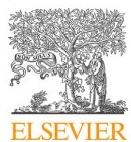
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| **Salience theory and cryptocurrency returns**  Charlie X.Caia,\*,Ran Zhaob  *University ofLiverpool Management School,University of Liverpool,United Kingdom of Great Britain and Northern Ireland*  Fowler College of Business,San DiegoState University,United States of America | | |  |
| **ARTI CLE INF O** |  | **A B S T R A C T** | |
| *JEL classification:*  G10 G11 G13 G40 G41  *Keywords:*  Salience theory  Asset pricing  Behavioral finance  Cryptocurrency Portfolio choice | The salience theory of choice under risk shows that investor behavior drives cross-sectional cryptocurrency returns.Investors place too much weight on salient payouts,causing overvaluation of cryptocurrencies with upward salience returns and undervaluation of those with downward salience returns,leading to negative expected returns for the former and positive expected returns for the latter.The salience effect in the cryptocurrency market is more pronounced than in equity markets,making it a significant risk factor for explaining other cross-sectional returns in the cryptocurrency market.Unlike other documented retum predictors,the salience theory uniquely contributes to understanding the cryptocurrency market. | |

**1.Introduction**

Cryptocurrency(crypto,hereafter)as an alternative asset class poses challenges to traditional asset-pricing theories while offering new av- enues for testing theories of investor behavior.Crypto assets can be challenging to value due to their unique characteristics.Unlike fiat currencies,they lack economic fundamentals.They also differ from traditional financial assets,because they do not generate cash flows. Furthermore,unlike precious metals,crypto assets do not have a long history of trust or cultural preferences as a means of storing value.The growing number of cryptos in the market gives rise to the following question:How do investors decidewhich crypto to invest in orwhether to invest at all?

Headlines have significantly influenced the crypto asset class,spark- ing investor fear of missing out on the“crypto-rush,”prompting studies (Sockin and Xiong,2023;Cong et al.,2021)to suggest the“network effect”(the increasing appeal of a platform as its user base grows)as a key driver of the crypto market's evolution.How investors process attention-grabbing fluctuations in the crypto market and the poten- tial consequences on future crypto returns have received less attention. To thisend,the salience theory,introduced by Bordalo et al.(2012), describes investors'behavior that closely matches that of the crypto market.

Salience theory is a context-dependent decision-making framework that explains choices under risk by replacing objective probabilities with distorted decision weights favoring salient payoffs that stand out compared to average alternatives (Bordalo et al.,2013a).Investors with a salience bias disproportionately prefer investments with salient up- ward returns and dislike those with salient downward returns.In equi- librium,the salience-based asset-pricing model proposed by Bordalo et al.(2013a)predicts that investments with conspicuous upside potential (downside risk)should generate lower (higher)returns.

Cosemans and Frehen(2021)and Cakici and Zaremba(2022)pro- vide evidence supporting the impact of the salience theory on cross- sectional pricing in the United States and international equity markets. Notably,thesalience effect was morepronounced for stocks with higher limits to arbitrageand during periods of elevated investor sentiment,re- inforcing the mispricing explanation (Cosemansand Frehen,2021).In line withthese findings,Cakici and Zaremba(2022)demonstrate that the salience effect is evident when arbitrage opportunities are limited such as in micro firms,high idiosyncratic risk countries,and during extreme market conditions characterized by significant economic un- certainty and volatility.The crypto market is an emerging asset class with highuncertainty and limited fundamental information available to investors.Hirshleifer(2001)argues that uncertainty allows investors to follow their subjective estimations and ignore objective valuations.

\*Corresponding author

**E-mail addresses:busxc@liverpool.ac.uk (C.X.Cai),rzhao2@sdsu.edu(R.Zhao).**

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The emerging and non-mainstream nature of the crypto market creates an environment that is more likely to attract investors with a salience bias.For example,Cakici and Zaremba(2022)note that sentiment and the resulting salience theory effect are more likely to influence retail eq- uity investors.Therefore,substantial evidence existsto conjecture that salience theory could be a critical mechanism in determining the pric- ing of cryptos;its effectwould be stronger in the crypto market than in other decision-making contexts,including equity markets.

T**his study examines whether the salience effect exists on cross**- sectional crypto returns.We use data from over 4,000 coins with a market value greater than one million USD from“Coinmarketcap.com”

**from January 2014 to June 2021.Following Cosemans and Frehen**

(2021),we construct a salience measure,ST,that effectively measures the difference between salience-and equal-weighted returns during the formation period (weekly or monthly).ST quantifies the extent of salience thinking in distorting investors'expectations of future re- turns compared to objectively realized past returns.The salience-based asset-pricing model primarily predicts that cryptos with salient upsides (positiveST)have lower future returns than those with salient down- sides (negative ST).

Our empirical study comprises two parts.First,we study the pre dictability of ST on cross-sectional crypto returns.Second,we investi- gate the viability of ST as a cross-sectional pricing factor,assessing its ability to account for other cross-sectional predictabilitiesin the crypto market.

The predictability study employed single-portfolio sorting to illus- trate the economic and statistical significance of the ST effect.Our findings indicate that cryptocurrencies with salient upsidesyield lower returns over the following month than those with salient downsides. The univariate portfolioanalysis revealed that the average return for the zero-cost strategy,which involves purchasing high-ST cryptocurrencies, varies from -25.9%(t-value =-8.7)monthly for the equal-weighted (EW)portfolio to-32.4%(I-value =-2.3)for the value-weighted (VW) portfolio.These figures are over 20 times greater than those reported in the US equity market (Cosemans and Frehen,2021)and are consid- erably larger than the micro-stock results,the most substantial findings documented in the international equity markets of Cakici and Zaremba (2022).¹Moreover,the salience effect is on par with the strongest fac- tors documented thus far in crypto market research (Liu et al.,2022).

Subsequently,we demonstrated the robustness of ST's predictabil- ity,showing that it yields significant alpha when controlled for the Liu-Tsyvinski-Wu (LTW)three-factor model (Liu et al.,2022).Further- more,ST has incremental predictability for future crypto returns in the Fama-MacBeth regression analyses when accounting for cross-sectional determinants in the ST and crypto literature (Cosemans and Frehen, 2021;Liu et al.,2022).

In the pricing factor study,if the ST serves as one of the primary pricing effects in the crypto market,we anticipate its ability to ex- plain other cross-sectional pricing patterns.For example,Bordalo et al. (2013a)demonstrate that the ST is valuable in deciphering equity asset pricing anomalies such as the preference bias for highly skewed assets, the growth-value puzzle,and the aggregate equity premium puzzle.We created an ST factor using the factor construction method proposed by Liu et al.(2022)to investigate this potential in the cryptomarket.Our findings suggest that the ST factor could potentially supplement the momentum factor in the LTW three-factor model,accounting for other cross-sectional return strategies documented in Liu et al.(2022)and additional behavioral anomalies,including prospect theory (Barberis et

al.,2016),skewness (Harvey and Siddique,2000),and downside beta (Angetal.,2006).



1 Cryptocurrency market returns were generally quite large during our in- vestigation period,as documented by Liu and Tsyvinski(2021),who show an average monthly return of 20.44%and a standard deviation of 70.80%.

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**We conducted additional robustness tests to deepen our understand- ing of the crypto market's ST return predictability and pricing factor roles.Regarding ST's predictability,we demonstrate that 1)the ST ef-**

fect is also observable in a time-series context,where the salience of

**crypto market returns,compared to other investment opportunities, negatively predicts the asset class's future returns.Furthermore,2)the cross-sectional ST effect is positively correlated with uncertainty and at-**

tention in thecrypto market but negatively correlated with uncertainty in the stock market and the economy.These findings confirm that in-

**vestors influenced by salience bias will likely be risk-seekers drawn to crypto markets when other asset markets are relatively calm.Their ac-** ti**vities intensify with greater investor attention to the crypto market**, c**orroborating that behavioral bias underlies this effect**.

Regarding the pricing factor study,we offer more detailed compar- isons between ST and existing factors,including the prospect theory fromKahneman and Tversky(1979)(KT),idiosyncratic volatility,mar- ket beta,momentum,and reversal using double sorting,correlations, and a pairwise comparisonof return predictability in Fama-Macbeth re- gressions.ST generally prevails over the other effects,confirming that the salience measure is theoretically and empirically distinct.The ST measure captures the cross-sectional and time-series information on crypto returns.Each returnfor a given period is initially compared cross-sectionally with other crypto returns to obtain a salience measure. We then apply this measure in a time-seriescontext for each crypto to determine how much the salience factor influences its expected re- turn,thereby capturing information that differs from the existing cross- sectional characteristics

This study offers new insights into the valuation of crypto assets and the relevance of the ST in asset pricing.First,we demonstrate that the behavior of crypto investors can be explained by the ST in decision-making,thereby expanding the theoretical and empirical ef- forts to understand the drivers ofthis market.According to Sockin and Xiong(2023),network effects suggest that news and investor sentiment explain token price fluctuations and expected returns.Similarly,Cong etal.(2021)provide a dynamic model illustrating the impact of endoge- nous user adoption on a platform's success and token price.Speculative motives and sentiments can influence potential users'decisions to par- ticipate on a platform,explicitly connecting investor attention to and expectations of the platform's growth.Salience theory goes one step further by describing how investors may form expectations based on salient payoffsthat capture their attention.Ourempirical evidence con- firms a strong ST effect in crypto returns'cross-section and time series. This approach demonstrates that ST is a contender as one of the risk factors for cross-sectional returns,which is particularly appealing,asit stems from a behavioral theory model,providing a solid foundation for interpreting the factor

Second,we present additional evidence on the conditions under which the ST may be more relevant in explaining asset prices.The crypto market aligns well with the conditions Cakici and Zaremba (2022)and others identified for observing the ST effect:micro caps extreme uncertainty,and potentially less sophisticated investors.We show that a strong STeffect dominates prospect theory and the prefer- ence for skewness explanations.Furthermore,we demonstrate that the ST effect differs from short-term reversal,which is challenging to dis- entangle in an equity market.Our findings confirm that the salience effect is much stronger for assets more difficult to value,mainly when fundamental information is reduced.

Finally,we reveal that the salience efects are significantly stronger in the crypto market than in the traditional financial market,even by microcap standards.This finding implies a disproportionately large group of salience-driven investors in the crypto market,underscoring the importance of regulations and investor protection.

The remainder of this study is organized as follows.Section 2 de- scribes the data source and construction ofa salience effect measure Section 3 analyzes the effect of ST on cross-sectional returnpredictabil- ity,and Section 4 reports the analyses that considered ST as a risk

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factor.Section 5 outlines the series of robustness checks,and we con- clude with our findings in Section 6.

2.Data and methodology

*2.1.Data sources*

Following similar studies,we retrieved crypto prices from Coinmarketcap.com (Liu and Tsyvinski,2021;Liu et al.,2022).Our sample's dailycrypto price observations ranged from January 1,2014, to June 30,2021.The collected dataset contained crypto symbols as identifiers,daily prices,trading volume in USD,and market cap italization of the included cryptos.The samples did not contain any stablecoins.Cryptosare traded on centralized or decentralized electric exchanges,24 hoursa day,7 days a week.In general,the crypto market has no exchangeclose time.We include all calendar days with crypto transactions and calculate the returns using the whole day cosing price from 0:00:00.000 to 23:59:59.999 UTC.

*2.2.ST measure*

Following Bordalo et al.(2016)and Cosemans and Frehen(2021), we constructed an ST measureusing the following steps.First,we calcu- lated thesalience of each crypto's daily payoff within the measurement period.When choosing among cryptos,we assumed that investors infer a set of future return states from the distribution of past returns.Our primary analysis assumed that the daily returns over the past week or month form this state space.We measured the salience of the return (₁g)of crypto i on day s by its distance from the average return across all cryptos in the market on that day (F,):



(1)

where  with N denoting the number of cryptos avail- ableon the market.θ is included to control for thesalience of Opayoffs Following Cosemans and Frehen(2021),we set θ=0.1.

Second,we calculated the salience weights.Given the salience func- tion in Equation(1),the salient thinker ranks each payoff and replaces the objective state probabilities with the salience weights.For the objec- tive state probabilities,S denotes the setof states,which is the number of trading days within the ranking period,where each state s occurs with an equal probability π,so that πg=1/S.The salience-weighted probability is then given by:

元，=πg×O;,g, (2)

Here,元，gdenotes the salienceweighted subjective state probability and

①;g is the salience weight defined as

(3)

here δ captures the degree to which salience distorts the decision.When δ=1,no distortion occurs;when δ→0,there is a maximum salience distortion in that the investor only considers the most salient payoff Following Bordalo et al.(2012)and Cosemans and Frehen (2021),we set δ=0.7 in our analyses.Furthermore,k;g is the rank of the salience payoff r,g among the daily returnof a given crypto in the measurement period and ranges from 1(most salient)to S (least salient);πg=1/S denotes the objective probability for each state.

Third,the salience effect —the extent to which salience thinking influences the expected return —is then measured by the covariance of the decision weights(@g)and the crypto return(r₁g)over the esti- mation period according to the salience-based asset-pricing framework (Bordalo et al.,2013a).

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Table 1

Summary statistics on portfolio analysis

Year Counts Market Cap(million USD) Volume(thousand USD)

Mean Median Mean Median

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| 2014 | 100 | 309.38 | 5.97 | 1,655 | 47 |
| 2015 | 83 | 179.88 | 4.70 | 1,583 | 15 |
| 2016 | 171 | 210.32 | 4.44 | 2,488 | 25 |
| 2017 | 796 | 632.23 | 13.91 | 31,778 | 201 |
| 2018 | 1,592 | 497.38 | 12.51 | 30,156 | 212 |
| 2019 | 1,957 | 293.18 | 5.90 | 75,832 | 172 |
| 2020 | 2,614 | 763.91 | 6.71 | 134,423 | 281 |
| 2021 | 3,701 | 1,108.23 | 13.72 | 232,859 | 516 |

Table 1 presents the number of cryptos,the mean and median mar- ket capitalizaton,and the mean and median trading volume in USD per year.The sample comprises actively traded cryptos with a mar- ket capitalization of over 1 million USD within the sample period from January 2014 toJune 2021.



(4)

=EST[s]-F Vi∈N,

where EST[.]denotes the salience-biased expected value.ST,effec- tively measures differences between salience-weighted and EW returns in the measurement period (second equality).It quantifies the extent of salience thinking on distorting investors'expectations about future re- turns compared to objectively realized past returns.When ST<0,it suggests that the lowest payoffs of an asset are the salient ones;the in- vestors focus on downside risks,leading to a positive“risk”premium (positive expected return in the next period).When ST>0,it suggests that the highest payoffs of an asset are the salient ones;the investors focus on upside potential,resulting in a negative “risk”premium(neg ative expected return in the next period).

The derivation of the salience effect measure is grounded in the salience-based asset-pricing theory of Bordalo et al.(2013a)and closely adheres to the empirical design of Cosemans and Frehen(2021).This salience measure is theoretically and empirically distinct,capturing both cross-sectional and time-series information on a crypto's return. First,each return for a given period is compared cross-sectionally with other returns to obtain a salience measure.Second,eachsecurity em- ploys this salience measure in a time-series context to determine how much the salience factor influences its expected return.

Ourportfolio sorting analysis computed the ST parameter specified in Equation(4)using the daily salience measure for each crypto week ormonth.We construct a quintile portfolio by sorting the ST measures and calculating the excess portfolio returns for the next period.

*2.3.Summary statistics*

Table1 presents thenumber ofcryptos.The number of coinsand to- kens in the sample that satisfied all filters increased from 100 in2014 to 3,701 in 2021;the sample's mean(median)market capitalization also increased significantly during this period.A significant difference be- tween the mean and median suggests a substantial outlier(notably Bit- coin).Volume increases much faster than market capitalization,which is consistent withthe emergingnature and growthof this class of assets

Previous asset-pricing studies,ST,and crypto markets inform addi- tional control variables,mainly constructed from the trading prices and volumes ofcryptos.OnlineAppendix 2 discusses these variableswhile Appendix Table A.1 summarizes all variable constructions.2



2 Summary statistics and correlations of the key variables can be found in Online AppendixTable OA1.

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**Table 2**

Salience Theory effect —portfolio sorting

Weekly Returns Monthly Returns Equal-Weighted Value-Weighted Equal-Weighted Value-Weighted

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| 1 (Low) | 0.020\*\* | 0.054 | 0.175\*\* | 0.381\*★ |
| [4.065] | [5.850] | [7.149] | [2.682] |
| 2 | 0.000 | 0.013\* | 0.045 | 0.102\* |
| [0.162] | [2.7771 | [2.029] | [3.595] |
| 3 | 0.000  [0.130] | 0.014  [3.275] | -0.010  [-0.601] | 0.084\*★ [3.508] |
| 4  5(High) | -0.005\*\* | 0.016 | -0.033\* | 0.092\* |
| [-2.287] | [3.312] | [-1.842] | [2.514] |
| -0.014\* | 0.024\*\* | -0.084★ | 0.057\*\* |
| [-4.653] | [2.518] | [-4.197] | [2.227] |
| High -Low | -0.034\*\*★ | -0.030\*\* | -0.259★☆ | -0.324\* |
| t-Stat | [-5.223] | [-2.226] | [-8.701] | [-2.269] |

Table 2 presents the average returns of the single-sorted portfolios using the salience theory (ST)measure.The sample consists of actively traded cryptos with amarket cap- italization of over 1 million USD within the sample period from January 2014 to June 2021.Each week (month),the cryptos are sorted into quintile portfolios according to the salience effect measure of the previous week (month).Each portfolio was held for one week (months).The“Equal-Weighted”and“Value-Weighted”columns report the one week(one month)ahead excess returms ofeach portfolio with equal-weighted and value-weighted,respectively.Using the corresponding sorting variable,the“High -Low"row reports theaverage returm difference between the highest and lowest sort- ing value portfolios.The“I-Stat”row reports the Newey-West robust t-statistic.

**3.ST and the predictability of cross-sectional crypto returns**

*3.1.Univariateportfolio sorts*

Table 2 presents the average returns of the single-sorted portfolios using the ST measure.The sample comprises actively traded cryptos with a market capitalization of over 1 million USD during the sample period from January 2014 to June 2021.Each week (month),cryptos are sorted into quintiles according to the salience effect measure of the prior week(month).Each portfolio was held for one week (month).Two considerationsaffected the decision regarding different return windows. First,given the shorter history and potentially faster-moving market for crypto assets,the existing literature often uses weekly frequencies. Weekly frequencywas the primarychoice forcomparison with existing studies.Second,asset-pricing studies on equity markets have tradition- ally been based on monthly data,therefore,we present the monthly findings for our main baseline to compare the magnitudes with those in the equity market.We only reported the weekly frequency,for the other findings in this study.The monthlyfindings produced a consistent conclusion,which can be found in theOnline Appendix.

Table 2 shows that cryptos with salient upsidesearn lower returns over the next period than cryptos with salient downsides.This result is consistent with the findings in the equity market by Cosemans and Frehen(2021)and Cakici and Zaremba(2022).Three additional obser- vations arise from these crypto marketanalyses.First,the magnitude of the salience effect iseconomically much biggerthan those in the equity markets.For example,the average return for the long-short strategy that buys high and sells low ST cryptos generates -25.9%(t-value =-8.7) monthly for the EWportfolio and -32.4%(t-value =-2.3)for the VW portfolio.These are more than 20 times the magnitude of those doc- umented in the U.S.equity market with -1.28%and -0.6%monthly excess returns for EW and VW,respectively (Cosemans and Frehen, 2021).The ST effect in the crypto market is also markedly larger than in the micro stock results,representing thestrongestfindings in the equity market,as documented by Cakici and Zaremba(2022).They found that the ST strategy generated-1.0%and -0.52%monthly excess returnsfor EW and VW,respectively.

Second,the salience effect iscomparable to the strongest factors doc- umented in the crypto market research.For example,Liu et al.(2022) found a VW size factor premium of 3.4%to4.1%per week.Our weekly

findings for a 3.0%VW weekly return are comparable to this magni- tude.Furthermore,the monthly salience effect is much stronger in the crypto market.The monthly VW return for the ST effect in the crypto marketis annualized(multiplied by 12)to 388.8%,whereas the largest weekly size effect is annualized (multipliedby 52)to 213.2%;however it is important to be cautious about such large return strategies.The salience effects require supply (salience price movement)and demand (the attention of salience investors with fundsto participate);both can be time varying.In a subperiod analysis,we confirm that the ST effect is time-varying (in the Online Appendix).The key implication is that there is a risk of engaging in such a strategy every year

Third,the EW results weremuch stronger than the VW results,con- sistent with the potential size effect suggested by Cakici and Zaremba (2022).The EV results place more weight on small cryptos,demonstrat- ing a stronger effect,however,a later analysis shows that the ST effect in thecrypto market is not restricted to small-cap cryptos.In the robust- ness test section,we further study the relationship between the market cap and the ST effect (Section 5.3.3).Overall,Table 2 demonstrates a strong ST effect that is statistically significant and economically large.

*3.2.Controllingfor existing crypto risk factors*

We considered the relationship between the ST effect and known risk factors.Table 3 presents the alphas and details of the regression explaining crypto excess returns in quintile portfolios using the LTW three-factor model (Liu et al.,2022).We construct the crypto market in- dex using the EW returns of all available coinsand tokens.The size and momentum factors in the weekly return analysisfollow the construction approach proposed by Liu etal.(2022).The size factor was constructed like the weekly returns for the monthly factors.We constructed the monthly momentum factorusing one-month lagged returns.

Table 3 shows that ST generates a 3.2%alpha weekly (annualized 166.4%)and 24.6%alpha monthly (annualized 295.2%),as shown in the“High-Low”columns.3 Regarding the factor loading,the weekly re- gressions show that the ST portfolio loads a positive size factor but



3 Toalleviate the concem about the impactof outliers,we tried winsorizing the raw retum on [0.5%,99.5%]and [1%,99%],and the results remain with similar magnitude.Extreme cases do not drive portfolio alphas.

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**Table 3**

Risk factor analyses ofsalience effect using LTW three-factor model. Panel A:Weekly Returns

(Low) 2 3 4 5(High) High-Low

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
|  | 0.020\*\* | 0.001 | 0.000 | -0.005\*\* | -0.011\* | -0.032\* |
| t( | [3.635] | [0.270] | [-0.082] | [-2.198] | [-3.448] | [-4.326] |
| p(CMKT) | 0.096\*\* | 0.006 | -0.051 | -0.006 | 0.011 | -0.085 |
| t(p(CMKT)) | [1.998] | [0.250] | [-2.337] | [-0.264] | [0.376] | [-1.352] |
| (SIZE) | -0.023 | 0.009 | 0.003 | 0.000 | 0.029\*\* | 0.052\*★ |
| t(p(SIZE) | [-1.447] | [1.119] | [0.471] | [-0.031] | [3.037] | I2.474] |
| (MOM) | 0.021 | 0.009 | -0.004 | -0.001 | -0.038\*\*★ | -0.059\*\* |
| t(p(MOM) | [1.087] | [0.866] | [-0.401] | [-0.122] | [-3.263] | [-2.302] |
| Adj.R² | 0.0195 | 0.0078 | 0.0165 | 0.0002 | 0.0418 | 0.0307 |

Panel B:Monthly Returns

(Low) 2 3 4 5(High) High-Low

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
|  | 0.178\*\* | 0.051\* | 0.006 | -0.028 | -0.068\* | -0.246\* |
| t(a) | [5.882] | [1.932] | [0.321] | [-1.242] | [-2.698] | [-6.381] |
| β(CMKT) | -0.248\*\* | -0.273\* | -0.177\*★ | -0.154★ | -0.136\*\* | 0.112 |
| t(p(CMKT)) | [-3.224] | [-4.042] | [-3.563] | [-2.679] | [-2.112] | [1.138] |
| β(SIZE) | 0.013 | 0.027 | 0.043\* | 0.026 | 0.045 | 0.032 |
| t(β(SIZE) | [0.383] | [0.899] | [1.955] | [1.017] | [1.577] | [0.736] |
| (MOM) | 0.024 | 0.029 | 0.040 | 0.016 | 0.035 | 0.011 |
| t(p(MOM) | [0.666] | [0.912] | [1.674] | [0.592] | [1.145] | [0.230] |
| Adj.R² | 0.1148 | 0.1701 | 0.1669 | 0.0950 | 0.0813 | 0.0292 |

Table 3 presents the details of the regressions explaining the crypto-excess returns in the ST quintile portfolios using the LTW three-factor model proposed by Liu et al.(2022).The model specifications are as follows.

R₁-Ry=d+f₁CMKT+p₂SIZE+β₃MOM+ej.

CMKT is the VWcryptocurrency return.SIZE is the size factor constructed from the market capitalization of the coins.MOM is the cumulative past crypto returms.More detailed variable definitions are provided in Table A.1.The sample consists of actively traded cryptos with a market capitalization of over 1 million USD within the sample period from January 2014 to June 2021.\*\*\*,\*\*,and\*denote significant levels at 1%,5%,and 10%, respectively.

a negative momentum factor.No significant factor loading is shown in the monthly regression,suggestingthat the ST effects were independent of theexisting factors.The finding confirmsthat known risk factors can- not explain the salienceeffect.4

*3.3.Fama-MacBeth cross-sectional regressions*

We examined the cross-sectional predictability of crypto returns with and without ST measures,including a list of control variables. Table 4 reports the estimated regression coefficients and t-statistics (in parentheses)from the Fama-MacBeth cross-sectional regressions for

weekly (panel A)and monthly returns (panel B).Following Cosemans and Frehen(2021),we included a list of cross-sectional determinants.

The control variable is described in the Online Appendix 2 and Ta- ble A.1.

Panel Ain Table 4 shows that ST has significant predictability for fu- ture crypto returns in all specifications.It can explain 10%of the future cross-sectional weekly returns,asindicated by the average R².Further- more,the ST effectis robust when controlling for other firm-level risks, such as liquidity,lottery demand,prospective theory value,skewness preference,and downside risk measures.While the t-value indicates the statistical significance is reduced,the magnitude seems higher,espe cially when other behavioral controls,such as TK and SKEW,are added. A clear incremental improvement occurred in explanatory power when



4 We also test the alpha including equity factors —Fama and French (1993) three-factor and Carhart (1997)momentum factor —and including both eq- uity and LTW threefactors in a full seven-factor (Full7)model;however,these specifications do not explain the ST effect (Table OA2).

ST was included.The average adjusted R-squared increases from 32% (Column 11)to 45%(Column 10)when the ST variable was added to the regressionwith all control variables,representinga 39%increase in explanatory power.The monthly results in Panel B are consistent with the weekly findings,withthe ST variable having increased t-values

**4.ST as a potential risk factor in the cryptomarket**

If the ST effect captures one of the key trading behaviors of crypto investors,it may explain other return“anomalies”in this emerging asset class.We further explored the relationship betweenSTand other crypto market return anomalies,constructing the ST factor similar to that of Liu et al.(2022).Each week,we partitioned the cryptos into three salience groups using the ST measure:the bottom 30%(down-salience), the middle40%(non-salience),and the top 30%(up-salience).Further- more,we then formed VW portfolios for each group.The crypto-ST fac- tor is the return difference between the up-salience and down-salience portfolios;therefore,the ST premium is negative for this construction. We strictly followed Liu et al.(2022)to construct the other three crypto factors:the market,size,and momentum.5

Table 5 presents the alphas from the factor model regressions ex- plaining the crypto-excess returns in the hedge portfolios (high-low) sortedby crypto characteristic variablesstudied in the extant literature including six different factor model specifications.Specifically,Models



5 For completeness,we also constructed equal-weighted factor returns.We reported on VWanalyses to be consistent with Liu et al.(2022).Analyses ofEW portfolios using EW factors can be found in the Online Appendix Table OA3.

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**Table 4**

Fama-MacBeth cross-sectional regressions.

|  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Panel A:Weekly Returns | | | | | | | | | | | |
|  | (1) | (2) | (3) | (4) | (5) | (6) | 7) | (8) | (9) | (10) | (11) |
| ST | -0.355\*★ [-3.751] | -0.354\*★ [-3.861] | -0.374\*\* [-4.093] | -0.434\*\* [-4.504] | -0.452\*★ [-4.458] | -0.320\*\* [-1.993] | -0.309\* [-1.922] | -0.433\*\* [-2.514] | -0.450\*\* [-2.555] | -0.554\*\* [-2.564] |  |
| BETA |  | -0.002  [-0.882] | -0.002 [-0.943] | 0.000  [0.068] | 0.000  [-0.109] | -0.002 [-0.275] | -0.001  [-0.100] | 0.001  [0.143] | 0.000  [0.053] | 0.000 [0.064] | -0.001 [-0.123] |
| SIZE |  | -0.002\*★\* | -0.002\*\*★ | -0.004\*★☆ | -0.003\*★ | -0.003\*\*★ | -0.003\*\*★ | -0.002\* | -0.002\* | -0.001 | -0.001 |
|  | [-2.909] | [-2.813] | [-4.026] | [-3.541] | [-3.472] | [-3.130] | [-2.234] | [-1.707] | [-1.026] | [-0.832] |
| MOM |  |  | 0.005  [0.635] | 0.007  [0.998] | 0.005  [0.721] | 0.011  [1.401] | 0.009  [1.112] | 0.007  [0.754] | 0.008  [0.818] | 0.007  [0.750] | 0.007  [0.751] |
| AGE |  |  |  | 0.001  [0.236] | 0.000  [-0.024] | 0.000  [0.120] | -0.001  [-0.141] | -0.003 [-0.857] | -0.006 [-1.214] | -0.007 [-1.353] | -0.007 [-1.566] |
| IVOL |  |  |  | -0.035\*★  [-3.531] | -0.037\* [-3.068] | -0.007  [-0.213] | -0.008  [-0.221] | 0.006 [0.151] | 0.007  [0.183] | -0.011 [-0.277] | -0.016 [-0.427] |
| LLIQ |  |  |  |  | 116.409 [1.049] | 174.284 [1.390] | 218.263\* [1.752] | 265.542 [1.491] | 200.127 [1.097] | 219.45 [1.384] | 164.181  **[1.466]** |
| MAX |  |  |  |  |  | 0.011  [0.146] | 0.000  [0.002] | -0.072 [-0.793] | -0.081 [-0.857] | -0.066 [-0.687] | **0.040** **[0.471]** |
| MIN |  |  |  |  |  | 0.100  [1.173] | 0.084  [0.951] | 0.018  [0.196] | 0.039  [0.405] | 0.004 [0.040] | **0.073**  [0.822] |
| TK |  |  |  |  |  |  | 0.085  [0.996] | 0.146  [1.301] | 0.135 [1.157] | 0.119 [0.981] | 0.151 [1.247] |
| SKEW |  |  |  |  |  |  |  | 0.000  [0.176] | -0.000 [-0.006] | -0.002 [-0.450] | -0.003 [-0.774] |
| COSKEW |  |  |  |  |  |  |  | 1.821  [0.339] | 1.870 [0.341] | 2.050 [0.376] | 5.022  **[0.986]** |
| ISKEW |  |  |  |  |  |  |  |  | 0.000  [-0.061] | 0.001 [0.182] | 0.001  [0.216] |
| DBETA |  |  |  |  |  |  |  |  |  | -0.006 [-1.225] | -0.002  [-0.475] |
| Intercept | -0.001  [-0.148] | 0.036\*  [2.719] | 0.041  [2.864] | 0.072  [4.587] | 0.065  [4.141] | 0.058  [3.821] | 0.057\* [3.342] | 0.047\* [2.446] | 0.046  [2.192] | 0.042\* [1.866] | 0.035  [1.564] |
| Avg.R² | 0.1096 | 0.1665 | 0.2059 | 0.2664 | 0.2922 | 0.3614 | 0.3832 | 0.4181 | 0.4274 | 0.4475 | 0.3222 |

|  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | Panel B:Monthly Returns | |  | | | | | | | | |
| (3) | (4) | (5) | (6) | (7) | (8) | 9) | (10) | (11) |
| (1) | (2) |
| ST | 2.630\* [-4.533] | -2.685 [-4.617] | 2.652  [-4.773] | .2.529\* [-4.502] | .2.608\* [-4.619] | .2.054 [-4.324] | -1.979\*  [-4.523] | 1.803\* [-4.352] | 1.849\* [-4.089] | 1.802\*  [-4.104] |  |
| BETA |  | 0.001  [0.130] | -0.005 [-0.420] | -0.022\* [-1.734] | -0.020\* [-1.799] | -0.046\* [-1.870] | -0.058★ [-2.720] | -0.051★ [-2.497] | -0.050\*\* [-2.387] | -0.040\*\* [-2.079] | -0.046\*\*  [-2.476] |
| SIZE |  | 0.021\*☆ [6.552] | 0.022\*★ [7.812] | 0.027\*★ [7.813] | 0.027\*  [7.931] | 0.025\*\*  [8.269] | 0.025\*★南  [7.927] | 0.025\*  [5.383] | 0.022\*  [3.825] | 0.023\*  [3.304] | 0.022  [3.384] |
| MOM |  |  | 0.042\*★ [3.061] | 0.042\*★  [2.947] | 0.043\*☆ [3.034] | 0.036\*\* [2.328] | 0.049\*★☆ [3.023] | 0.049\*★ [3.202] | 0.052\*★★ [3.395] | 0.055\*  [3.626] | 0.053  [3.716] |
| AGE |  |  |  | -0.001 [-0.093] | -0.002 [-0.196] | 0.019  [0.838] | -0.003 [-0.257] | -0.027 [-1.627] | -0.030 [-1.534] | -0.015  [-0.890] | 0.000  [0.024] |
| IVOL |  |  |  | 0.134\*★★ [3.206] | 0.143\*  [3.060] | 0.082  [0.703] | 0.025  [0.242] | -0.024 [-0.225] | -0.02  [-0.173] | 0.018  [0.153] | 0.045  [0.373] |
| LLIQ |  |  |  |  | 75.142  [0.378] | -76.72 [-0.742] | 6.585  [0.051] | 359.266 [1.207] | 449.632 [1.322] | 548.692 [1.360] | 422.713 [1.259] |
| MAX |  |  |  |  |  | 0.459\*★  [3.117] | 0.576\*  [4.420] | 0.632\*★ [5.065] | 0.599\*\*  [4.603] | 0.654\*★ [4.365] | 0.747\*★ [4.957] |
| MIN |  |  |  |  |  | 0.155  [0.855] | 0.122  [0.737] | 0.134  [0.869] | 0.141  [0.844] | 0.255  [1.325] | 0.364\*\* [2.201] |
| TK |  |  |  |  |  |  | 0.143  [0.611] | 0.310  [0.986] | 0.324  [0.979] | 0.229  [0.517] | 0.302  [0.687] |
| SKEW |  |  |  |  |  |  |  | -0.002 [-0.463] | -0.004 [-0.283] | -0.003  [-0.194] | -0.005  [-0.326] |
| COSKEW |  |  |  |  |  |  |  | -0.141 [-0.227] | -0.186 [-0.288] | -0.497 [-0.793] | -0.579  [-0.886] |
| ISKEW |  |  |  |  |  |  |  |  | 0.008  [0.477] | 0.005  [0.320] | 0.005  [0.335] |
| DBETA |  |  |  |  |  |  |  |  |  | -0.001 [-0.038] | -0.000 [-0.014] |
| Intercept | 0.007 [0.502] | -0.327\* [-5.611] | -0342 [-6.503] | -0.453\*★☆  [-6.892] | —0440—  [-6.963] | -0.4608 [-7.573] | -0.457\*★☆ [-7.172] | -0.438  [-4.526] | -0.405  [-3.678] | -0.444\*\*★ [-2.799] | -0.443\*☆☆ [-2.905] |
| Avg.R² | 0.0614 | 0.1265 | 0.1627 | 0.2181 | 0.2338 | 0.3113 | 0.3331 | 0.3623 | 0.3732 | 0.3940 | 0.3755 |

**Table 4 reports theestimated regresioncoffients of the t-statistics in brackets)from Fama-MacBeth crosecional regresions for cryptoreturns.The sampl**e co**nsists of actively traded cyptos with a market capitalization of over 1 million USD within the sample period from January 2014 to Jume 2021,including 3**91

**weeks(90months).The Fama-MacBeth regresion uses weekly retums (Panel A)and monthlyretums Panel B).STis the salience theory measure.BETA denote**s t**he beta for themarke eturn.SIZEisthe marketcapitaliation o cryptos.MOM denotes thelaggedone day returm.VOIM is thelogaithm of thetradingvolum**e. IVOL denotes the idiosyncratic volatlit estimated from the market model.IJIQ denotes the liquidity level usingthe dailyAmihud measure.MAXandMIN are th**emaximum and minimum daily returns within the estimation period.TR is the prospecivetheory value.SKEW is the daily return skewess COSKEW is th**e **co-skewnes of the dalyreturns with the market returns.ISKEW is the idiosyncatic kewness of the residualsfom the market model.DBETA is the downside be**ta **esimated from the regresion of thedail exess rypto return on the daily market retum.The variabl definition is specified in Table A.1.Thet-statisticsreporte**d **in brackets are based on the Newey and West(1987)standard error**

**Table 5**

**Alpha of asset pricing models on different anomalies.**

**Panel** **A** **M1** M2 M3 M4 M5 M6

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| ST | -0.030\*\* | | -0.033\*\* | -0.033\*\* | -0.017 | -0.017 | -0.018 |
| t(a) | [-2.247] | [-2.353] | [-2.367] | [-0.519] | [-0.515] | [-0.538] |
| MCAP | t(a) | -0.127\*★\* [-5,297 | -0.010 [-1.563] | -0.009 [-1.3621 | -0.128\*☆☆ [-5.334] | -0.010 [-1.578] | -0.009 [-1.351] |
| PRC | t(a) | -0.033\*\* [-2.438] | 0.003  [0.215] | -0.015 [-1.316] | -0.039\*\* [-3.139] | -0.004 [-0.410] | -0.014  [-1.297] |
| MAXDPRC | t(a) | -0.038\* [-2.970] | -0.012 [-1.004] | -0.029 [-0.652] | -0.044  [-3.671] | -0.019\* [-1.658] | -0.029  [-0.655] |
| MOM 1-week | t(a) | 0.042\*  [4.107] | 0.036\* [3.457] | 0.026 [0.637] | 0.038  [3.901] | 0.032\*☆★ [3.169] | 0.027 [0.666] |
| MOM 2-week | (a) | 0.042  [4.335] | 0.040  [3.860] | 0.026 [0.675] | 0.0408  [4.139] | 0036  [3.602] | 0.026 [0.688] |
| MOM 3-week | t(a) | 0.027m  [2.503] | 0.022  [1.976] | -0.007 [-0.892] | 0.020\*\* [2.165] | 0.014  [1.461] | -0.006  [-0.855] |
| MOM 4-week | t(a) | 0.017  [1.579] | 0.018  [3.218] | -0.007 [-0.866] | 0.010  [1.100] | 0.010  [1.051] | -0.007  [-0.827] |
| PRCVOLM |  | -0.081\* | -0.008\* | -0.024\* | -0.087\* | -0.014 | -0.023\* |
|  | t(a) | [-4.174] | [-2.305] | [-1.858] | [-4.679] | [-1.170] | [-1.852] |
| STDPRCVOL | t(a) | -0.074\*  [-3.880] | -0.002 [-0.121] | -0.018 [-1.486] | -0.081\* [-4.423] | -0.009 [-0.737] | -0.017  [-1.471] |

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **Panel** **B** | M1 | M2 | M3 | M4 | M5 | M6 |

AGE

**MOM** **8-week** **MOM** **16-week**

**MOM** **50-week**

MOM 100-week

VOLM

VOLMSCALED

BETA

BETA SQ

IDIOVOL

RETVOL

RETSKEW

RETKURT

MAXRET

DELAY

**DAMIHUD**

t(a) t(a)

(a) t(a)

(a) t(a)

(a) t(a) t(a)

(a) (a) (a) (a) (a) (a) t(a)

-0.014 [-1.204]

-0.004 [-0.318]

-0.014 [-1.092]

-0.030

[-2.325]

0.010

[1.081]

-0.055

[-2.942]

-0.048★☆

[-3.777]

-0.012 [-1.206]

-0.010

[-0.980]

0.026\*

[2.004]

**0.041\*★**

[2.589]

0.011

[1.348]

0.012

[1.342]

0.052\*

[3.500]

0.005

[0.462]

0.066

[3.338]

-0.013 [-1.073]

-0.001 [-0.073]

-0.009 [-0.646]

-0.007 [-0.568]

0.011

[1.148]

0.0108

[3.032]

-0.013\*★★ [-4.585]

-0.019\* [-1.863]

-0.016 [-1.549]

**0.018**

[5.359]

**0.028\*☆★**

**[2.732]**

0.004

[0.448]

0.006

[0.694] 0.043\*

[2.803]

0.007

[0.663]

0.018

[1.014]

-0.030 [-0.640]

-0.025 [-0.634]

-0.028 [-0.566]

-0.029 [-0.665]

0.005

[0.478]

-0.005 [-0.368]

-0.030\*南 [-2.958]

-0.024\* [-2.294]

-0.020\* [-1.978] 0.034\*★ [2.657] 0.041★ [2.619]

-0.004 [-0.527]

0.015\* [1.667]

0.056\*

[3.710]

0.017

[1.631]

0.034\*

[1.893]

-0.017

[-1.396]

-0.011

[-1.116]

-0.018

[-1.473]

-0.036\* [-3.001]

0.009

[0.957]

-0.061\* [-3.384] -0.055

[-4.670]

-0.016\* [-1.714]

-0.014

[-1.455]

0.020

[2.220]

0.043\*\* [2.722]

0.006

[0.796]

0.013

[1.528]

0.052

[3.486]

0.007

[0.685]

0.073\*

[3.780]★

-0.016 [-1.284]

-0.010 [-0.915]

-0.013 [-1.046]

-0.014 [-1.193]

0.010 [1.010]

0.004 [0.311]

-0.020\*\* [-2.009]

-0.024\*

[-2.478]

-0.020\*★ [-2.118]

0.021 [1.565]

0.030\*

[1.870]

-0.003

[-0.398]

0.008

[0.891]

0.043前

[2.783] 0.010

[0.917]

0.025

[1.449]

(continued

-0.030 [-0.642]

-0.025 [-0.649]

-0.027 [-0.562]

-0.028 [-0.664]

0.005

[0.480]

-0.004 [-0.320]

-0.029\*☆ [-3.033]

-0.023 [-0.583]

0.020

[-0.498]

0.034

[2.656] 0.041★ [2.621]

-0.003

[-0.462]

0.015\* [1.662]

0.056

[0.944]

0.017

[1.617]

0.033\*

[1.876]

on next page)

**1-3 include three specifications of the LTW three-factor model (Liu et**

al.,2022).Models4-6 examine the incremental effects of the ST factor.

Panel A reports theanalysis of the nine anomalies identified by Liu et al.(2022)and our ST strategy,confirming the findings of Liu et al.(2022)that their three-factor model (M3)can explain all nine re- turn anomalies in the crypto market.Conversely,the LTW three-factor model did not explain the STeffect (Table 3).When combined with the marketand size factor,an additional ST factor can explain eight of the

ten anomalies (M5);however,the ST factor cannot explain short-term momentum (one-and two-week momentum effects).Finally,combin- ing the ST factor with the three existing factors produces an apparent benefit,asthis four-factor model(M6)can explain all ten anomalies.

We extend our factor analysis to other anomalies.Panel B includes the insignificant anomalies in Liu et al.(2022).Panel C identifies new anomalies relevant to the prospect theory and skewness.The three- factor model (M3)at a 5%significance cannot explain some new

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**Table** **5(Continued)**

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| **Panel** **C** |  | M1 | M2 | M3 | M4 | **M5** | M6 |
| TK | t(a) | -0.016 [-1.311] | -0.011 [-0.906] | -0.028\*\* [-2.390] | -0.020\* [-1.739] | -0.016 [-1.357] | -0.027\*\* [-2.375] |
| SKEW | t(a) | -0.005 [-0.746] | -0.007 [-1.071] | -0.006 [-0.847] | -0.005 [-0.757] | -0.007 [-1.086] | -0.006 [-0.835] |
| COSKEW | t(a) | -0.010 [-1.068] | -0.009 [-0.877] | 0.000 [0.008] | -0.005 [-0.570] | -0.003 [-0.322] | 0.000  [-0.003] |
| ISKEW | t(a) | -0.004 [-0.488] | -0.010 [-1.113] | -0.018\* [-2.141] | -0.008 [-1.004] | -0.014\* [-1.745] | -0.017\*\* [-2.154] |
| DBETA | t(a) | -0.002  [-0.169] | -0.005 [-0.513] | -0.003 [-0.308] | -0.002 [-0.182] | -0.005 [-0.530] | -0.003  [-0.296] |

**Panel** **D** M1 M2 M3 M4 M5 M6

9

**One-tail(4|>=2.336)** **Two-tail(|t|>=2.588)**

13

8

11

4 3

3

13

6

4

13

Table 5 presents the details of the regression explaining the crypto excess returns in quintile portfolios using the following asset pricing model specifications.

R₁-Ry=d+pCMKT+e, (M1)

*R₁-Ry=d+pCMKT+₂SIZE+e,* (M2)

R₁-Ry=α+pCMKT+pSIZE+ MOM+ej, (M3)

R₁-Ry=d+p|CMKT+pST+e, (M4) R₁-Ry=d+f|CMKT+p₂SIZE+yST+ej, (M5) R₁-Ry=α+p|CMKT+p₂SIZE+fyMOM+p₄ST+ej. (M6) The sample consists of actively traded cryptos with a market capitalization of over 1 million USD within thesample period from January 2014 to June 2021,induding 391 weeks.The analysis is based on the weekly returns of VW

portfolios and factor construction regimes.Panel A reports the significant anomalies in Liu et al.(2022).Panel B shows the insignificant anomalies reported by Liu et al.(2022).Panel Creports the behavioral anomalies,including the prospect theory value,skewness,co-skewness,idiosyncratic skewness,and downside beta.Panel D summarizes the statistical significance ofall Panels A to C anomalies.The t-statistics reported in parentheses are based on the Newey and West (1987)standard errors.\*\*\*,\*\*,and\*denotesignificant levels at 1%,5%,and 10%,respectively.

anomalies,including VOLMSCALED,BETA (betting against BETA),ID- IOVOL,RETVOL,MAXRET,TK,and ISKEW.Replacing the MOM fac- tor with the ST factor (M5)can explain IDIOVOL,RETVOL,TK,and ISKEW.Interestingly,combining theMOM and ST reduces the explana- tory power of these anomalies (M6).The results forM6 resembled those of M3(size withmomentum)more than those of M5 (size with ST).

Panel D summarizes the number of significant anomalies at 1%for the model.The new three-factor model,including market,size,and ST, is a strong contender among the specifications.It can explain as much as the combined model does,suggesting that size and ST are the two key factors in the crypto market.Momentum factors are essential for explaining momentum-related anomalies.The ST factor performed bet- ter when the comparison was made outside of the momentum types of anomalies.This new three-factor model,consisting of the market,size, and ST factors in Column(5),can be an alternative risk factor model to the existing LTW three-factor model in the crypto market

**5.Further analyses and robustness test**

*5.1.The salience ofcryptos as an asset class*

Salience is determined relative to the average market payoff,com- pared to alternative investment.Comparing the salience of crypto re- turns with other assets allows a better understanding of the potential influence of the salience of this new asset class on fund flowsinto crypto assets.

This section examined the salience effect of cryptos compared with other investment opportunities.To this end,we considered a group of 50investment instruments,includingindices of equity and bonds,major

exchange rates,and commodities (AppendixTable A.2).We constructed a salience measure using the 50-return series and the returns of the cryptocurrency index.When the crypto market return is more salient, we anticipate a lower return in the subsequent period.

Panel B of Table 6 summarizes the crypto returns in quintiles of the crypto salience measure,applying Equation(4)for the 51 assets universe.The sample was divided into five groups according to the crypto market's weekly ST measures.We then report the excess return

**for the following week,calculated by deducting the EW return of the**

51 assets from the crypto market index return.The resultsindicate that following the most downward salience period,excess crypto returns

**are significantly higher than those following the most upward salience. Calculating the mean spread between the high and low ST periods is**

**-2.19%with a t-value of -2.1 weekly.In other words,compared to other investment opportunities,the salience of the crypto market re-** tu**rnnegatively predicts future return ofthe asset class**.

**Cong et al.(2021)showed that investor sentiment toward an asset can influence the average crypto market payoff,which our evidence extends this by showing that the salience of the crypto index return is a source o investor sentiment that affects its returns.**

We also considered the possible cross-sectional ST effect in this 51- asset universe,presenting the ST effect using the 50 instruments and the crypto market index in the Online Appendix Table OA4.The findings further confirm that the ST effect is behavioral and not observable in traditional asset markets,where fundamental information is essential forinvestors'decisions.In other words,allocating capital among these assets in the global financial market is moreefficient and less influenced by salience bias

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**Table 6**

The salience of cryptos as an asset class among the investment opportunities—weekly returns.

Panel A 1(low Period) 2 3 4 5 (High Period)

Mean ST -0.0127 -0.0017 0.0000 0.0017 0.0098

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Panel p | 1(Low Period) | 2 | 3 | 4 | 5 (High Period) |
| Mean | 1.77% | 1.58% | 3.34% | 0.39% | -0.42% |
| Maximum | 65.96% | 32.11% | 33.88% | 27.04% | 27.13% |
| Median | 12.05% | 4.09% | 4.60% | -6.20% | 0.63% |
| Minimum | -19.84% | -34.03% | -19.24% | -22.01% | -23.72% |

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| PanelC | 1 (Low Period) | 2 | 3 | 4 | 5(High Period) |
| 1(Low) | 0.0257\*★亩 [3.328] | 0.0150\*\* [2.004] | 0.0342\*\* [2.531] | 0.0087 [0.572] | 0.0163 [1.493] |
| 2 | 0.0034 [0.837] | -0.0035 [-0.719] | 0.0056  [1.036] | 0.0019 [0.245] | -0.0076  [-1.307] |
| 3 | 0.0047 [1.141] | -0.0021 [-0.386] | -0.0067 [-1.319] | 0.0024 [0.460] | 0.0009 [0.182] |
| 4 | -0.0033 | -0.0125\* | -0.0024 | -0.0066 | -0.0010 |
| 5(High) | [-0.755] -0.0101\* [-1.695] | [-2.364] -0.0106 [-1.554] | [-0.570] -0.0203\*\* [-2.569] | [-1.086] -0.0129\* [-1.740] | [-0.215] -0.0157\* [-2.584] |
| ST High -Low | -0.0358\*☆ [-3.164] | -0.0256\* [-2.540] | -0.0545\* [-3.024] | -0.0216 [-1.088] | -0.0319  [-2.359] |

Table 6reports the crypto-related measuresin different salience among 51 assets,including equity indexes,credit indexes, foreign exchanges,and futures.The completelist of the investment instruments is presented in Table A.2.The asset return is calculated weekly.The groups'number indicates the quintile portfolio in which cryptosalience is among all assets;1 represents the most down-salience quintile period,and 5 represents themost up-saliencequintileperiod.PanelA lists the mean ST measure in each quintileperiod.Panel B has the crypto market index'smean,median,maximum,and minimum excess returns (compared to the 50 assets'equal-weighted return)for the following month.Panel C presents the single ST cross-sectional sorting results among the cryptos in each quintile period.The t-statistics reported in parentheses are based on the Newey and West(1987)standard error.

Nevertheless,the salience of return in the crypto market can serve as a signal that may further exacerbate the croSS-sectional ST effect We further studied whether the time-series salience effect of the crypto market index affects the crOSS-sectional salience effects documented in the previous sections.Panel C in Table 6 reports the cross-sectional ST effect in the five quintiles of the subperiods sorted by the crypto in- dex's salience measure for the 51 assets (Panel A).The resultshowsthat when crypto asan asset class is more salient,the cross-sectionalsalience effects are stronger,regardless of upward or downward salience.The cross-sectional ST effect measured by the high-low rows was highly significant in most down-and up-salience columns,and we observed an“unconditional”cross-sectional salience effect.The strongest cross- sectional salience effect for the non-salience period is in Group 3, suggesting that specialized crypto investors (under-diversified)do not consider the relative movement of cryptos to other investments.This type of investor is a major driver of the salience effect in crypto mar- kets.6

*5.2.Uncertainty and attention effect*

Cakici and Zaremba(2022)showed that the ST effect,as a mispric- ing phenomenon,is more evident following extreme market states (such as high economic uncertainty and volatility).We examined whether a similar mechanism plays a role in the crypto markets.Following Cakici and Zaremba (2022),we partitioned the entire sample period into high and low uncertainty subperiodsusingvarious uncertainty measures.We selected the traditional measures of financial market uncertainty,in-



6 Findings in this section arealso robustly documented in the monthlyanaly- ses reported in Table A05.

cluding the CBOE VIX index and the Federal Reverse Bank economic policy uncertainty index⁷(EUC)developed by Baker et al.(2016).

Table 7 reports the variations of the cross-sectional ST effects in the five periodssorted by the uncertainty indexes,showing the average weekly ST high-low portfolio returns following the formation periods that fall into one of these five subperiods.

Unlike theequity market finding of Cakici and Zaremba(2022),we found that the ST effect is stronger (measured by a high-minus-low on the ST strategy)in the crypto market when uncertainty is low in the equity market,as shown in Panel A (VIX)or the economy in Panel B (UNC).This finding is consistent with the conjecture that salience investors are thrill-seekers;they are more active in the crypto market when the alternative market is relatively quiet (with less volatility). This finding is also consistent with our analyses of the cross-sectional ST effect on the time-series salienceof the crypto asset class among the other 50 assets;whenthe crypto market is more salient,either upside or downside,the cross-sectional salience effects are pronounced in the crypto markets.

Furthermore,we considered the effects of uncertainty on the crypto market.We used the past month's volatility of daily Bitcoin returns as the cryptovolatility index (BTC VOL).⁸Panel C shows that if we com- pare the cross-sectionalST effect in high and low BTC VOL periods,the ST effect is stronger in high BTCVOL periods consistent with Cakici and Zaremba(2022),who examined the global equity market.This finding suggests that underlying market uncertanty isan essential determinant of the ST effect.9



7 <https://fred.stlouisfed.org/series/USEPUINDXD>.

8The CVI(crypto vol index)was created in 2019,but wehave a longer sam- ple period than CVI;therefore,we constructed our own measurements.

9 We obtainthe same conclusion from that of the equal-weighted portfolio returns(Table A06).

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**Table 7**

The salience effect of crypto market —uncertainty and attentions.

Panel A:Uncertainty Measured by VIX

1(Low) 2 3 4 5 (High) High -Low

|  |  |  |  |
| --- | --- | --- | --- |
| HighVIX 0.0084 0.0035 0.0001 -0.0037 -0.0112 -0.0197 | | | |
| Low VIX | 0.0316 -0.0027 0.0005 -0.0063 | -0.0169 | -0.0485 |
| High-Low | -0.0232\*\* 0.0061 -0.0004 0.0026 | 0.0057 | 0.0288\*\* |
| t-Stat | [-2.368] [1.212] [-0.078] [0.598] | [0.936] | [2.424] |
|  | Panel B:Uncertainty Measured by UNC  (Low) 2 3 4 |  |  |
| 5 (High) | High -Low |
| **High** **UNG** | 0.0068 -0.0002 0.0049 -0.0008 | -0.0155 | -0.0223 |
| **Low** **UNG** | 0.0331 0.0010 -0.0043 -0.0092 | -0.0126 | -0.0457 |
| **High-Low** | -0.0263\*★★ -0.0012 0.0093\*★ 0.0084\* | -0.0029 | 0.0234\* |
| **t-Stat** | [-2.696] [-0.235] [2.091] [1.914] | [-0.483] | [1.798] |
|  | Panel C:Uncertainty Measured by BTC VOL  (Low) 2 3 4 |  |  |
| 5(High) | High-Low |
| **High** **BTCVOL** | 0.0207 0.0017 -0.0025 -0.0043 | -0.0160 | -0.0366 |
| **Low** **BTC** **VOL** | 0.0193 -0.0009 0.0031 -0.0058 | -0.0121 | -0.0314 |
| **High-Low** | 0.0014 0.0026 -0.0056\* 0.0015 | -0.0038 | -0.0053\* |
| **t-Stat** | [0.550] [-0.126] [-2.307] [-0.434] | [0.141] | [-2.350] |
|  | Panel D:Attention Measured by Google Search Index  (Low) 2 3 4 |  |  |
| 5 (High) | High -Low |
| **High** **Google** **Search** | 0.0240 -0.0008 -0.0011 -0.0065 | -0.0162 | -0.0402 |
| **Low** **Google** **Search** | 0.0124 0.0036 0.0037 -0.0022 | -0.0090 | -0.0214 |
| **High** **-Low** | 0.0116 -0.0044 -0.0048 -0.0042 | -0.0072 | -0.0188\* |
| **t-Stat** | [1.452] [-0.991] [-1.222] [-1.056] | [-1.220] | [-1.678] |
|  | Panel E:Attention Measured by BTC Trading Volume  1(Low) 2 3 4 |  |  |
| 5 (High) | High-Low |
| High BTC Volume | 0.0229 0.0026 -0.0007 -0.0014 | -0.0101 | -0.0330 |
| Low BTCVolume | 0.0075 0.0074 -0.0028 0.0017 | -0.0181 | -0.0256 |
| High -Low | 0.0154 -0.0048 0.0021 -0.0031 | 0.0080 | -0.0074\*\* |
| t-Stat | [1.714] [-0.716] [0.422] [-0.668] | [1.249] | [-2.141] |

Table 7 reports the average weekly returns of the single-sorted portfolios using the salience theory,with the ful

sample spliting into high and low uncertainty and attention periods.The sample periods are split into the high and

low periods by the median of the uncertainty indexes:VIX(PanelA),UNC Panel B),the volatility of Bitcoin returns (Panel C),Google search index on cryptocurrency in the formation period Panel D),and thetrading volume of the Bitcoin in the formation period Panel E).Each week,the assets are sorted into quintiles according to the salience effect measure in theprior week.Each portfolio is held for one week.The portfolio retum is constructed in an equal- weighted manner.The“High-Low”row reports the average return difference between the quintile portfolios in high and low uncertainty periods.The“t-Stat”row reports theNewey-West robust t-staistic.

