[Full Title]

Salience Theory and Cryptocurrency Returns

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Abstract

We document that the salience theory of choice under risk provides a good explanation for the cross-sectional cryptocurrency returns. Investors overweigh salience payoffs, payoffs that stand out from the average of the alternatives. This leads to overpricing (underpricing) the cryptocurrencies with upward (downward) salience returns and generating negative (positive) expected returns in the subsequent period. The salience effect in the cryptocurrency market is over 20 times stronger than those observed in the equity markets. It is different from existing return anomalies documented in the cryptocurrency market and is a strong contender for a risk factor that can explain other cross-sectional strategy returns in the cryptocurrency market.

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1 Introduction

Cryptocurrency (crypto, hereafter) as an alternative asset class has posed challenges to traditional asset pricing theories but also offered new venues for testing theories of investor behaviors.[1] The originality of the currency was by design decentralized and free from the backing of any existing asset and institution. This makes it one of the hardest-to-value assets with unique characteristics including the lack of economic fundamentals as a fiat currency has, the lack of real cash flow as a traditional financial asset has, and the lack of historical trust and cultural preference as a means of value storage as the precious metals have.[2] With the growing number of cryptos available in the market, the question is: how investors decide which one to invest in, or whether they should invest at all?[3]

The development of this emerging asset class has been significantly influenced by attention-grabbing headlines. Investors are anxious about being left out in this new 'crypto-rush' a phenomenon known as FOMO (fear of missing out).[4] This partially motivates theoretical studies which suggest that the 'network effect' is an important driver for the evolution of the crypto market (Sockin and Xiong, 2020; Cong et al., 2021b). In the words of Sockin and Xiong (2020), "...each user's desire to join the platform grows with the number of other users on the platform...". What has been less studied is how investors process the attention-grabbing rises and falls in the crypto market and the potential consequence on future crypto returns. To this end, the salience theory (ST), introduced by Bordalo et al. (2012), offers a description of investors' behavior that could be closely matched with those observed in the

[1] As the cryptocurrency market develops, the term 'cryptos' has been used by the media and practitioners in short for 'crypto currencies' or 'digital coins'. In this paper, we follow this notation by using cryptos instead of cryptocurrencies.

[2] The debate on crypto valuation frequently appears in the media. For example, https://www.cnbc.com/2018/01/16/skeptics-say-bitcoin-has-no-value-heres-why-theyre-wrong.html

[3] As of 2021, there are over three thousand cryptos in the market.

[4] See media coverage: What influences cryptocurrency values? Financial Times. https://www.ft.com/content/06119305-82e3-4f7e-9bdb-387392571d45. Accessed December 8th, 2021; https://www.bloomberg.com/news/articles/2021-06-08/moelis-likens-crypto-to-gold-rush-watches-for-opportunities. Accessed December 7th, 2021. Bonaparte (2021) constructs a financial market FOMO index and shows that it increases the value of PE ratio and the Bitcoin price and volume which provide evidence of the influence of FOMO in the financial market.

crypto market.

ST is a context-dependent theory of choice under risk where the objective probability is replaced by distorted decision weights that are in favor of salient payoffs, payoffs that stand out compared to the average of the alternatives. Under the influence of salience bias, investors prefer more on investments with salient upward returns and less on those with salient downward returns. This creates predictable price reversal. