon and the significance of IVOL and ILLIQ further contribute to our knowledge of the factors driving asset pricing in the cryptocurrency market.

Our empirical asset pricing study in the cryptocurrency domain demonstrates a significant and stable ST effect, albeit less pronounced than in the findings of Cai & Zhao (2023). But the ST effect is more influential when based on volume significance. The REV phenomenon remains significant, IVOL shows predictive power, and ILLIQ remains significant even after expanding the experiment. This suggests that we have found a more suitable vector for the ST effect in the cryptocurrency market.

In summary, our bivariate analysis and Fama-MacBeth regression results collectively demonstrate that both STR and STV effects exert robust and consistent influences on the trends in cryptocurrency market. The observed patterns underscore the persistent influence of STR and STV phenomena, suggesting their relevance in understanding and predicting price movements in the cryptocurrency market. These findings contribute to the growing body of literature on the dynamics of digital asset pricing.

3.5. *Persistence analysis*

While bivariate and regression analyses have confirmed the negative effects of Short-Term Reversal (STR) and Short-Term Volatility (STV), the duration of the sustainability of these negative effects has not been explored. Consequently, we employ an extended time interval approach to investigate the effective duration of the ST effect. Cryptocurrencies are categorized into deciles based on their STR (STV) values each month, ranging from the lowest to the highest. Long positions are taken in the highest STR (STV) decile, while short positions are established in the lowest STR (STV) decile. Subsequently, the returns for this hedged portfolio are calculated for the following month. We compute the returns, t-values, three-factor alpha values, and associated t-values for each hedged portfolio, culminating in the creation of four distinct graphs. As shown in the fig. 1. Our results suggest that the ST effect persists well beyond the one-month horizon, with no reversal observed at the six-month horizon, which is more persistent than what Sun et al. (2023) found in the stock market. Moreover, the analysis indicates that, from a t-value perspective, the negative effect of ST based on trading volume (STV) manifests a more enduring and statistically significant impact. This suggests that in the cryptocurrency market, investor responses to mispricing arising from both trading volume and price movements exhibit persistent effects, refraining from short-term reversals. Additionally, the sustained influence of STV is notably more enduring.

4. Potential alternative mechanisms

In the realm of capital markets, various theories have been proposed by scholars to explain the reasons behind the abnormal fluctuations in asset prices and trading volumes. Among these, Salience Theory provides a perspective that focuses on the distortions in investors' subjective decision-making weights as an explanation for these anomalies. According to this theory, investors tend to overestimate (underestimate) cryptocurrencies that have experienced significant price increases and trading volume expansions (significant price decreases and trading volume contractions) in the past. This behavior leads to lower (higher) future returns for these cryptocurrencies. Following our investigation into the existence of the ST effect, our next objective is to explore whether this effect can be encompassed by other market phenomena already identified in financial studies.

4.1. *the Salience Effect and the Size Effect*

The results from the previous bivariate analysis indicate that the ST effect might be influenced by market capitalization. Consequently, we expand our experimental investigation to examine the robustness of the STR (STV) phenomenon across different market capitalization levels. To achieve this, we conduct an extended experiment by dividing the sample of cryptocurrencies into three groups based on market capitalization: Big, Mid, and Micro. The division is done proportionally, with a distribution of 30%, 40%, and 30% respectively.

Within each month, we calculate the difference in returns between the high and low STR (STV) groups for each market capitalization group. Additionally, we compute the three-factor alpha returns for these groups. This approach allows us to assess whether the STR (STV) effect remains consistent and robust across different market capitalization levels.

Based on the results presented in table 7, we observe that the STR (STV) effect is generally valid across the three market capitalization conditions. However, it is found to be most pronounced in the medium market capitalization group, while being somewhat attenuated in the big and micro market capitalization groups.

Specifically, under the medium market capitalization condition, the difference in returns between the high and low STR (STV) groups for an equally-weighted portfolio amounts to -14.3% (-21.5%), which is statistically significant at the 99% confidence level. In contrast, for the big market capitalization condition, the difference in returns for the equally-weighted portfolio is -4.9% (-1.8%), also significant at the 99% confidence level. Additionally, across all market capitalization conditions, the multi-factor alpha values are consistently significant and negative. Similar patterns are observed when considering value-weighted portfolios.

Our result aligns with the experimental findings of Cai & Zhao (2023), indicating a unique phenomenon within the cryptocurrency market. We propose that the reason behind this observation could be attributed to the relatively smaller overall market capitalization of cryptocurrencies compared to traditional stock markets. Thus, the moderate market capitalization in the cryptocurrency market is equivalent to micro-cap stocks in the stock market, giving rise to this phenomenon. This implies that a stronger ST effect is not necessarily associated with smaller market capitalization, aligning with the consistent behavior of STV and STR in this aspect.

Our study in the cryptocurrency domain reveals a distinct phenomenon where the group with moderate market capitalization exhibits the strongest zero-cost hedge return differential, contrary to the findings of Cosemans & Frehen (2021). We hypothesize that this phenomenon arises due to the relatively smaller overall market capitalization of cryptocurrencies compared to traditional stock markets. Consequently, the moderate market capitalization in the cryptocurrency market is akin to micro-cap stocks in the stock market, leading to the observed result. Thus, it becomes evident that a stronger ST effect is not solely dependent on smaller market capitalization, consistent with the behavior of both STV and STR.

4.2. limits to arbitrage

In Bordalo et al. (2013)'s paper, the authors assume that all investors are irrational and susceptible to cognitive biases influenced by the ST effect. However, it is important to note that not all investors in the market are irrational, nor do all investors exhibit erroneous pricing due to the influence of the ST effect. On the contrary, rational investors utilize objective probabilities to estimate future returns and make investment decisions. Rational investors are likely to exploit mispriced cryptocurrencies by short selling, aiming to bring the prices back to their fundamental values. Moreover, due to market frictions, pricing errors do not immediately revert to their expected values but persist (McLean & Pontiff (2016)), thereby attenuating the size and significance of the ST effect. Consequently, when arbitrage trading is restricted, a more pronounced ST effect is expected to emerge.

To evaluate our model, we employ three proxy variables related to arbitrage restrictions: cryptocurrency market capitalization, inadequate liquidity levels, and cryptocurrency-specific volatility. We select these proxy variables because cryptocurrencies with small market capitalization, low liquidity levels, and high volatility tend to have higher costs associated with arbitrage trading and are less likely to exhibit arbitrage opportunities Brav et al. (2010).

Table 8 presents the regression results after incorporating arbitrage restrictions, indicating the ST effect under average arbitrage costs. The results indicate that cryptocurrencies with small market capitalization, low liquidity levels, and high volatility tend to exhibit a stronger STR (STV) effect.

4.3. STV and abnormal turnover

In this study, our objective is to investigate the potential substitution of the STV (Salience Theory Effect based on Volume) metric with ABTURN (Abnormal Turnover), as price variations resulting from unusual trading volumes might be attributable to ABTURN. Our research involves a comprehensive comparison and analysis of ABTURN and STV, aiming to isolate the potential impacts of ABTURN and determine if STV consistently exhibits a negative effect under such circumstances.

Theoretically, these two metrics should not be interchangeable. The STV factor measures the relative prominence of a specific cryptocurrency in the market compared to others, reflecting its market position. On the other hand, ABTURN calculates unique fluctuations over a time series, providing insights into temporal market dynamics. Additionally, studies by Chuen et al. (2017), Liu et al. (2019), and Momtaz (2021) suggest that abnormal trading volume, both in the stock market and the cryptocurrency market, may be influenced by investor sentiment rather than distorted investor decision weights. This distinction holds significant importance as it highlights the different market aspects captured by each indicator, emphasizing their respective contributions to understanding market behavior in the cryptocurrency domain.

To test the non-substitutability of STV and ABTURN, we conduct a bivariate analysis. The results, presented in table 9, consisted of two components: on the left side, we examine the average returns for high and low STV groups while controlling for ABTURN; on the right side, we analyze the average returns for high and low ABTURN groups while controlling for STV. The findings demonstrate that even after controlling for ABTURN, the significant negative difference in returns between the high and low STV groups persists across multiple categories. This outcome indicates that STV possesses unique characteristics that cannot be replicated by ABTURN, reaffirming its distinct and irreplaceable role in comprehending market dynamics in the cryptocurrency sector.

4.4. Lottery preference

As shown in table 4, factors related to lottery demand such as MAX, SKEW, ISKEW, and IVOL exhibit extreme values under extreme STR (STV) conditions, indicating that the ST (Salience Theory) effect may be influenced by lottery preferences. Just like in the stock market, where investors are often driven by gambling tendencies (Cox et al. (2020); Han & Kumar (2013)), the cryptocurrency market is no exception. Therefore, cryptocurrencies with extreme ST values could also be considered a form of lottery. To further investigate this hypothesis, we introduce a proxy variable for lottery demand called LIDX to assess the impact of ST.

Each month, all cryptocurrencies are divided into ten groups based on their LIDX values, ranging from low to high. Within each group, cryptocurrencies are further divided into ten subgroups based on their STV (STR) values. For each LIDX group, we calculate the average returns of the highest and lowest STV (STR) subgroups for the following month. Additionally, we calculate the difference between these high and low returns. These calculations aim to test the effects of STV and STR separately, and the results are documented in table 10. The left side of the table shows the results of the STV tests, while the right side provides detailed results for the STR tests.

As depicted in table 10, it is evident that cryptocurrencies generally exhibit a negative STR (STV) effect across various lottery preference environments. Importantly, this effect appears to intensify with increasing lottery preferences. This differs from the experimental findings of Cosemans & Frehen (2021), where the ST effect in the stock market did not significantly change when introducing a lottery proxy variable.

These experimental results indicate that while lottery preferences may influence the ST (Salience Theory) effect, they are not its fundamental cause. This conclusion is derived from the observation that both STV and STR effects remain unaffected by the phenomenon of lottery preferences, suggesting different mechanisms driving the ST effect in the cryptocurrency market.

4.5. Reversal effect and the salience effect

As shown in table 6, when conducting Fama-MacBeth regressions while controlling for the Reversal effect (REV), the results indicate a significant impact of REV on Salience Theory Return (STR), while STR remains statistically significant. However, the influence of REV on Trading Volume (STV) is not as pronounced. This observation underscores the need to differentiate between the effects of STR and REV, emphasizing the importance of ensuring that the observed STR is not merely a manifestation of the REV effect. This feature is crucial for accurately assessing the unique characteristics and effects of STR in financial markets, especially in the context of asset pricing and trading volume dynamics. So we need to extend the experiment to rule out the possibility that the ST effect is a substitute effect for REV. We extend the experiment by conducting univariate ranking experiments on weekly, monthly, and quarterly ST indicators to exclude the possibility that ST is a substitute for short-term inversion.

As shown in table 11, the results for weekly Salience Theory (ST) are not as pronounced as those for monthly ST. However, regardless of whether the time horizon is extended or shortened, the return differential between the high and low fifth percentiles of ST remains negative, with no signs of reversal even within an extended time frame. Figure 1 further confirms this observation, indicating that the ST effect does not reverse within a certain time interval but consistently exhibits a negative impact. Furthermore, bivariate analysis results suggest that even after controlling for the Reversal effect (REV), the return differential between the high and low fifth percentiles of Salience Theory Return (STR) remains significant and negative. This finding suggests that the ST effect is not merely a byproduct of the REV effect but represents a unique and independent influence in financial markets.

4.6. Investor sentiment and the salience effects

After discussing whether the STR effect serves as a substitute for short-term reversal, it is necessary to examine whether the ST effect is influenced by different investment periods. For instance, during periods of elevated investment sentiment, investors are more likely to be influenced by positive buying pressure from their surroundings, leading to a higher probability of buying and a greater likelihood of subjective probability weighting distortions, resulting in a more pronounced ST effect. As noted by Sockin & Xiong (2023), the cryptocurrency market exhibits different behaviors during different investment sentiment cycles, with periods of investor optimism more likely to result in aggressive buying behavior.

To measure investor sentiment in the cryptocurrency market, we introduce the FNG index from CoinMarketCap. This index ranges from 0 to 1, with values closer to 0 indicating lower investor sentiment and values closer to 1 indicating higher investor sentiment. Its calculation incorporates sentiment expressed in news, including Twitter, among other sources. We define high sentiment periods as months with sentiment index values above the median and low sentiment periods as months with sentiment index values below the median. We then conduct experiments using the returns of high and low ST groups during different sentiment periods. The results of the analysis are shown in the table 12. The experimental results demonstrate that during high sentiment periods, the equal-weighted return difference between high and low STR (STV) is -0.481% (-0.719%) and statistically significant at the 1% level. During low sentiment periods, the equal-weighted return difference between high and low STR (STV) is -0.072% (-0.21%), significant at the 90% level. It is evident that the return difference during low sentiment periods is lower than that during high sentiment periods. The final two rows show similar results for the three-factor alpha. Our findings align with those of Cakici & Zaremba (2022).

In conclusion, we find that the STR (STV) exhibits a significant negative effect across different periods. Moreover, the impact of the ST effect is amplified during high sentiment periods compared to low sentiment periods.

4.7. *Salience and investor attention*

Barber & Odean (2008) propose the attention theory, which suggests that individual investors tend to be net buyers of attention-grabbing stocks due to the challenges they face in searching through numerous options. According to this theory, attention determines the choice set, while preferences influence the final selection. Furthermore, Smales (2022) also argues that the Attention effect impacts investment choices in the cryptocurrency market, leading to price pressure and resulting in mispricing. To test whether the attention effect could be an alternative to the Salience effect, Referring to the experiment of Barber & Odean (2008) and Gervais et al. (2001), we utilize four proxy variables related to attention phenomena: ABNRETD, ABNRETM, ABNVOLD, and ABNVOLM. The first two are related to abnormal returns, while the latter two are related to abnormal trading volumes. We conduct a bivariate analysis on STR and STV using these proxies, initially categorizing cryptocurrencies into ten groups based on these variables at the end of the previous month, and then subdividing each group into ten subgroups based on STR (STV). We calculated the difference in equal-weighted returns between the lowest and highest STR (STV) subgroups in each category, as well as the multifactor alpha values, forming Panel A. Panel b involved a Fama-Macbeth regression to examine the influence of the attention effect on STR (STV), with results presented in table 13.

For Panel a, it is observed that the difference in returns between the high and low categories diminished under the influence of the attention proxy variables, yet significant effects are still evident both statistically and from the perspective of multifactor alpha values. In Panel b, the addition of attention-related proxy variables does not significantly alter the impact of either STR or STV on future returns, maintaining substantial statistical significance. The effect of STR (STV) on future returns remains negative and significant at the 95%-99% confidence level.

In contrast to the results presented in Cosemans & Frehen (2021), which indicate that volume-based attention effects do not affect the ST effect, the cryptocurrency market exhibits a different pattern. In this market, both extreme trading volume and extreme returns exert an influence on the ST effect. Moreover, these factors have the additional effect of weakening the ST effect. This observation suggests that, in the context of the cryptocurrency market, trading volume seems to play a more prominent role in reflecting market phenomena compared to the stock market.

The impact of extreme trading volume and extreme returns on the ST effect in the cryptocurrency market can be attributed to the unique characteristics of this market. Cryptocurrencies are known for their high volatility and rapid price movements, which can generate significant attention from investors and the media. As a result, attention is more likely to be driven by extreme trading volume and returns, which subsequently affect the ST effect.

These findings have important implications for the empirical asset pricing literature in the cryptocurrency domain. They highlight the need to consider attention dynamics and the role of different attention indicators, such as trading volume and returns, when examining the ST effect. Understanding how attention interacts with market variables in the cryptocurrency market can provide valuable insights into market efficiency, investor behavior, and the pricing dynamics of digital assets.

In summary, unlike the findings in traditional stock markets, the cryptocurrency market demonstrates that extreme trading volume and returns have a significant impact on the ST effect, ultimately weakening it. And although the attention effect cannot erase the ST effect, it still have an impact on the specific performance of ST.

4.8. Price variation of high and low STR (STV) portfolios

Barber & Odean (2008) posit that temporary positive price pressures explain why stocks that initially garner attention often yield lower future returns. Bali et al. (2017) argue that price pressures driven by lottery demand account for the beta anomaly. In this section, we further explore the price pressures induced by prominence to better understand the negative prominence effect in the cryptocurrency market.

We directly calculate the high and low STR (STV) investment portfolios at the end of month t-1, tracking price changes over the past and future five months. Subsequently, we compute the time series average of the average prices of these two portfolios over these 11 periods and the time series average of the price differences between the high and low STR (STV) portfolios. The results are presented in fig. 2. Panel A reports the price changes following the analysis of STR. Both high STR and low STR portfolios experienced fluctuations near time t, delaying their upward trend. The high STR portfolio underwent a decline at time t, then reverted to its original trend, indicating that investors faced positive price pressure at t-1, leading to the subsequent fall. Conversely, the low STR portfolio experienced a rise at time t, then returned to its original state, suggesting negative price pressure at t-1 led to the subsequent rise.

Panel C reports the price changes following the analysis of STV. The high STV portfolio shows an increase at t-1, resulting in positive price pressure and a subsequent decline. On the other hand, the low STV portfolio, after a decline at t-1, experiences a rapid increase, indicating that undervalued cryptocurrencies yield higher future returns.

Panels B and D support our findings, with the price differences reverting at time t due to positive and negative price pressures, then returning to their original trends. Unlike the stock market, the cryptocurrency market is more volatile and in a quicker growth phase. Therefore, the STV effect may appear more persistent in this period. However, considering the continued influence of STR in rising markets, it demonstrates an undeniable significant impact.

In summary, this study provides support for the existence of the negative ST effect and highlights the significant impact of ST and short-term volatility in the cryptocurrency market. Unlike the sustained findings of Sun et al. (2023) and others in the stock market, the cryptocurrency market exhibits higher volatility and faster growth rates. Consequently, the ST effect may appear more persistent during this period. However, considering the continued influence in emerging markets, it demonstrates an undeniable significant impact.

5. Conclusion

This study examines the role of Salience Theory (ST) in the cryptocurrency market. In contrast to traditional research focusing on return perspectives, we argue that both trading volume and returns are subject to excessive attention from salient thinkers, leading to overvaluation in the current period and subsequent reversals. Our findings also indicate that emerging assets like cryptocurrencies exhibit a stronger negative ST effect compared to relatively mature assets like stocks. Importantly, in contrast to the similar behavior of trading volume and returns in the stock market, investors in the cryptocurrency market are more sensitive to fluctuations in trading volume, resulting in larger zero-cost hedge returns. Additionally, the duration of the ST effect is significantly longer in the cryptocurrency market compared to the stock market.

By conducting robustness tests through bivariate sorts and feature analyses, we examine alternative effects that could potentially explain the ST effect. Our results demonstrate that in the cryptocurrency market, the ST effect is not influenced by factors such as market capitalization, abnormal trading volume, short-term reversals, investor sentiment, investor attention, or arbitrage constraints. Across different groups, cryptocurrencies consistently exhibit a stable negative ST effect, even when controlling for these factors. It is worth noting that in the cryptocurrency market, the ST effect does not overshadow factors such as IVOL or ISKEW, which still have significant effects, unlike the findings in the stock market. Furthermore, we conduct persistence analysis and price trend analysis to provide further evidence that salient thinkers in the cryptocurrency domain are more sensitive to trading volume fluctuations rather than returns. Mispricing induced by trading volume fluctuations often generates a stronger and longer-lasting negative predictability. Additionally, when discussing attention effects, we acknowledge that the negative effect displayed by the ST effect may be influenced, as there are some similarities in their impact on future returns, despite their different underlying logics. Nevertheless, the ST effect remains robust even when considering attention effects.

In conclusion, this study contributes to the empirical asset pricing literature in the cryptocurrency field by examining the ST effect. The results support the presence of a negative prominence effect and emphasize the significant impact of prominence and short-term volatility in the cryptocurrency market. Importantly, the findings highlight that the ST effect is more pronounced and persistent in the cryptocurrency market compared to the stock market.

Table 1: Summary Statistics

	STR	STV	TK	BETA	DBETA	ILLIQ	ISKEW	ME	MOM	REV	TURN	MAX	MIN	SKEW	ISKEW	IVOL
mean	0.181	0.011	0.022	0.401	0.221	-0.081	0.019	0.473	0.289	0.01	-4.002	0.246	-0.16	0.466	0.019	0.017
median	0.185	0.008	0.014	0.174	0.157	-0.227	0.009	0.482	-0.008	-0.012	-3.815	0.186	-0.143	0.416	0.009	0.009
std	0.774	0.043	0.09	5.832	0.253	0.622	0.043	0.124	2.754	0.256	1.751	0.301	0.096	0.78	0.043	0.03

Table 2: Linear correlations

	STR	STV	TK	BETA	ILLIQ	ISKEW	ME	MOM	REV	TURN	MAX	MIN	SKEW	IVOL
STR	1													
STV	0.189	1												
TK	-0.542	0.241	1											
BETA	0.038	0.001	-0.042	1										
ILLIQ	-0.086	0.244	0.111	-0.026	1									
ISKEW	0.045	0.142	-0.239	-0.026	0.355	1								
ME	0.162	0.09	0.022	0.01	-0.025	-0.303	1							
MOM	-0.025	0.135	0.076	-0.02	0.683	0.544	-0.215	1						
REV	0.081	0.205	0.347	-0.02	0.436	0.121	0.041	0.369	1					
TURN	-0.376	-0.298	0.207	-0.06	0.296	0.294	-0.093	0.162	0.068	1				
MAX	0.164	0.45	0.442	-0.116	0.18	-0.388	0.09	0.085	0.177	-0.205	1			
MIN	-0.211	-0.162	0.002	0.111	-0.169	0.388	-0.211	0.016	-0.03	0.264	-0.742	1		
SKEW	0.078	0.388	0.376	-0.002	-0.016	-0.22	-0.04	0.063	0.15	-0.216	0.468	0.03	1	
IVOL	-0.045	-0.158	-0.25	-0.027	0.327	0.996	-0.306	0.518	0.117	0.293	-0.436	0.428	-0.244	1

Table 3: Decile portfolios for STR and STV

Portfolio	STR				STV			
	EW portfolio		VW portfolio		EW portfolio		VW portfolio	
Decile	Raw Return	3ff alpha	Raw Return	3ff alpha	Raw Return	3ff alpha	Raw Return	3ff alpha
Low ST	0.258***	0.096	0.156***	0.109**	0.109***	0.107**	0.127***	0.081**
	(6.682)	(1.331)	(4.344)	(2.187)	(5.595)	(2.123)	(3.116)	(2.212)
2	0.168***	0.065***	0.151***	0.101***	0.093***	0.022	0.082***	0.064***
	(3.117)	(3.114)	(5.380)	(3.183)	(4.079)	(1.210)	(2.735)	(3.321)
3	0.108***	0.004	0.08***	0.069***	0.076***	0.023	0.054***	0.044***
	(2.983)	(0.171)	(4.199)	(2.683)	(3.57)	(1.274)	(3.428)	(5.260)
4	0.088***	-0.009	0.069***	0.051*	0.071***	-0.016	0.052**	0.039***
	(4.853)	(-0.324)	(4.835)	(1.901)	(2.979)	(-0.734)	(2.196)	(3.138)
5	0.085***	-0.048	0.068**	0.056	0.047***	-0.07**	0.04***	0.027***
	(3.462)	(-1.256)	(2.498)	(1.124)	(2.667)	(-2.388)	(2.595)	(3.311)
6	0.079*	-0.054	0.053**	0.029***	0.045**	-0.031	0.035	0.022
	(1.888)	(-1.317)	(2.237)	(2.795)	(2.252)	(-0.15)	(0.859)	(1.616)
7	0.078**	-0.093*	0.049	0.027	0.044***	-0.027	0.031	0.031**
	(2.419)	(-1.838)	(1.612)	(1.608)	(2.721)	(-1.137)	(0.667)	(2.132)
8	0.047**	-0.031***	0.019	0.015	0.025*	-0.057*	0.029	0.01
	(2.152)	(-2.832)	(1.126)	(1.097)	(1.693)	(-1.734)	(1.580)	(1.147)
9	0.068***	-0.037*	0.056***	0.042***	0.044**	-0.06*	0.027	0.016**
	(3.306)	(-1.799)	(3.724)	(4.111)	(2.308)	(-1.863)	(1.455)	(2.164)
High ST	0.111***	0.071**	0.097**	0.06***	0.052**	-0.052	0.041**	0.021**
	(3.950)	(2.359)	(2.577)	(3.083)	(2.257)	(-1.417)	(2.321)	(2.336)
High-Low	-0.147***	-0.025**	-0.059***	-0.049**	-0.056**	-0.159**	-0.086***	-0.093***
	(-5.181)	(-2.467)	(-3.071)	(-2.543)	(-2.088)	(-2.445)	(-4.066)	(-3.333)

Notes: This table reports the original returns and multi-factor alphas values of decile portfolios formed based on the values of the variable STR (STV) generated from the Salience Theory. Additionally, the weighted average and value-weighted returns of each portfolio are calculated under both equal weighting and value weighting. The data period covers from March 2013 to March 2023. At the end of each month, all cryptocurrencies are divided into ten investment portfolios based on their STR (STV) values, ranging from low to high. The average monthly returns of each portfolio for the following month are computed, and the constituents of each portfolio are recalculated at the beginning of the next month. The time series average values for all portfolios are calculated and reported in the table. Returns are expressed in decimals, and the "High-Low" row represents the time series average of the return difference between the highest and lowest STR (STV) portfolios. The values in parentheses represent the t-values for each portfolio, calculated using the NEWEY & WEST (1987) robust t-statistic.

Table 4: Return spreads on Bivariate ST portfolios

Panel A: STR EW portfolios														
Decile	STV	mom	MAX	MIN	ILLIQ	BETA	TURN	IVOL	REV	TK	SKEW	ISKEW	DBETA	me
Low	-0.28***	-0.88***	-0.01	-1.01***	-0.28***	-0.13	-0.24***	-0.11**	-0.32	-0.12	-0.18	-0.20	-0.54	-0.98***
	(-3.06)	(-5.14)	(-0.18)	(-3.83)	(-3.55)	(-0.51)	(-4.75)	(-2.57)	(-0.74)	(-0.58)	(-0.67)	(-1.24)	(-1.3)	(-7.51)
2	-0.52***	-0.07	-0.06	-0.38***	0.05	-0.88*	-0.54*	0.11	0.27	-0.44***	-0.67**	-0.29	0.05	-0.07
	(-2.82)	(-0.89)	(-1.33)	(-6.34)	(0.60)	(-1.67)	(-1.86)	(0.91)	(0.72)	(-7.69)	(-2.34)	(-1.45)	(0.71)	(-0.38)
3	-0.58***	-0.49***	-0.14*	-0.02	-0.80***	-0.05	-0.16	-0.21***	-0.36	-0.26**	-0.23	-0.59***	-0.03	-0.60**
	(-3.46)	(-3.65)	(-1.84)	(-0.29)	(-4.38)	(-0.23)	(-1.61)	(-3.66)	(-1.23)	(-2.32)	(-1.14)	(-2.69)	(-0.30)	(-2.57)
4	-0.08	0.22	-0.37*	-0.20*	-0.07**	-0.89***	-0.02	-0.22	-0.39***	-0.58***	-0.46	-0.53**	-0.27**	-0.48***
	(-0.17)	(0.85)	(-1.88)	(-1.80)	(-2.17)	(-4.98)	(-0.31)	(-0.83)	(-5.25)	(-5.55)	(-1.04)	(-2.03)	(-2.28)	(-3.40)
5	0.33**	-0.28***	-0.11	-0.12	-0.03	-0.03	0.06	-0.17	-0.57***	-0.09***	-1.04***	-0.47*	-0.02	-0.46***
	(1.96)	(-3.39)	(-0.98)	(-1.54)	(-0.68)	(-1.16)	(0.71)	(-1.54)	(-2.79)	(-3.27)	(-3.99)	(-1.99)	(-0.12)	(-8.56)
6	-0.14	-0.04	0.20***	0.40**	-0.03	0.05	-0.26**	0.04	0.15	-0.32	-0.59***	-0.36	-0.10	-0.72***
	(-1.23)	(-0.61)	(3.24)	(2.55)	(-0.81)	(1.57)	(-2.51)	(0.26)	(1.29)	(-1.41)	(-3.02)	(-1.29)	(-0.91)	(-7.54)
7	-0.20***	-0.05	0.05*	0.21*	-0.15***	-0.37***	-0.14	-0.30***	-0.11	-0.13***	-0.70**	-0.62*	-0.14*	-0.41***
	(-3.65)	(-0.58)	(1.70)	(1.87)	(-5.23)	(-2.64)	(-0.88)	(-2.66)	(-0.88)	(-2.89)	(-2.00)	(-1.78)	(-1.87)	(-3.58)
8	-0.38***	-0.10	0.01	-0.20***	0.09**	0.14	-0.12**	-0.16	-0.54***	-0.30***	-0.73***	-0.12	0.02	0.34***
	(-5.18)	(-1.16)	(0.12)	(-3.31)	(2.21)	(1.18)	(-2.05)	(-1.10)	(-5.81)	(-4.82)	(-4.37)	(-0.39)	(0.24)	(3.62)
9	0.17	-0.32	-0.02	-0.03	0.05	0.26	0.12**	0.07	0.05	0.06	-0.11	-0.8*	-0.12*	-0.35*
	(1.31)	(-1.07)	(-0.2)	(-0.45)	(1.35)	(1.12)	(2.17)	(0.39)	(0.58)	(0.98)	(-0.14)	(-1.84)	(-1.76)	(-1.65)
High	-0.38	0.21	-1.08***	-0.31***	0.03	0.08	-0.11	-0.95*	-0.11	-0.17**	-0.13	-1.25**	-0.65***	0.25
	(1.31)	(0.64)	(-3.17)	(-4.68)	(0.66)	(0.83)	(-0.81)	(-1.86)	(-0.95)	(-2.37)	(-0.31)	(-2.44)	(-2.87)	(1.01)
Mean H-L	-0.2***	-0.18***	-0.15***	-0.16***	-0.11***	-0.18*	-0.14***	-0.19***	-0.19***	-0.23**	-0.48*	-0.52**	-0.18***	-0.35***
	(-4.1)	(-3.49)	(-5.63)	(-3.46)	(-3.61)	(-1.79)	(-5.34)	(-4.1)	(-4.2)	(-2.12)	(-1.77)	(-2.2)	(-3.23)	(-3.23)
FF3	-0.19**	-0.19***	-0.2*	-0.25***	-0.09***	-0.1**	-0.07**	-0.21*	-0.12***	-0.15***	-0.48***	-0.52***	-0.16***	-0.36***
	(-2.18)	(-3.49)	(-1.81)	(-3.04)	(-2.83)	(-2.47)	(-2.46)	(-1.69)	(-2.85)	(-2.7)	(-2.76)	(-2.6)	(-3.69)	(-2.65)

Notes: This table reports the monthly return differences between high and low STR (STV) portfolios within each decile portfolio formed based on a control variable and the STR (STV) values of cryptocurrencies. The control variables used include STR (STV), MOM, MAX, MIN, ILLIQ, BETA, TURN, IVOL, REV, TK, SKEW, DBETA, and ME. At the beginning of each month, we divide all cryptocurrencies into decile portfolios based on the value of a control variable. Within each control variable portfolio, we further divide them into five portfolios based on their STR (STV) values, resulting in a total of 50 portfolios each month. We calculate the return difference between the highest and lowest portfolios for the next month within each control variable portfolio, while adjusting the composition of the portfolios accordingly. Finally, we calculate the time series average returns for all control variable portfolios and report them in the table. We provide two calculation methods for the portfolio returns: equal weighting and value weighting. Panel A and Panel C represent the return differences under equal weighting, while Panel B and Panel D represent the return differences under value weighting. The bottom of each panel reports the average sub-portfolio return differences for the ten control variables and their corresponding multi-factor alphas. The values in parentheses represent the t-values for each portfolio, calculated using the NEWEY & WEST (1987) robust t-statistic. The data used covers the period from March 2013 to March 2023.

Panel B: STV EW portfolios

Decile	STR	mom	MAX	MIN	ILLIQ	BETA	TURN	IVOL	REV	TK	SKEW	ISKEW	DBETA	me
Low	-1.60***	-0.25***	0.11***	-0.87**	-0.65***	-0.98**	-1.73***	-0.13**	-0.62	-0.47***	-0.28***	-0.18***	-0.47**	-0.15
	(-3.00)	(-2.76)	(6.12)	(-2.55)	(-5.64)	(-2.15)	(-3.30)	(-2.71)	(-3.22)	(-4.06)	(-3.43)	(-4.03)	(-2.30)	(-1.08)
2	0.49***	-0.25***	0.07***	0.05	-0.35	-0.96***	0.12**	-0.17	-0.05	-0.17***	-0.58***	-0.31***	-0.02	-0.31***
	(8.01)	(-5.21)	(3.96)	(0.96)	(-1.46)	(-4.74)	(2.02)	(-1.19)	(-0.19)	(-3.10)	(-3.00)	(-4.06)	(-0.51)	(-6.53)
3	0.01	0.08	0.15***	0.18**	-0.54***	-0.35*	-0.12*	-0.15*	-0.23	0.34***	-0.30***	-0.21**	-0.10	-0.01
	(0.35)	(1.63)	(4.39)	(2.45)	(-4.85)	(-1.87)	(-1.93)	(-1.75)	(-0.55)	(2.93)	(-6.10)	(-2.55)	(-0.95)	(-0.18)
4	0.12***	-0.08	-0.03	-0.28***	-0.01	-0.24	-0.04**	-0.26	-0.45**	-0.24***	0.07	-0.18	-0.51***	-0.03
	(4.83)	(-0.67)	(-1.02)	(-4.06)	(-0.07)	(-1.47)	(-2.06)	(-0.95)	(-2.50)	(-3.98)	(1.00)	(-0.90)	(-4.65)	(-0.82)
5	-0.07**	0.27***	-0.08**	0.04	-0.14*	0.34	-0.33***	0.21**	0.24	-0.07*	-0.08	0.51***	-0.15	-0.20***
	(-2.56)	(5.54)	(-2.49)	(0.53)	(-1.94)	(1.11)	(-4.07)	(2.04)	(1.30)	(-1.92)	(-1.24)	(4.75)	(-1.42)	(-7.84)
6	0.04	-0.06	-0.14***	0.08**	-0.08	0.62*	0.08	0.33**	-0.05	-0.51***	-0.21**	-0.13	-0.24**	-0.14**
	(1.16)	(-1.55)	(-3.08)	(2.26)	(-1.61)	(1.93)	(1.61)	(2.26)	(-0.42)	(-5.04)	(-2.00)	(-1.17)	(-2.31)	(-2.02)
7	-0.17***	-0.12**	-0.32***	-0.13	-0.33***	-0.11	-0.27***	0.42**	-0.18**	-0.17***	-0.28**	0.01	0.25**	-0.08
	(-6.47)	(-2.44)	(-4.07)	(-1.54)	(-5.52)	(-0.93)	(-2.90)	(2.09)	(-2.46)	(-2.99)	(-2.14)	(0.14)	(2.49)	(-1.06)
8	-0.05	0.02	-0.04	-0.34***	0.08	0.30***	-0.16**	-0.51***	-0.45**	-0.26**	0.14	0.34	0.07	-0.15***
	(-1.30)	(0.38)	(-0.70)	(-5.34)	(0.76)	(2.80)	(-2.06)	(-4.86)	(-2.41)	(-2.44)	(1.12)	(1.56)	(1.21)	(-5.69)
9	-0.13	-0.04	-0.05	-0.01	-0.02	-0.25	-0.37***	-0.23	-0.36**	-0.05	-0.11	-0.34***	-0.08**	-0.03
	(-1.00)	(-0.52)	(-1.02)	(-0.12)	(-0.23)	(-1.18)	(-5.01)	(-1.47)	(-2.09)	(-0.48)	(-1.48)	(-3.42)	(-2.23)	(-0.38)
High	0.14*	-1.58***	-0.87**	0.03*	-0.05	-0.17***	-0.25***	-1.99***	0.39	0.56***	-0.51**	-1.86***	-0.23*	-2.03***
	(1.89)	(-3.17)	(-2.43)	(1.79)	(-1.12)	(-3.48)	(-4.10)	(-2.83)	(0.98)	(2.58)	(-2.00)	(-3.36)	(-1.74)	(-3.51)
Mean H-L	-0.12*	-0.20***	-0.12**	-0.12***	-0.21***	-0.18***	-0.31***	-0.25***	-0.18***	-0.10***	-0.21***	-0.23***	-0.15***	-0.31***
	(-1.86)	(-3.81)	(-2.29)	(2.69)	(-3.02)	(-3.73)	(3.07)	(-3.93)	(-2.59)	(-3.04)	(-6.92)	(-7.09)	(-5.78)	(-3.52)
FF3	-0.17**	-0.13***	-0.15***	-0.17***	-0.19**	-0.29***	-0.16**	-0.35**	-0.37**	-0.31**	-0.21***	-0.36**	-0.26*	-0.19*
	(-2.11)	(-3.08)	(-3.30)	(-3.32)	(-2.38)	(-3.83)	(-2.46)	(-2.39)	(-2.38)	(-2.10)	(-3.15)	(-2.45)	(-1.93)	(-1.72)

Panel C: STR VW portfolios														
Decile	STV	MOM	MAX	MIN	ILLIQ	BETA	TURN	IVOL	REV	TK	SKEW	ISKEW	DBETA	ME
Low	-0.11***	-0.09*	-0.04*	-0.20***	-0.39***	-0.12**	-0.06***	-0.04	-0.14**	-0.04	-0.04	-0.03	-0.12**	-0.09
	(-3.13)	(-1.95)	(-1.65)	(-4.04)	(-3.18)	(-2.50)	(-4.08)	(-1.48)	(-2.24)	(-0.72)	(-0.87)	(-1.14)	(-2.48)	(-1.25)
2	-0.13***	-0.08**	-0.11**	-0.08	-0.15	-0.22***	-0.14***	-0.05**	-0.11***	-0.10***	-0.03	-0.03	-0.07*	-0.01
	(-2.71)	(-2.53)	(-2.19)	(-1.45)	(-1.23)	(-2.91)	(-3.64)	(-2.45)	(-2.68)	(-2.65)	(-0.69)	(-1.12)	(-1.86)	(-0.26)
3	-0.14*	-0.10*	-0.12	-0.07	-0.34***	-0.03	-0.07	-0.15***	-0.12	-0.21**	0.02	-0.16***	-0.12**	-0.11**
	(-1.76)	(-1.66)	(-1.63)	(-0.64)	(-5.40)	(-0.64)	(-1.19)	(-3.17)	(-1.26)	(-2.09)	(1.30)	(-3.00)	(-2.36)	(-2.32)
4	-0.27	0.10	-0.49**	-0.09***	-0.02	-0.11***	-0.13*	-0.31	-0.06	-0.10**	-0.12**	-0.27	-0.26	-0.10
	(-1.44)	(0.22)	(-2.18)	(-3.17)	(-0.67)	(-3.51)	(-1.85)	(-1.54)	(-0.79)	(-2.11)	(-2.28)	(-1.37)	(-1.32)	(-1.34)
5	0.01	-0.08	0.02	-0.23*	-0.01	-0.01	-0.08***	-0.04*	-0.11**	-0.03	-0.20***	-0.04*	-0.01	0.01
	(0.07)	(-1.38)	(0.32)	(-1.95)	(-0.20)	(-0.37)	(-2.97)	(-1.81)	(-2.40)	(-1.33)	(-5.39)	(-1.76)	(-0.54)	(0.35)
6	-0.10**	-0.10**	-0.04	0.01	-0.03	-0.04**	0.21**	-0.04	-0.06	-0.11***	-0.07***	-0.06*	-0.24***	-0.06
	(-2.07)	(-2.33)	(-0.95)	(0.34)	(-0.67)	(-2.31)	(2.24)	(-0.99)	(-0.87)	(-5.76)	(-2.82)	(-1.78)	(-2.68)	(-1.26)
7	-0.04	0.03	-0.07*	-0.06**	-0.08	-0.24**	-0.08**	-0.06**	-0.08***	-0.08*	-0.04	-0.14***	0.01	-0.05**
	(-1.45)	(0.83)	(-1.77)	(-2.17)	(-1.15)	(-2.40)	(-2.45)	(-2.37)	(-3.31)	(-1.65)	(-0.88)	(-2.84)	(0.65)	(-2.00)
8	-0.04*	-0.01	-0.10**	0.00	-0.02	-0.05*	-0.06	-0.12*	-0.06***	-0.10**	0.03	-0.03	-0.07**	0.02
	(-1.78)	(-0.36)	(-2.17)	(0.06)	(-0.53)	(-1.67)	(-1.32)	(-1.66)	(-2.58)	(-2.52)	(0.57)	(-0.50)	(-2.23)	(0.42)
9	-0.02	-0.04	-0.17***	-0.03	0.01	-0.06**	0.02	-0.08	-0.04	-0.02	-0.05	-0.22***	0.01	-0.13***
	(-0.53)	(-0.75)	(-3.24)	(-1.15)	(0.15)	(-2.01)	(0.79)	(-1.47)	(-0.55)	(-0.71)	(-0.70)	(-2.98)	(0.45)	(-3.05)
High	-0.25***	0.07	-0.10	-0.08***	-0.03	0.01	-0.04	-0.05	0.12***	0.01	-0.21***	-0.03	-0.03	-0.04
	(-3.36)	(0.41)	(-0.73)	(-3.37)	(-0.81)	(0.63)	(-1.58)	(-0.38)	(2.68)	(0.14)	(-4.62)	(-0.19)	(-0.43)	(-0.75)
Mean H-L	-0.11*	-0.03	-0.12**	-0.08**	-0.11**	-0.09***	-0.04**	-0.09*	-0.07**	-0.08**	-0.07**	-0.10*	-0.09**	-0.06*
	(-1.88)	(-0.75)	(-2.20)	(-2.16)	(-2.34)	(-3.08)	(-2.12)	(-1.83)	(-2.06)	(-2.37)	(-2.50)	(-1.79)	(-2.40)	(-1.73)
H-L FF3	-0.10*	-0.09***	-0.14***	-0.08*	-0.10**	-0.07**	-0.04	-0.12***	-0.06*	-0.09***	-0.07***	-0.13***	-0.08**	-0.04
	(-1.86)	(-2.70)	(-2.88)	(-1.74)	(-2.06)	(-2.07)	(-0.94)	(-2.86)	(-1.76)	(-2.70)	(-2.75)	(-3.05)	(-2.22)	(-1.44)

Panel D: STV VW portfolios

Decile	STR	mom	MAX	MIN	ILLIQ	BETA	TURN	IVOL	REV	TK	SKEW	ISKEW	DBETA	me
Low	-0.02	-0.14	-0.04*	-0.16***	-0.4***	-0.13***	0.08**	-0.04	-0.07**	-0.08**	-0.04	-0.05**	-0.06	-0.30***
	(-0.18)	(-1.50)	(-1.80)	(-4.60)	(-4.48)	(-3.78)	(2.53)	(-1.59)	(-2.12)	(-2.31)	(-1.37)	(-2.06)	(-1.33)	(-4.61)
2	-1.10***	-0.02	-0.11***	-0.18***	-0.17**	-0.23***	-0.37***	-0.04**	-0.02	-0.10***	-0.07**	-0.01	-0.02	0.02
	(-3.76)	(-0.36)	(-2.72)	(-6.22)	(-2.23)	(-4.49)	(-4.16)	(-2.34)	(-0.35)	(-4.73)	(-2.56)	(-0.1)	(-0.52)	(0.43)
3	-0.04	-0.22*	-0.09*	-0.13**	-0.39***	-0.02	-0.06*	-0.15***	-0.09	-0.10***	-0.09***	-0.10*	-0.28***	-0.11***
	(-1.00)	(-1.95)	(-1.71)	(-2.22)	(-7.28)	(-0.46)	(-1.75)	(-2.68)	(-1.46)	(-4.60)	(-3.44)	(-1.69)	(-10.11)	(-2.92)
4	-0.21***	-0.48	-0.28	-0.01	-0.04***	-0.12***	-0.12**	-0.28	-0.10***	-0.07	-0.31***	-0.28	-0.33*	-0.11**
	(-3.70)	(-1.24)	(-1.53)	(-0.20)	(-2.77)	(-8.92)	(-2.40)	(-1.59)	(-2.78)	(-1.47)	(-6.45)	(-1.59)	(-1.97)	(-2.36)
5	-0.11***	-0.14***	0.02	-0.16*	-0.06***	-0.04*	-0.01	0.05	0.01	-0.01	-0.04	0.01	-0.02*	0.02
	(-5.02)	(-4.79)	(1.06)	(-1.80)	(-4.37)	(-1.81)	(-0.35)	(1.43)	(0.23)	(-0.47)	(-0.65)	(0.25)	(-1.68)	(1.07)
6	-0.06	-0.13**	-0.10***	-0.06	-0.05**	0.20*	-0.16**	-0.11***	-0.06***	-0.19***	-0.02	-0.14***	0.01	-0.09*
	(-1.48)	(-2.45)	(-3.82)	(-1.39)	(-2.40)	(1.91)	(-2.43)	(-3.02)	(-2.59)	(-4.40)	(-1.05)	(-4.59)	(0.40)	(-1.87)
7	0.04	0.07	-0.07**	-0.07***	-0.09*	-0.03	-0.10***	-0.09***	-0.09***	-0.01	0.01	-0.13***	0.06***	-0.11***
	(1.01)	(1.13)	(-2.22)	(-4.30)	(-1.78)	(-1.01)	(-4.33)	(-3.79)	(-4.96)	(-0.13)	(0.11)	(-2.83)	(3.77)	(-3.98)
8	-0.09**	-0.02	-0.11***	-0.03	0.02	0.01	-0.06***	-0.21***	-0.01	-0.11***	-0.04*	-0.06	0.03*	-0.08***
	(-2.16)	(-0.46)	(-3.01)	(-1.50)	(0.74)	(0.22)	(-3.14)	(-4.49)	(-0.40)	(-3.66)	(-1.98)	(-1.30)	(1.89)	(-3.68)
9	-0.13	0.03	-0.15***	0.04***	-0.04	-0.01	-0.05**	-0.13***	-0.23***	-0.08**	-0.01	-0.21***	0.05*	-0.06
	(-1.19)	(0.58)	(-3.78)	(2.70)	(-1.15)	(-0.45)	(-2.57)	(-4.08)	(-3.07)	(-2.10)	(-0.51)	(-3.66)	(1.67)	(-0.68)
High	-0.29***	-0.48***	-0.23	-0.01	-0.05***	-0.06***	0.02	-0.51***	-0.13***	-0.02	-0.40***	-0.19	-0.10*	-0.23***
	(-3.24)	(-3.45)	(-1.40)	(-0.42)	(-4.21)	(-3.81)	(0.95)	(-3.62)	(-3.61)	(-0.49)	(-3.08)	(-1.10)	(-1.81)	(-4.06)
Mean H-L	-0.20***	-0.15***	-0.12***	-0.08***	-0.13***	-0.04*	-0.08***	-0.15***	-0.08***	-0.07***	-0.10***	-0.12**	-0.06**	-0.10***
	(-5.42)	(-2.84)	(-3.02)	(-3.29)	(-4.84)	(-1.65)	(-3.67)	(-4.52)	(-5.59)	(-4.93)	(-7.47)	(-2.45)	(-2.09)	(-5.88)
H-L FF3	-0.20***	-0.18***	-0.22***	-0.07**	-0.10**	-0.10***	-0.08*	-0.21***	-0.11***	-0.09***	-0.11***	-0.23***	-0.07**	-0.08**
	(-3.11)	(-3.52)	(-2.95)	(-2.43)	(-2.02)	(-2.80)	(-1.82)	(-4.05)	(-3.57)	(-3.24)	(-3.09)	(-3.29)	(-2.31)	(-2.20)

Table 5: Characteristics of ST-sorted portfolios

Panel A : STR-sorted portfolios																
Decile	STR	STV	Price	TURN	ME	beta	IVOL	mom	ILLIQ	REV	min	max	TK	skew	ISKEW	DBETA
Low	-2.63	0.20	46.91	0.10	17.46	1.95	0.12	2.93	0.16	0.01	-0.15	0.37	0.28	-0.34	0.11	1.16
2	-0.57	0.30	157.78	0.10	17.81	1.72	0.06	1.26	0.13	0.03	-0.11	0.20	0.25	-0.36	0.16	1.56
3	-0.34	0.27	194.75	0.15	17.91	1.55	0.05	1.07	0.13	0.04	-0.11	0.17	0.22	-0.27	0.12	1.39
4	-0.13	0.29	185.87	0.22	17.80	1.33	0.04	1.40	0.17	0.04	-0.10	0.15	0.25	-0.14	0.09	1.11
5	0.04	0.27	253.55	0.24	17.74	1.44	0.04	1.14	0.16	0.05	-0.09	0.16	0.44	0.04	0.07	1.22
6	0.21	0.34	152.09	0.14	17.70	1.41	0.05	1.15	0.14	0.06	-0.09	0.18	0.39	0.20	0.10	1.43
7	0.39	0.31	118.11	0.11	17.41	0.93	0.05	1.11	0.16	0.06	-0.10	0.20	0.32	0.37	0.07	1.31
8	0.62	0.36	46.86	0.14	17.12	1.27	0.06	1.17	0.13	0.04	-0.11	0.22	0.33	0.48	0.05	1.21
9	0.90	0.39	49.68	0.12	17.15	1.31	0.07	1.44	0.06	0.07	-0.11	0.25	0.42	0.61	0.06	1.71
High	2.94	0.29	48.82	0.15	18.69	1.30	0.11	1.61	0.06	0.15	-0.15	0.44	0.50	0.86	0.04	1.89
High-low	5.57	0.09	1.91	0.05	1.23	-0.65	-0.01	-1.32	-0.10	0.14	0.00	0.07	0.22	1.20	-0.07	0.73
Panel B : STV-sorted portfolios																
Decile	STV	STR	Price	TURN	ME	beta	IVOL	mom	ILLIQ	REV	min	max	TK	skew	ISKEW	DBETA
Low	-2.05	0.42	81.62	0.07	17.48	0.60	0.10	2.82	0.20	0.14	-0.23	0.38	0.41	0.15	0.12	1.52
2	-0.83	0.56	214.09	0.10	17.02	0.95	0.06	1.14	0.13	0.09	-0.16	0.22	0.05	0.21	0.07	0.83
3	-0.43	0.49	201.84	0.17	16.99	1.38	0.05	1.21	0.10	0.07	-0.15	0.19	0.03	0.25	0.06	1.10
4	-0.15	0.41	177.61	0.35	16.98	1.50	0.05	1.11	0.10	0.06	-0.13	0.17	0.06	0.28	0.05	1.26
5	0.09	0.35	178.62	0.26	16.96	1.64	0.05	1.33	0.10	0.03	-0.13	0.18	0.15	0.32	0.05	1.08
6	0.34	0.38	140.34	0.11	17.02	2.24	0.05	1.28	0.10	0.06	-0.14	0.18	0.21	0.31	0.05	1.11
7	0.63	0.45	64.70	0.14	16.90	0.89	0.06	1.23	0.11	0.12	-0.15	0.20	0.18	0.38	0.06	0.84
8	0.98	0.64	111.76	0.09	16.68	0.91	0.06	1.18	0.11	0.00	-0.15	0.21	0.30	0.53	0.06	1.13
9	1.43	0.84	43.57	0.09	16.64	0.78	0.07	1.50	0.12	0.04	-0.16	0.25	0.43	0.65	0.07	1.18
High	3.00	1.43	50.16	0.12	18.06	0.48	0.09	1.69	0.18	0.07	-0.20	0.38	0.80	0.93	0.11	1.34
High-low	5.05	1.01	-31.46	0.05	0.58	-0.12	-0.01	-1.12	-0.03	-0.08	0.04	-0.01	0.40	0.78	-0.01	-0.18

Notes: In this table, we present the time series average values of characteristics of decile portfolios formed based on the significant variable STR (STV). At the end of each month, we divide all cryptocurrencies into ten groups based on their STR (STV) values, ranging from low to high. We calculate the equal-weighted average values of the related characteristics within each portfolio, and the composition of each portfolio is reassigned in the following month. PRICE represents the price of each cryptocurrency in dollars, and ME represents the logarithm of the current market value of the cryptocurrency. All ratio-based characteristics are expressed as decimals, for example, returns are presented as absolute values. The bottom of each panel displays the time series average values of the difference in characteristic values between the highest and lowest STR (STV) portfolios. All variables are truncated within the 1st to 99th percentile range. The data period covers from March 2013 to March 2023.

Table 6: FamaMacBeth regression

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
STR	-1.127**	-1.168**	-0.493***	-0.388***	-0.210**						-0.941**	-0.194**
	(-2.335)	(-2.219)	(-3.239)	(-2.894)	(-2.331)						(-2.446)	(-2.153)
STV						-1.773*	-1.897*	-0.762**	-0.726**	-0.502***	-1.396*	-0.491***
						(-1.824)	(-1.918)	(-2.230)	(-2.226)	(-2.680)	(-1.766)	(-2.658)
ME		0.080**	0.114**	0.030	-0.029		0.068**	0.107**	0.106**	-0.025		-0.020
		(2.478)	(2.423)	(1.117)	(-1.604)		(2.195)	(2.216)	(2.200)	(-1.276)		(-1.103)
MOM		0.003***	0.003**	0.001	0.001		0.004***	0.003**	0.003**	0.001		0.001
		(3.679)	(2.504)	(1.253)	(0.907)		(3.649)	(2.542)	(2.537)	(1.118)		(0.911)
BETA		-0.001*	0.001	0.001	0.001		0.001	0.001	0.001	0.001		0.001
		(-1.702)	(-1.505)	(-0.793)	(-0.704)		(-1.403)	(-1.257)	(-1.265)	(-1.270)		(-0.712)
REV			0.325*	0.292*	0.259*			0.328*	0.328*	0.257*		0.255*
			(1.779)	(1.762)	(1.732)			(1.781)	(1.782)	(1.721)		(1.730)
TURN				0.003***	0.004***				0.003***	0.003***		0.004***
				(3.892)	(3.828)				(3.779)	(4.267)		(3.773)
MAX				0.202***	-0.014					-0.020		-0.022
				(3.649)	(-0.926)					(-1.488)		(-1.394)
MIN					0.770*					0.822*		0.759*
					(1.895)					(1.993)		(1.885)
IVOL					3.089***					3.195***		3.067**
					(2.586)					(2.695)		(2.576)
TK					0.020					0.028		0.022
					(0.199)					(0.285)		(0.227)
SKEW					-0.006					-0.008*		-0.001
					(-1.045)					(-1.763)		(-0.348)
DBETA					-0.002					-0.002		-0.002
					(-0.309)					(-0.238)		(-0.263)
ISKEW					-0.016					-0.015		-0.016
					(-1.199)					(-1.065)		(-1.176)
ILLIQ					-0.064***					-0.065***		-0.063***
					(-8.181)					(-9.184)		(-8.327)

Notes: This table presents the results of the Fama-Macbeth regression, displaying the regression coefficients and corresponding t-values when different variables are included. Due to space constraints, we did not include the results of sequentially adding all variables. Instead, we selected a subset of variables that led to significant changes in the STR (STV) values. All variables are truncated within the 1st to 99th percentile range. The data period covers from March 2013 to March 2023. The values in parentheses represent the t-values for each portfolio, calculated using the NEWEY & WEST (1987) robust t-statistic.

Table 7: Salience Effect and the Size Effect

STR-sorted Portfolios								
	EW Portfolios				VW Portfolios			
SIZE	All	Big	Mid	Micro	All	Big	Mid	Micro
H-L	-0.147***	-0.049***	-0.143***	-0.066***	-0.059***	-0.049***	-0.149***	-0.302***
	(-5.181)	(-3.292)	(-5.495)	(-4.715)	(-3.071)	(-3.303)	(-2.711)	(-2.762)
FF3	-0.025**	-0.017***	-0.309**	-0.039**	-0.049**	-0.046***	-0.338*	-0.049**
	(-2.467)	(-3.465)	(-2.062)	(-2.158)	(-2.543)	(-2.701)	(-1.943)	(-2.078)
STV-sorted Portfolios								
	EW Portfolios				VW Portfolios			
SIZE	All	Big	Mid	Micro	All	Big	Mid	Micro
H-L	-0.056**	-0.018**	-0.215***	-0.005**	-0.086***	-0.03**	-0.306***	-0.086***
	(-2.088)	(-2.128)	(-4.184)	(-2.211)	(-6.802)	(-2.401)	(-3.881)	(-3.327)
FF3	-0.159**	-0.013**	-0.283**	-0.012	-0.093***	-0.004	-0.239*	-0.040*
	(-2.445)	(-2.148)	(-2.435)	(-0.514)	(-3.333)	(-0.312)	(-1.758)	(-1.73)

Notes: This table reports the time series average return differences between the highest and lowest STR (STV) portfolios in the cryptocurrency market, categorized by different market capitalization groups. At the end of each month, we divide the cryptocurrencies into three groups: Big, Mid, and Micro, based on their market capitalization proportions of 30%, 40%, and 30% respectively. Within each group, we further divide the cryptocurrencies into ten portfolios based on their STR (STV) values, resulting in a total of thirty portfolios. The following month, we adjust the portfolios and calculate the equal-weighted and value-weighted average return differences between the highest and lowest STR (STV) portfolios within each market capitalization group. The calculated values are then reported in the table. The table presents the time series average values of the return differences and their corresponding multi-factor alpha values. The values in parentheses represent the t-values for each portfolio, calculated using the Newey and West (1987) robust t-statistic.

Table 8: Fama-MacBeth regressions: limits to arbitrage

	STR			STV		
	(1)	(2)	(3)	(1)	(2)	(3)
ST	-0.218**	-0.217**	-0.298*	-0.641*	-0.525***	-0.514***
	(-2.414)	(-2.420)	(-1.651)	(-1.737)	(-2.702)	(-2.642)
ST*ME	0.007***			0.074***		
	(3.562)			(4.354)		
ST*ILLIQ		-0.003			-0.053*	
		(-0.086)			(-1.807)	
ST*IVOL			-0.053*			-0.023*
			(-1.817)			(-1.678)
ME	-0.036*	-0.036*	-0.038*	-0.024	-0.024	-0.026
	(-1.820)	(-1.920)	(-2.056)	(-1.250)	(-1.249)	(-1.342)
ILLIQ	-0.063***	-0.064***	-0.064***	-0.065***	-0.065***	-0.065***
	(-8.483)	(-8.771)	(-8.269)	(-9.420)	(-9.494)	(-8.539)
IVOL	3.076**	3.069**	3.124**	3.184***	3.187***	3.198***
	(2.564)	(2.539)	(2.559)	(2.687)	(2.690)	(2.634)

Notes: The table presents the regression results of the negative effects of arbitrage constraints, measured using the Fama-Macbeth regression analysis, on the Salience Theory indicator STR (or STV) in the cryptocurrency market. The monthly cross-sectional regressions examine the relationship between the returns of cryptocurrencies in month t+1 and the interaction between the proxy variables for STR/STV (referred to as ST in the formula) and arbitrage constraints in month t. Among them, Z_it represents one of the three proxy variables for arbitrage constraints: size (ME), Amihud illiquidity (ILLIQ), and idiosyncratic volatility (IVOL). denotes the Salience Theory indicator STR or STV, and represents a set of control vectors, including the mentioned control variables. For brevity, this table does not display the control variables again. The values in parentheses represent the t-values for each portfolio, calculated using the robust t-statistic proposed by Newey and West (1987).The data used in the analysis covers the period from March 2013 to March 2023, and all variables have been standardized.

Table 9: STV and abnormal turnover

	Conditional on ABTURN				Conditional on STV		
	lowest	highest	H-L		lowest	highest	H-L
lowest ABTURN	0.452***	0.331***	-0.122**	lowest STV	1.662***	0.167*	-1.495***
	(4.618)	(5.709)	(-2.439)		(4.076)	(2.323)	(-3.037)
2	0.069	-0.046***	-0.115*	2	0.131**	0.357***	0.225***
	(1.404)	(2.852)	(-1.794)		(2.029)	(6.018)	(5.105)
3	2.035***	0.743*	-1.292***	3	0.184***	0.331***	0.147***
	(4.666)	(1.833)	(-3.256)		(3.847)	(3.895)	(3.810)
4	0.081*	0.012***	-0.069	4	0.170***	-0.009	-0.179**
	(1.669)	(3.075)	(-1.292)		(4.500)	(-0.154)	(-2.335)
5	0.088**	0.052	-0.036	5	0.025	-0.107	-0.132***
	(2.230)	(1.385)	(-0.397)		(0.451)	(-1.525)	(-5.136)
6	0.059*	-0.006	-0.065*	6	0.236***	0.211***	-0.026
	(1.838)	(-0.447)	(-1.994)		(3.785)	(3.051)	(-0.768)
7	0.011	-0.099	-0.110**	7	0.201***	-0.016	-0.216***
	(0.363)	(-0.725)	(-2.115)		(4.248)	(-0.229)	(-2.699)
8	0.057	-0.068	-0.125*	8	0.182***	0.162**	-0.020
	(1.174)	(-0.824)	(-1.778)		(3.149)	(2.451)	(-0.305)
9	0.069**	-0.003	-0.072	9	0.119***	0.035	-0.084
	(2.234)	(0.202)	(-1.064)		(2.948)	(0.483)	(-1.289)
highest ABTURN	0.007	-0.165**	-0.171***	highest STV	0.048	0.265***	0.218***
	(0.130)	(-2.422)	(-3.906)		(0.883)	(4.825)	(5.283)
mean	0.293***	0.075	-0.218**	mean	0.296***	0.140***	-0.156**
	(3.130)	(0.443)	(-2.529)		(3.859)	(2.699)	(-2.095)

Notes: The table compares the effects of Salience Theory Value (STV) and Abnormal Turnover (ABTURN) by running a bivariate portfolio analysis. The left four columns present the performance of STV effects under ABTURN conditions, while the right four columns show the performance of ABTURN effects under STV conditions. At the beginning of each month, cryptocurrencies are divided into ten groups based on their ABTURN or STV values. Within each investment portfolio, cryptocurrencies are further classified into five subgroups based on their STV or ABTURN, resulting in fifty investment portfolios each month. H-L represents the return spread between the highest and lowest quintiles of STV or ABTURN. The average is the average return or return spread of the five quintiles for the control variables. t-values are shown in parentheses. The sample period covers from March 2013 to March 2023. Significance levels at 1%, 5%, and 10% are indicated by ***, **, and *, respectively. The values in parentheses represent the t-values for each portfolio, calculated using the robust t-statistic proposed by NEWEY & WEST (1987).

Table 10: Lottery preference and the salience effects

	STV					STR			
	Lowest	Highest	H-L	ff3		Lowest	Highest	H-L	ff3
Lowest LIDX	0.029***	0.025***	-0.004	-0.006	Lowest LIDX	0.038***	0.011	-0.027**	-0.041**
	(2.620)	(3.374)	(-0.410)	(-1.182)		(4.113)	(0.951)	(-2.133)	(-2.069)
2	0.047***	0.019*	-0.028***	-0.012***	2	0.026**	0.024**	-0.001	-0.015*
	(3.859)	(1.982)	(-3.685)	(-3.189)		(2.462)	(2.423)	(-0.266)	(-1.754)
3	0.066***	0.036***	-0.030	-0.040	3	0.038***	0.032**	-0.005	-0.008
	(4.131)	(2.806)	(-1.119)	(-0.019)		(3.404)	(2.277)	(-1.123)	(-1.562)
4	0.024	0.039***	0.015**	0.016*	4	0.033***	0.007	-0.026***	-0.026***
	(1.520)	(3.126)	(2.031)	(1.690)		(3.221)	(0.685)	(-3.661)	(-2.765)
5	0.069***	-0.022**	-0.091***	-0.065***	5	0.042***	0.001	-0.042***	-0.070***
	(5.231)	(-1.987)	(-5.841)	(-4.765)		(4.775)	(-0.031)	(-3.549)	(-2.776)
6	0.049***	0.017	-0.032***	-0.012*	6	0.031**	-0.026	-0.057***	-0.050***
	(2.781)	(1.045)	(-2.889)	(-1.784)		(2.289)	(-1.341)	(-3.205)	(-2.474)
7	0.093***	-0.012	-0.105***	-0.077***	7	-0.014	-0.040	-0.026	-0.007
	(5.515)	(-0.789)	(-4.329)	(-3.262)		(-1.144)	(-1.608)	(-1.408)	(-0.416)
8	0.070***	0.058***	-0.012**	-0.018**	8	-0.004	-0.026	-0.023	-0.002
	(2.894)	(3.584)	(-2.303)	(-2.130)		(-0.187)	(-0.853)	(-1.017)	(-0.102)
9	0.114***	0.061***	-0.053**	-0.039**	9	0.069***	0.023	-0.045*	-0.075*
	(5.465)	(3.647)	(-2.140)	(-2.245)		(4.665)	(1.370)	(-1.960)	(-1.685)
Highest LIDX	0.142***	0.067***	-0.075***	-0.093**	Highest LIDX	0.097***	0.060***	-0.038**	-0.088**
	(4.766)	(3.471)	(-2.676)	(-2.291)		(4.404)	(4.280)	(-2.286)	(-2.064)

Notes: The table reports the impact of lottery preferences on the salience effect. We construct a proxy variable for lottery demand, LIDX, and present the average monthly excess returns of stock portfolios sorted by LIDX and Salience Theory Value (STR or STV). At the beginning of each month, cryptocurrencies are divided into 10 groups based on their LIDX values, and within each LIDX investment portfolio, cryptocurrencies are further classified into 5 subgroups based on their STR (STV) values. Lowest LIDX and Highest LIDX represent the lowest and highest deciles of LIDX, respectively. Lowest and Highest represent the lowest and highest sub-quintiles of STR (STV), respectively. H-L denotes the average excess return difference between the highest and lowest STR (STV) investment portfolios. Additionally, we present the results of the multi-factor alpha. The values in parentheses are t-values, and we use cryptocurrency data from March 2013 to March 2023.

Table 11: Reversal effect and the salience effect

	STR					
	EW Portfolio			VW Portfolio		
Period	Week daily	Month daily	Quarter daily	Week daily	Month daily	Quarter daily
H-L return	-0.057**	-0.147***	-0.028***	-0.020*	-0.059***	-0.020***
	(-2.495)	(-5.181)	(-3.798)	(-1.735)	(-3.071)	(-3.416)
H-L 3F α	-0.020**	-0.025**	-0.025**	-0.007**	-0.049**	-0.031**
	(-2.352)	(-2.467)	(-1.986)	(-2.041)	(-2.543)	(-2.017)

Notes: The table reports the time series average of the return spread between the highest and lowest STR (Salience Theory Value) groups in the cryptocurrency market within a specified time interval. At the end of each month, we first categorize cryptocurrencies into three groups: Week daily, Month daily, and Quarter daily, based on the calculation period of STR. Within each group, cryptocurrencies are further divided into ten groups based on their STR values, ranging from low to high. Each group is then adjusted in the next period according to its respective calculation period, and the equal-weighted return spread between the highest and lowest STR is calculated and recorded in the table. The return spreads are reported as numerical values in the table. The table presents the time series average of the return spreads and the corresponding multi-factor alpha values. The values in parentheses represent the t-values for each portfolio, calculated using the robust t-statistic proposed by NEWEY & WEST (1987).

Table 12: Investor sentiment and the salience effects

	STV				STR			
	High Sent		Low Sent		High Sent		Low Sent	
	EW	VW	EW	VW	EW	VW	EW	VW
low ST	1.014***	0.272***	-0.052	-0.022	1.076***	0.237***	-0.088*	0.042**
	(2.865)	(2.947)	(-0.567)	(-0.957)	(3.232)	(5.642)	(-1.909)	-2.180
high ST	0.295*	0.081***	-0.262*	-0.024	0.595***	0.125***	-0.159***	-0.018**
	(1.982)	(3.380)	(-1.949)	(-0.726)	(2.972)	(4.291)	(-2.648)	(-2.065)
HL	-0.719***	-0.190***	-0.210***	-0.002***	-0.481***	-0.112***	-0.072*	-0.060*
	(-6.604)	(-4.150)	(-3.238)	(-2.888)	(-4.634)	(-5.921)	(-1.846)	(-1.767)
FF3	-1.113*	-0.234***	-0.267***	-0.028***	-0.491***	-0.088***	-0.018*	-0.024**
	(-1.997)	(-3.325)	(-4.065)	(-5.055)	(-5.321)	(-4.807)	(-1.821)	(-2.183)

Notes: The table presents the results of the ST (Salience Theory) effect under different investment sentiment periods based on the STR (Salience Theory Value). We utilize the Fear and Greedy Index (FNG) as the investor sentiment indicator in the cryptocurrency market. "High Sent" refers to periods when investor sentiment is above the median, while "Low Sent" refers to periods when investor sentiment is below the median. We present the time series average of the single-variable STR (STV) categorized portfolio returns during different investment sentiment periods. For portfolio returns, we calculate the results using both equal-weighted and value-weighted approaches. We show the value-weighted and equal-weighted average monthly returns of the highest and lowest STR (STV) decile portfolios, as well as the return spread (H-L) and the results of the multi-factor alpha. The returns are presented as actual numerical values. Due to the nature of sentiment indices, our data covers the period from March 2018 to March 2023. The values in parentheses represent t-values, with * indicating significance at the 10% level, ** indicating significance at the 5% level, and *** indicating significance at the 1% level.

Table 13: Salience and investor attention

Panel A : Bivariate portfolio sorts: controlling for Attention Factors								
	STR				STV			
Attention Variables	ABNRETD	ABNRETM	ABNVOLD	ABNVOLM	ABNRETD	ABNRETM	ABNVOLD	ABNVOLM
High-low return	-0.045*	-0.090***	-0.046***	-0.035***	-0.063*	-0.103***	-0.026***	-0.028***
	(-1.912)	(-2.893)	(-7.236)	(-5.715)	(-1.969)	(-2.907)	(-5.873)	(-3.221)
High-low 3F alpha	-0.131***	-0.164**	-0.069***	-0.071***	-0.097***	-0.166**	-0.061***	-0.052***
	(-2.619)	(-2.270)	(-4.905)	(-5.902)	(-3.068)	(-2.277)	(-6.121)	(-7.752)
Panel B : Fama-MacBeth regressions: Considering Attention Factors								
STR	-0.204**	-0.22**	-0.214**	-0.218**				
	(-2.312)	(-2.485)	(-2.404)	(-2.452)				
STV					-0.498***	-0.501***	-0.502***	-0.502***
					(-2.693)	(-2.717)	(-2.675)	(-2.633)
ABNRETD	0.014*				0.016*			
	(1.688)				(1.869)			
ABNRETM		-0.008***				-0.009***		
		(-2.852)				(-2.963)		
ABNVOLD			-0.001**				-0.001	
			(-2.363)				(-0.324)	
ABNVOLM				-0.007*				-0.007*
				(-1.734)				(-1.761)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The table presents the results of bivariate portfolio analysis and Fama-Macbeth regression analysis. We first consider four indicators related to significance based on Cosemans (2021): Maximum Absolute Abnormal Daily Returns (ABNRETD), Absolute Abnormal Monthly Returns (ABNRETM), Maximum Abnormal Daily Trading Volume within each month (ABNVOLD), and Abnormal Monthly Trading Volume (ANBVOLM). Abnormal returns are calculated as the difference between cryptocurrency returns and market returns. Abnormal daily (monthly) trading volume is calculated by dividing the daily (monthly) trading volume of cryptocurrencies by the average daily (monthly) trading volume of the previous year. Panel A reports the results of bivariate sorting analysis. At the beginning of each month, we first divide cryptocurrencies into 10 groups based on the Attention indicator value. Then, within each Attention investment portfolio, cryptocurrencies are further classified into 5 subgroups based on their STR (Salience Theory Value) from low to high. High-low return represents the return value of the average highest STR (STV) subgroup minus the average lowest STR (STV) subgroup among all decile portfolios, with equal-weighted returns calculated for each portfolio. We also present the results of multi-factor alpha for the high-low difference portfolios. Panel B shows the results of the Fama-Macbeth regression analysis. We include Attention-related proxy variables to analyze STR (STV) in the regression. A cross-sectional regression is conducted using next month's excess returns and this month's STR (STV), Attention proxy variables, and control variables. For trading volume, we analyze the logarithmic values. The sample period covers from March 2013 to March 2023. The values in parentheses represent the t-values for each portfolio, calculated using the robust t-statistic proposed by NEWEY & WEST (1987).

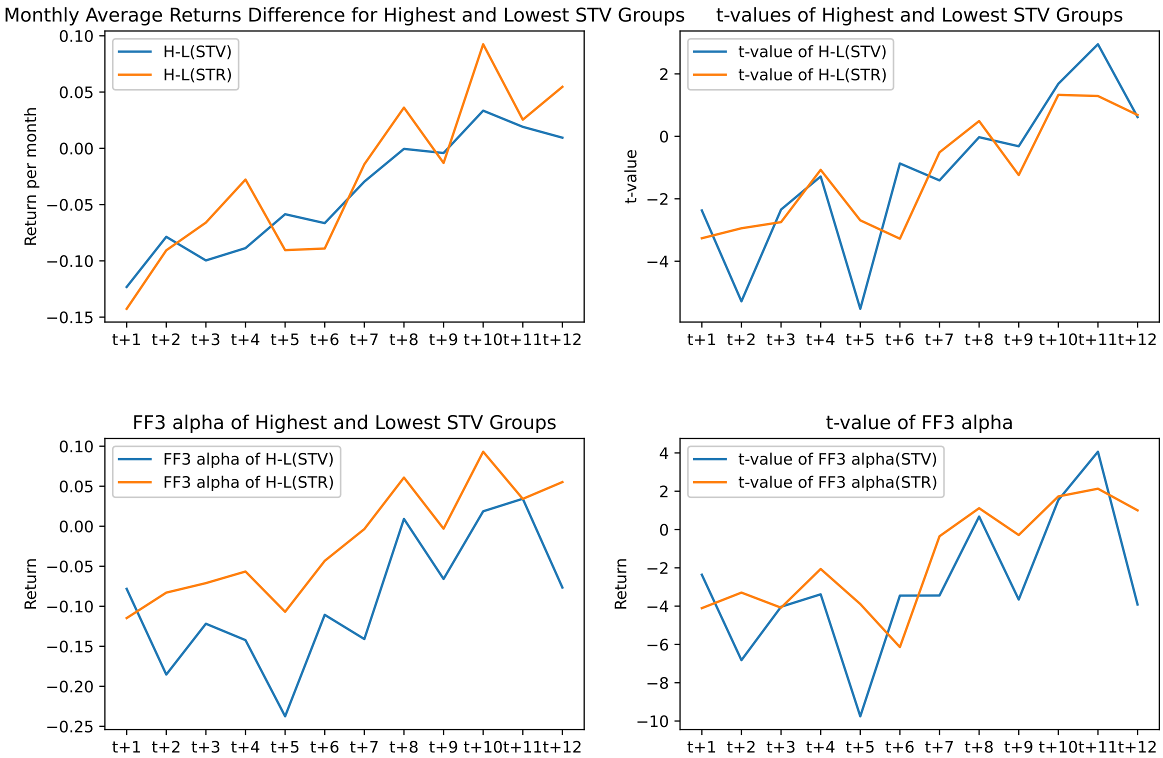

Figure 1: Persistence analysis

Note: We form a zero-cost hedging strategy based on the STR(STV) values of cryptocurrencies for each month by going long on the STR(STV) top decile portfolios and short on the STR(STV) bottom decile portfolios. Finally, the return movement of the portfolio over the next twelve months is calculated and plotted as a time series average, along with the t-value based on NEWEY & WEST (1987), the three-factor Alpha value, and the t-value corresponding to the three-factor Alpha, which are plotted in four separate graphs.

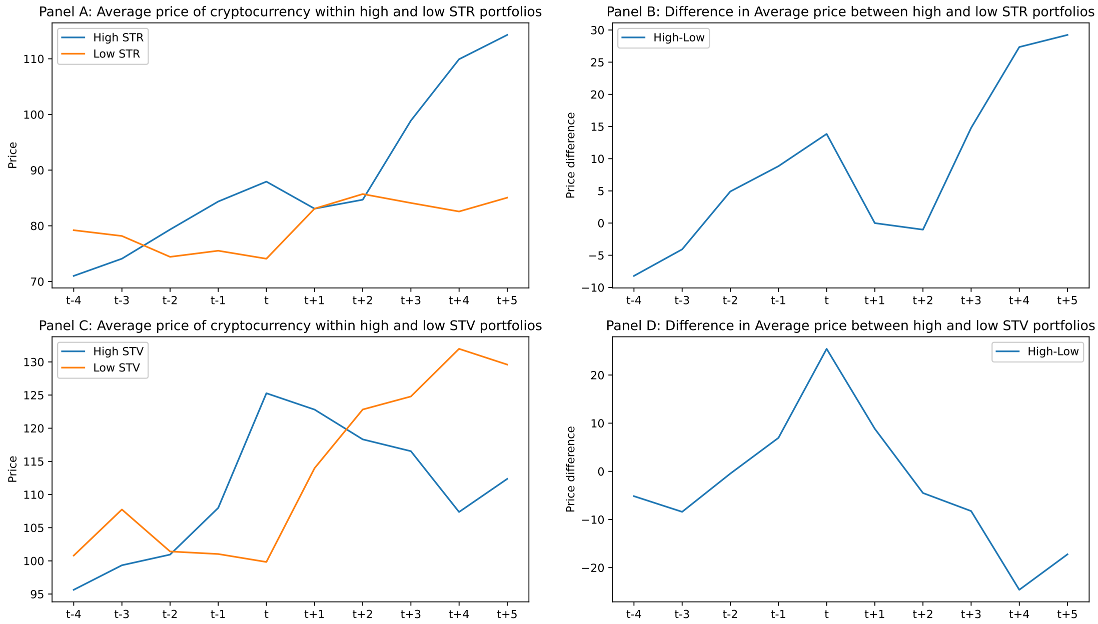

Figure 2: Price variation of high and low STR (STV) portfolios

Note: We plotted the price change in the average price of the highest STR(STV) and lowest STR(STV) portfolios for each month for the 10 months before and after the past future, and also calculated the change in the difference between the prices of the highest and lowest STR(STV) groups. These four graphs were eventually plotted.

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