Attracting salience investors is necessary for the ST effect,and BTC volatility may also be a proxy for investor attention.To understand the effectof attention,we studied two proxies for investor attention in Panels D(Google Search Trends)and E(BTC volume),confirming that th**e ST effect is strongerwhen investor attention is relativelyhigher**

Overall,our analyses suggest that the cross-sectional crypto mar- ket's STeffect positively correlates with uncertaintyand attention in the crypto market but negatively correlates with uncertainty in the stock market and economy.These findings further confirm that investors influenced by salience bias will likely be risk-seekers.They also high- light thepotential diversification effect of cryptos as a non-fundamental investment asset classwith areturn dynamic different from other tradi- tional asset classes(Chuen et al.,2017;Hu et al.,2019).

*5.3.Comparing ST and otherfactors*

*5.3.1.Salience,market beta,and idiosyncratic volatility*

This section used double sorting to study the interactions between ST and systematic and idiosyncratic risk.Table 8 reports the weekly

excess returns of crypto portfolios independently sorted by ST and the two factors.

Panel A of Table 8 reports the double sorting between ST and the crypto market beta.The ST effect was much more substantial in high beta cryptos (Groups 4 and 5).This finding is consistent with the ST in that being systematically important in the crypto market may modify the context of the salience-biased investors'subjective weighting.In other words,the historically high beta,suggesting more extreme co- movement with average peers,will amplify salience bias.In contrast beta cannot explain the cross-sectional returns within the ST groups. The exception is the lowest ST group,in which a higher beta earns a higher return.

Cakici and Zaremba(2022)show that markets with high average idiosyncratic risk observe higher ST effects that alignwiththe arbitrage explanation limits.Panel B ofTable 8 reports the double sorting of ST and IVOLin the crypto market,indicating thatthe ST effect differs from the IVOL effect oncross-sectional crypto returns.The ST effects were the strongest in the middle IVOL sort(Groups 2,3,and 4).highlighting the difference between the crypto and equity markets.This result suggests that a high IVOL does not limit the“arbitrageurs”from correcting ST

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**Table 8**

Salience effect,market beta,and idiosyncratic volatility.

1(Low 2 3 4 5 (High) High -Low t-Stat

Panel A:Sorted by ST Controlling for Market Beta

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| Equal-Weighted |  |  |  |  |  |  |  |
| 1(Low) | -0.009 | 0.032 | 0.020 | 0.035 | 0.027 | 0.035\*\* | [2.556] |
| 2 | 0.007 | 0.003 | 0.002 | -0.001 | 0.009 | 0.002 | [1.004] |
| -0.005 | 0.000 | 0.001 | 0.009 | 0.001 | 0.007 | [1.167] |
| 4 | -0.016 | -0.009 | 0.000 | 0.000 | -0.004 | 0.012 | [1.177] |
| 5(High) | -0.015 | -0.006 | -0.011 | -0.014 | -0.017 | -0.002 | [-0.380] |
| High -Low | .0.006 [-0.723] | -0.038 [-1.443] | -0.031\* [-2.292] | -0.049\*南 [-3.835] | -0.044 [3.334] |  |  |
| Value-Weighted |  |  |  |  |  |  |  |
| 1 (Low) | 0.038 | 0.050 | 0.039 | 0.049 | 0.067 | 0.029\* | [1.703] |
| 2 | 0.021 | 0.013 | 0.015 | 0.014 | 0.023 | 0.002 | [1.085] |
| 0.015 | 0.009 | 0.005 | 0.020 | 0.013 | -0.001 | [0.153] |
| 0.001 | 0.008 | 0.011 | 0.012 | 0.021 | 0.020 | [1.437] |
| 5(High) | 0.065 | 0.018 | 0.002 | 0.000 | 0.009 | -0.056 | [-2.195] |
| High-Low | 0.027 | -0.032 | -0.037 | -0.049\*\* | -0.058\*☆ |  |  |
| [1.272] | [-0.472] | [-1.642] | [-2.208] | [-3.249] |  |  |

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
|  | 1 (Low) 2 3 4  Panel B:Sorted byST ControllingforIdiosyncratic Volatility | | | | 5(High) High -Low t-Stat | | |
|  | | |
| Equal-Weighted |  | | | |  |  |  |
| 1(low) | 0.018 | 0.024 | 0.034 | 0.021 | 0.006 | -0.011★ | [-2.428] |
| 2 | 0.008 | 0.008 | 0.000 | 0.001 | -0.017 | -0.026★南 | [-3.237] |
| 3 | 0.004 0.010 | 0.000 -0.003 | 0.008 0.001 | -0.007 -0.016 | -0.012 -0.017 | -0.016\* -0.028\*☆ | [-1.745] [-2.598] |
| 5(High) | 0.002 | -0.002 | -0.015 | -0.021 | -0.020 | -0.021\*\* | [-2.334] |
| ST High-Low | -0.016\* [-1.882] | -0.0250 [-4.197] | -0.049\* [-5.979] | -0.042\* [-4.542] | -0.026\* [1.886] |  |  |
| Value-Weighted |  |  |  |  |  |  |  |
| 1 (Low) | 0.018 0.016 0.013 0.020 | 0.044 0.015 0.011 0.009 | 0.065 0.013 0.016 0.014 | 0.051 0.017 0.008 0.014 | 0.063 0.009 0.024 0.009 | 0.045\*\* -0.007 0.011 -0.011 | [2.441] [-0.742] [0.487] [-0.364] |
| 5(High) | 0.009 | 0.008 | -0.004 | -0.005 | 0.032 | 0.023 | [0.387] |
| ST High-Low | -0.009 [-0.880] | -0.036\*☆ [-3.819] | -0.069\*★ [-6.395] | -0.056\*☆南 [-4.135] | -0.031 [-1.078] |  |  |

Table 8 presents the average weekly returms of the double-sorted portfolios of the ST measure,controlling for other factors. The sample consists of actively traded cryptos with a market capitalization of over 1 million USD within the sample period from January 2014 to June 2021.The cryptos weresorted independently into 5×5 groups depending on the ST measure and existingcrypto risk factors each week.Each portfolio was held for one week.We reported the one week-ahead excess retuns of each portfolio with EW and VW constructions on the grid.The portfolio sorted by ST is reported in rows,and the portfolio sorted by the existing factors is reported in columns.Using the corresponding sorting variable,the“High -Low” row reports the average retum difference between the highest and lowest sorting value portfolios.The"I-Stat"row reports the Newey-West robust t-statistic.PanelA presents the portfolioreturns with the market beta's control variables,and Panel B presents idiosyncratic volatility

mispricing,or the limit of arbitrage is less of an explanation in this market with no fundamentals.Arbitrageurs are unlikely to exist in these markets,only speculators.

*5.3.2.Salience,prospect theory,and preference for skewness*

Bordalo et al.(2013a)pointed out that the ST and the prospect the- ory of Kahneman and Tversky(1979)(KT)assume the decision-makers focus on the probability weightspeople use to make choices that are dif- ferent from the objective probability.The primary difference between the salience theory of decision-making and prospect theory is that in ST,these weights depend on the actual payoffs and their salience(a broader context).Bordalo et al.(2013a)showed that,ST and KT will produce similar decision weights in many cases;however,ST will pro- duce different probability weighting when small probabilities are not attached to salient payoffs or when lotteries are correlated.Which of these decision systems provides a more accurate description of a given market is an empirical question.Thoma(2020)followed Barberis et al.

(2016)and showed that cryptos with high (low)prospect theory values

earn low (high)subsequent returns using monthly historical distribu- tionanalyses.They confirm that a high prospect theory value exhibits a significant positive skew,which is more likely to distort the weighting, making it different from the standard expectation model.

Moreover,Bordalo et al.(2013a)theoretically predicted and con- tributed to understanding the preference for positive skewness.They demonstrated that when certain asset payoffs“stand out”relative to the market,they can distort the perception of asset-specific risks and, consequently,in asset prices due to salience.This finding provides in- sight into why the right-skewed assets tend to be overvalued.

This section empirically analyzed the relationship among the salience effect,prospect theory,and skewness on cross-sectional crypto retums.The prospect theory value is constructed based on a standard approach specified for stock returns (Barberis et al.,2016).One ex- ception is that we selected a relatively short estimation period to form the prospect theory value.We used daily returns within the past one- month look-back period for the weekly crypto-return analysis.This setupaligns withtheshorter investor horizon in the crypto market than

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**Table 9**

Fama-MacBeth cross-sectional regressions —behavioral anomalies.

**Panel** **A** (1) (2) (3) (4) (5)

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| ST | -0.306\* [-3.146] | -0.387\* [-3.940] | -0.311  [-3.229] | -0.3650 [-3.857] | -0.307\*★\* [-2.928 |
| TK | 0.141★ [2.587] |  |  |  |  |
| SKEW |  | -0.003 [-1.523] |  |  |  |
| COSKEW |  |  | -0.830  [-0.196] |  |  |
| ISKEW |  |  |  | -0.003  [-1.240] |  |
| DBE TA |  |  |  |  | -0.002  [-0.629] |
| Intercept | 0.008 [1.478] | 0.000 [0.063] | 0.001  [0.251] | 0.000  [0.103] | 0.001  [0.187] |
| Avg.R | 0.149 | 0.129 | 0.1453 | 0.1314 | 0.1405 |

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **Panel** **B** | ST | TK | SKEW | COSKEW | ISKEW | DBETA |
| ST | 1.000 |  |  |  |  |  |
| TK | -0.310 | 1.000 |  |  |  |  |
| SKEW | -0.028 | 0.234 | 1.000 |  |  |  |
| COSKEW | 0.043 | 0.003 | 0.030 | 1.000 |  |  |
| ISKEW | -0.054 | -0.001 | 0.603 | -0.087 | 1.000 |  |
| DBETA | -0.013 | -0.004 | 0.013 | -0.354 | 0.071 | 1.000 |
| Table 9 reports the estimated regression coefficients of the t-statistics from Fama-MacBeth cross-sectional regressions for crypto returms (Panel A)and the correlation matrix among behavioral anomaly measures (Panel B).The sample consists of actively traded cryptos witha market capitalization of over 1 million USD withinthe sample period from January 2014 to June 2021.The regression is based on weekly returms with 391 different periods.The Fama-MacBeth is performed using weekly returms.ST is the salience theory measure.TK is the prospective theory value.SKEW is the daily return skewness.COSKEW is the co-skewness of the daily returns withthe market returns.ISKEW is the idiosyn- cratic skewness of the residuals from the market model.DBETAis the downside beta estimated from the regression of the daily excess crypto return on the daily marketreturn.The variable definition is specified in Table A.1.The t-statistics reported in brackets are based on the Newey and West(1987)standard error.  in stock markets.Given the shortexistence of the crypto market,using a short-term formation period enables us to retain most observations in our sample period.Appendix B presents the detailed construction of prospect theory value  We compared the pairwise cross-sectional predictability of thesebe- havioral characteristics in the crypto market.Panel A of Table 9 reports the Fama-MacBethregressions,and Panel B reports the pairwise correla- tions among the behavioral characteristics.Furthermore,ST dominates all the other measures in explaining croSs-sectional crypto returns,par- ticularly for skewness-related measures and downside risks.This result is consistent with the theoretical predictions of Bordalo et al.(2013a) Additionally,KT measures negatively correlate with ST in the crypto market.10  Overall,these findings support the link between these measure- ments.Our study further proves the link between ST and other behav- ioral theories.The ST differs from prospect theory in the crypto market and describes of cross-sectional crypto pricing well.1  *5.3.3.Salience and size effect*  In the equity market,smaller firms behave differently than their larger counterparts in the context of cross-sectional return anomalies (Hong et al.,2000;Fama and French,2008).Thisbehavior may be due to lower liquidity—resulting in stronger anomalies —and a weaker | | | | | | |

10 We obtained a similar conclusion from monthly retumanalysis.The results are presented in Table A07.

11 Theconclusions of double sorting usingSTand these altemative behavioral measures are consistent with the findings here (Online Appendix Table OA8).

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information environment with fewer newS watchers to start someof the trends for momentum traders to chase,resulting in weaker anomalies (Cai et al.,2023).Cakici and Zaremba (2022)show that the salience anomaly appearsto be exclusively a microcap phenomenon(accounting for only 3%of the market cap).

We start with the independentdouble sorting in Panel A ofTable 10 to study the interactions between ST and the size effect.A key obser- vation isthat these two factors are important and independent.The ST effects were stronger in the medium and large size groups (3,4,and 5 sizegroups)and vice versa.This finding highlights a key difference be- tween crypto and equitymarkets.The ST mispricing effect in the crypto market is not confined to the smallest securities as documented in the international equity market Cakici and Zaremba(2022).Notably,most cryptosare relatively small,with a median market cap of approximately 10 million USD,piratically considered a microcap in the equity market.

We replicated the size test of Cakici and Zaremba(2022)in Panel B of Table 10 to further study the microcap argument.We double-sorted the cryptos independently using ST and market cap and grouped them according to their representation of the total market cap (Cakici and Zaremba,2022).“Big”cryptos refer to the largest,which account for 90%of the total market capitalization,and“small”cryptos refer to those constituting the next 7%of the market capitalization;“micro” cryptos are the smallest,accounting for the remaining 3%of the mar- ket.

Consistent with their findings,we show that ST effects are promi- nent in the micro-sizecryptos with both EW and VW(bottom 3%in capitalization,but account for 87%of the number of cryptos on av- erage).The small cryptos(middle 7%in market cap and 11%in the number of cryptos)also show a significant ST effect on the EW portfo- lio.The largest cryptos,which comprise 90%of the market share and only have approximately 12 cryptos,show no significant ST effect

One concern is the accessibility of the returns from the smallest (in terms of the market cap)cryptocurrencies in the trading strate- gies.Were-examine the salience effect,excluding cryptocurrencies with market caps of less than 10,25,and 50 million USD.The salience ef- fect remains,especially for equally weighted portfolios.Furthermore, we retested the long-short portfolio using the top 100 cryptocurren- cies (ranked by market cap)to eliminate the concern that the salience strategy return may only be obtained in microcap cryptocurrencies. The salience effect is robust for the largest and most liquid cryptocur- rencies.The salience effect is the strongest among the 100 largest cryptocurrencies,judging by the magnitude of the high-low return and

t-values.We present the empirical results in the Online Appendix Ta- ble OA9.

Overall,these findings provide two further insights into the effect of ST in thecrypto market.First,although the ST effect is more promi- nent in the crypto market,there is still a predictable difference in the effect of the ST on pricing.The largest cryptos are more likely to at- tract institutional investors'attention given their size and liquidity, which match the size of the investment.With more relatively sophis- ticated investors in these cryptos,pricing is less influenced by the ST bias,confirming that ST is a behavioral bias moderated by investor so- phistication.This finding suggests that,as the markets have developed, regulated,and integrated with mainstream finance,sophisticated in- vestorsreduce the influence of behavioral bias in this market.Second, mispricing is more relevant to micro cryptos,which account for 3%of the market cap;however,these cryptos account for approximately 87% of the number of cryptos.This result is still economically important as the market efficiency of the small but numerouscryptos would be es- sential in determining whether cryptos can become an asset class to promote innovative finance and distribution effectively.As the market develops,micro cryptos may become leaders in their fields.

***5.3.4.Salience,momentum,and reversal***

Section 4 suggested that ST can replace momentum in explaining other cross-sectional return variations.Cosemans and Frehen(2021)

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**Table 10**

The Salience effect of crypto market —controlling for size effect.

Panel A:Double-sorted by ST and Market Capitalization in Quintiles

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
|  | 1 (Low) | 2 | 3 | 4 | 5(High) | MCHigh-Low | f-Stat |
| Equal-Weighted |  |  |  |  |  |  |  |
| 1 (Low) | 0.073 | -0.004 | 0.001 | 0.006 | 0.027 | -0.045\*★★ | [3.468] |
| 2 | 0.028 | 0.002 | -0.005 | -0.008 | 0.002 | -0.0260 | [-3.443] |
| 3 | 0.031 | 0.001 | -0.002 | -0.003 | -0.003 | -0.033\*\*南 | [-4.649] |
| 4 | 0.016 | -0.007 | -0.006 | -0.010 | -0.006 | -0.022\*\* | [3.906] |
| 5(High) | 0.023 | -0.023 | -0.036 | -0.012 | -0.035 | -0.058\* | [-5.491] |
| ST High -Low | -0.049\*★ [-4.062] | -0.019 [-1.335] | -0.037 [-2.351] | -0.018  [-2.829] | -0.063\*★ [-5.399] |  |  |
| Value-Weighted |  |  |  |  |  |  |  |
| 1 (Low) | 0.160 | 0.061 | 0.057 | 0.058 | 0.048 | -0112\* | [-6.425] |
| 2 | 0.061 | 0.036 | 0.022 | 0.013 | 0.011 | -0.050\*\*★ | [-5.127] |
| 3 | 0.067 | 0.034 | 0.029 | 0.020 | 0.012 | -0.055\* | [-5.530] |
| 0.078 | 0.030 | 0.026 | 0.015 | 0.011 | -0.067\*\*南 | [-2.732] |
| 5(High) | 0.127 | 0.037 | 0.021 | 0.035 | -0.001 | -0.128\*\*\* | [-4.491] |
| ST High -Low | -0.033 | -0.024 | -0.036\* | -0.022\*\* | -0.049\*★ |  |  |
| [-0.632] | [-1.119] | [-2.340] | [-2.703] | [-3.274] |  |  |

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Panel B:Double-sorted by ST and Market Capitalization in Size Groups | | | | | | | | |
|  | Equal-weighted  Full | Big | Smal | Micro | Value-weighted Full | Big | Small | Micrc |
| Avg.N | 501.6 | 11.8 | 54.3 | 435.5 | 501.6 | 11.8 | 54.3 | 435.5 |
| 1(Low) | 0.0200 | 0.046\* | 0.065\* | 0.019 | 0.054 | 0.038\* | 0.060 | 0.059 |
| [4.065] | [5.477] | [6.010] | [4.357] | [5.850] | [4.886] | [5.316] | [6.445] |
| 2 | 0.000 | 0.017\* | 0.020\*\*☆ | -0.002 | 0.013\* | 0.013 | 0.019\* | 0.011 |
| [0.162] | [3.174] | [4.226] | [-0.787 | [2.777] | [2.286] | [3.489] | [2.385] |
| 3 | 0.000 | 0.025\* | 0.011★ | -0.001 | 0.014\*★ | 0.0240 | 0.016\*★ | 0.009\*\* |
| [0.130] | [4.261] | [2.658] | [-0.266] | [3.275] | [3.815] | [3.112] | [2.365] |
| 4 | -0.005 | 0.032\*☆ | 0.017\* | -0.006\* | 0.016\*★ | 0.028\* | 0.016\* | 0.013\*★ |
|  | [-2.287] | [3.142] | [3.340] | [-2.608] | [3.312] | [2.880] | [2.373] | [2.976] |
| 5(High) | -0.014\* | 0.059\*★ | 0.002 | -0.014\*★ | 0.024 | 0.057\* | 0.026 | 0.016\*\* |
| [-4.653] | [2.139] | [0.129] | [-4.739] | [2.518 | [2.094] | [1.433] | [2.3251 |
| ST High-Low | -0.034\*☆★ | 0.013 | -0.064\*☆ | -0.033\* | -0.030\*\* | 0.020 | -0.034 | -0.044\* |
| t-Stat | [-5.223] | [0.450] | [-3.522] | [-6.292] | [-2.226] | [0.689] | [-1.605] | [-3.796] |

Table 10 presents the weekly portfolio returns of cryptocurencies contoling for the size effect.Panel A contains the double-sorted portolio returns on ST and market capitalization.The cryptos are independenty sorted into 5×5 groups based on the weekly ST measure and market capitalization.Each portfolio was held for one week.Panel B shows the average weekly returns of the singlesorted portfolios of cryptocurencies in different size groups using the salience theory measure.The“Full”columnsshow the portfolio returnsusing the full ample.“Big”includes the cryptocurencies that cover 90%ofthe total market capitalization of the week,“Small”group covers the next 7%of the total market capitalization,and“Micro”captures the remaining 3%Each portfolio was held for one week.The sample consists of actively taded cryptos with a market capitalization of over 1 milion USD within the sample period from January 2014 to June 2021.According to the ST measure, the cyptos are sorted into quintiles during the portfolio formation period.The row “Avg.N”tracks each size group's average number of cryptocurencies.Using the corresponding sorting variable,the“High-Low”row reports the average retumndifference between the highest and l**owest sorting value portfolios.The“t-Stat”row reports the Newey-West robust t-statistic**

and Cakiciand Zaremba(2022)showed that ST is closely related to the reversal effect in the equity market literature.In the cryptomarket,the momentum factor introduced by Liu et al.(2022)is a “reversal”factor in the equity market setting;the strategy does not skip one period(week or month)to allow for potential reversal.This strategy's positive crypto- momentum factor return suggestsno simple reversal effect in the crypto market.

When studying the correlation of the factors,we observed that the ST factor premium indeed has a high correlation with the momentum factor premium(27.8%for EVand 46.8%forVW factors).12

We further studied the interactions between these two factors using double sorting.Panel A ofTable 11 shows that the ST effect is gener- ally stronger than the momentum or reversal effects.The ST effect was observed in four of five quintiles in EW and two of five quintiles in VW when controlling for momentum.In contrast,the momentum or rever- sal effect was weaker when controlling for the ST effect.This finding



12 We present the risk factor correlation table in Table A010.

explains why including the ST factor can explain the excess return of the momentumstrategy,whereas including the momentum factor can- not explain excess return of the ST strategy in Table 5.

We next studied whether our ST results hold when the most recent days(1-3 days)are excluded from the estimation period in a monthly setting.This approach allowed us to elevate the concern that ST is only a reflection of the short-term momentum or reversal effect,following Cakici and Zaremba (2022).The findings are presented in Online Ap- pendix Table OA11.While the magnitude and significance weaken as more days are skipped between the formation and return calculaton, the magnitude and significance are still substantial and economically significant.This finding confirms that ST differs from the short-term re- versal or momentum effects and highlights the benefit of testing the ST theory in this asset class,which has a different clientele and dynamic from the equity market.This result allowed us to identify the theory's explanatory power more clearly

Benedetti and Kostovetsky (2021)documented that the ICO under- pricing is over 170%,and the price quickly reverses after the first

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**Table 11**

The salience effect of crypto market —controlling for momentum.

1(low) 2 3 4 5(High) MON High-Low t-Stat

Sorted by ST Controlling for Momentum

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| Equal-Weighted |  |  |  |  |  |  |  |
| 1(Low) | 0.034 | 0.034 | 0.036 | 0.023 | 0.004 | -0.030\* | [-1.996] |
| -0.006 | 0.003 | 0.008 | 0.006 | -0.001 | 0.005 | [0.575] |
| 0.002 | 0.000 | 0.007 | 0.004 | -0.021 | -0.023\*\* | [-2.410] |
| 4 | 0.003 | -0.001 | 0.004 | -0.007 | -0.038 | -0.041 | [-4.659] |
| 5(High) | -0.024 | -0.014 | -0.013 | -0.029 | 0.017 | 0.041\* | [2.549] |
| ST High-Low | -0.058\*★ [-5.570] | -0.048\*☆★ [-3.877] | -0.048\* [-4.469] | -0.052\* [-5.641] | 0.013  [1.495] |  |  |
| Value-Weighted |  |  |  |  |  |  |  |
| 1(Low) | 0.032 | 0.043 | 0.047 | 0.041 | 0.075 | 0.043 | [3.157] |
| 3 | -0.011 | 0.008 | 0.015 | 0.022 | 0.023 | 0.033 | [3.467] |
| 0.002 | 0.003 | 0.014 | 0.011 | 0.006 | 0.004 | [0.924] |
| 4 | 0.010 | 0.004 | 0.015 | 0.015 | -0.010 | -0.019\* | [-1.816] |
| 5(High) | -0.021 | 0.008 | 0.014 | -0.006 | 0.047 | 0.068\* | [2.889] |
| ST High-Low | -0.052\*★★ [3.580] | -0.035  [-1.605] | -0.034  [-1.123] | -0.047\* [-3.374] | -0.028  [-0.874] |  |  |

Table 11 presents the average weekly returns of the double-sorted portfolios of the ST measure controlling for the momentum factor.The sample consists of actively traded cryptos with a market capitalization of over 1 million USDwithin the sampleperiod fromJanuary 2014 to June 2021.The cryptos are sorted independently into 5×5 groups based on the weekly ST measure and momentum factor.Each portfolio was held for one week.We reported the one-week-ahead excess returns ofeach portfolio with EW and VW constructions on the grid.The portfolio sorted by ST is reported in rows,and the portfolio sorted by the existing factors is reported in columns.Using the corresponding sorting variable,the “High -Low”row reports the average retum differencebetween the highest and lowest sorting value portfolios.The“l-Stat”row reports the Newey- West robust t-statistic.

trading day.To mitigate the concern that ICO underpricing and re- versals may be key drivers of our findings,we repeated our study by excluding each crypto's first month of observation.The magnitude and statistical significance only reduced slightly compared to the baseline results.13 These results further support that ST operates as a distinct price driver,separate from mean-reversal or ICO underpricing mecha- nisms.

*5.4.Other robustness tests*

We also performed other robustness tests,showingthat the ST effect is time varying in theyearly sub-sample analysis.The ST effect is gener- ally observed,with negative EW strategy returns for all eight years;the ST effect was statistically significant in five of theeight years.We stud- ied the robustness of the ST effect for different formation periods and altered the salienceeffect specification.These findings and discussions can be found in theOnline Appendix.

**6.Conclusion**

The introduction of Bitcoin has provided an enormous opportunity to experiment with decentralized technology for trading and record- ing financial transactions.Simultaneously,the increasing appetite for speculation has fueled the rapid growthof the crypto market.Since 2009,cryptos have become a new asset cass within a decade of their first existence.The critical role ofsocial media in developing thisasset class cannot be overstated,and it continues to influence pricing.This study contributes to the literature on crypto pricing by formally ex- amining how investors'disproportional attention to salience outcomes influences time-series and cross-sectional crypto pricing predictably.

Salience theory isintuitive yet embedded in the fundamental theory of context-dependent preference.Salience thinkers cannot objectively evaluate the distribution of outcomes,especially when other objective



13 Empirical results are presented inOnline Appendix Table OA12

measures are lacking,and salience is amplified through social media. The salience effect documented in this study is the strongest in the ST literature,which is unsurprising,given that this asset lacks fundamen- tals and has a concentrated retail clientele.This situation confirms that ST is much more relevant for emerging assets with high uncertainties; however,it is possible that once this asset market becomes more ma- ture and mainstream(with more institutional investors involved),other pricing mechanisms may dominate.Before then,ST offers a close de- scription of the return dynamics in the crypto market.

**CRediT authorship contribution statement**

**Charlie Cai:Conceptualization,Writing-Original draft preparation Writing-Reviewing and Editing.Ran Zhao:Methodology,Software.**

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The authors have no relevant financial or non-financial interests to disclose.

**Data availability**

**Data will be made available on request. Acknowledgements**

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**Appendix A**

*A.1.Supplementary tables*

**Table A.1**

Variable definitions.

|  |  |
| --- | --- |
| Variable | Definition |
| ST | Thesalience theory measure is calculated from Equation (4)in Section 2.2.We compute the wekly(monthly)ST using asample periodof one week(one month)before the portfolio holding period. |
| GMKT | The cryptocurrency market retum.The market returnis based on equal-weighted calculation if not otherwise specified. |
| BETA | The estimated coeffcient p in the regressin R₁-Ry=a²+PMKT+e.The modelis estimated using daily returns of the trailing30(365)daysfor the formation week (month). |
| SIZE | Log last day market capitalization in the portfolio formation week(month). |
| MOM kW | k-weekmomentum,as the cumulative return for the past k weeks.MOM represents the lagged oneweek return if not otherwise specified. |
| AGE | Time in friction of year(s)from the listing on Coinmarketcap.com. |
| IVOL | The idiosyncratic volatlity iscalculated s thestandard devation of the residuals from the market model R₁-Ry=a+PMKT+e.The modelis estimated |
| LLIQ | using daily returns of the previous 30(365)days before the week(month).  The average absolute daily return divided by USDvolume in the portfolio formation week(month). |
| MAX | The maximum daily return ofthe cryptowithin the sample period. |
| MIN | The minimum daily return of the cryptowithin the sample period. |
| MCAP | Log last day market capitalization in the portfolio formation week(month). |
| PRC | Log last day pricein theportfolio formation week (month). |
| MAXDPRC | The maximum price of the portfolio formation week (month). |
| PRCVOLM | Log average daily volume times price in the portfolio formation week (month). |
| STDPRCVOL | Log standard deviation ofUSD volume in the portfolio formation week (month) |
| VIX | The CBOE published S&P500 implied volatility index. |
| UNC | The economic policy uncertainty index developed by Baker et al. (2016). |
| BTC VOL | The standard deviation of the daily Bitcoin returns within the week (month). |
| TK | Theprospecive theory value is computed asspecifiedin Bordalo etal. (2016).The measure is calculated using dalyreturnsfrom traling 30(365)daysprior to the formation week(month). |
| SKEW | The daily return skewness estimated from the trailing one-month crypto returns |
| COSKEW | The co-skewness of thedaily cryptoreturns over the one-month window using the approach of Harvey and Siddique (2000). |
| ISKEW | Theidiosyncratic skewnessof the residuals from the market model using trailing 30 (365)days before formation week(month). |
| DBETA | Thedownside beta estimated rom the regresin of the daily excesserypto return on the daily market return Ang etal. (2006)over theprevious 30(365)days before formation week(month). |

**Table A.2**

Full list of 51 assets

Category

Ticker

Description

Crypto () Equity(16)

Volatility(4)

Forex(8)

CMKT

DIA EFA QQQ VWo RUI RUT RUA EEM

DAX

NSE CAC NKY HSI EU50

EU100

FXI

VIX

VXX

VSTOXX

UVXX

USD

USD/JPY GBP/USD EUR/USD AUD/USD USD/CAD USD/TRY FXE

Equal-weighted crypto market index

Dow Jones Industrial Average

Shares MSCIEAFE NASDAQ 100 Index

Vanguard Emerging Markets Stock Index

Russell 1000 Index Russell 2000 Index Russell 3000 Index

Shares MSCI Emerging Markets Gemman Stock Index DAX30

India Nifty 50 Index

France stock market index CAC 40

NIKKEI225 Index Hang Seng Index

EURO STOXX 50

FTSE Euro 100 Index

iShares China Large-Cap

VIX index future (most active)

Barclays iPath Series VIX Short-Term Futures ETN EURO STOXX50 Volatility

ProShares Ultra VIX Short-Term Futures ETF

Dollar IndexFuture

Japanese Yen Future British Pound Future Euro US Dollar

Aust.Dollar

Canadian Futures Turkish Lira

Invesco CurrencyShares Euro TrustETF

(continued on next page)

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**Table** **A.2(continued)**

|  |  |  |
| --- | --- | --- |
| Category | Ticker | Description |
| Commodity(10) | GDX | VanEck Gold Miners |
| GOLD | Gold future(most active) |
| XAU/USD | Gold Spot US Dollar |
| BRENT | ICE Brent Crude (most active) |
| OL | WTI Crude(most active) |
| GAS | Natural Gas(most active) |
| SILVER | Silver future(most active) |
| COPPER | Copper future(most active) |
| CORN | Corncommodity (most active) |
| WHEAT | Wheat commodity(mostactive) |
| Rate/Credit (9) | HYG | iShares iBoxx High Yield Corporate Bond |
| LQD | Shares iBoxx Investment Grade Corporate Bond |
| US 2 YR FUT | U.S.2-year treasury note future(cheapest to deliver) |
| US5 YR FUT | U.S.5-year treasury note future (cheapest to deliver) |
| US 10 YR FUT | U.S.10-year treasury note future(cheapest to deliver) |
| US 30 YR FUT | U.S.5-year treasury bond future (cheapest to deliver) |
| ES 10 YR | Spain 10-year bond yield |
| BUND 10 YR | Germany 10-year bond yield |
| TRY 2 YR | Turkey 2-yearbond yield |
| Others (3) | IVR | iShares US Real Estate Index |
| ARKK | ARK Innovation ETF |
| INRG | Shares Global CleanEnergyUCITS |

Appendix B.Construction ofprospect theory value on cryptocurrencies

We follow the standard prospect theory value (PTV)construction

process specified in Barberis et al.(2016)for cryptocurrencies.The for- mation of the prospect theory for stocks looks back to the past 60-month return monthly.Crypto assets emerge in a relatively short period.To avoid losing a majority of the observations for the cryptos,we use daily returnsof the crypto assets and form the prospect theory estimation pe- riod of 1 month for weekly crypto return analysis and an estimation period of 1 year for the monthly crypto return analysis.We perform robustness checks on the selection of the formation period and find that lengthening the PTV formation period does not alter the main con- clusion in our paper.The empirical results remain when we vary the formation period of PTV from 1-week to 1-year for weekly returns and the formation period of PTV from 1-month to 1-year for monthly re- turns.

Besides the reason for the short time of existence of the crypto mar- ket,using daily returns and a shorter PTVestimation period makes the information formation time frame more consistent with the construc- tion of the salience effect measurement used in this paper.We describe the construction of PTV using the 1-month formation period in more detail.

Based on the daily crypto returns,we first define the functional form of the value functionas in Kahneman and Tversky (1979).



where the parameter α measures the risk aversion,and the λ parameter measures loss aversion.We follow Kahneman and Tversky(1979)and Barberis et al.(2016)and select the functional form of the probability weighting function as



where γ and δ are distortion parameters.The values of γ and δ are negatively related to the degree of distortion on probability P.

For the parameter choice,we use the value of the parameters as

α=0.88,λ=2.25,γ=0.61,δ=0.69.

In unreported empirical results,we shock the parameterselection in certain ranges (varying eachparameter from 0.5 to 2 times its original

value).The empirical conclusions are consistently the same.We first rank the past 30 days'crypto return in ascending order for the return distribution estimation.Denote m as the number of days with a nega- tive return,and n=30-mas the number ofdays with a positive return. We assume the past 30 daysof thecrypto returns to have a uniform dis- tribution,i.e.,the occurrence probability of each day's return is equal. The return distribution is specified as



where r,is the ranked daily crypto returns.Furthermorei∈{-m,-m+ 1,...,-1,1,...,n-1,n}.r\_mrepresents thelowest cryptoreturns (most negative)in the past month,andr,represents the highest(most posi- tive)returns

If we combine these components,we can define the PVT for the cryptocurrency returns as

(5)



Our paper's construction of the PVTis similar to the empirical specifi- cation for stocks (Barberis et al.,2016)and cryptocurrencies (Thoma,

2020).

Appendix C.Supplementary materia

Supplementary material related to this article can be found online

at <https://doi.org/10.1016/j.jbankfin.2023.107052>.

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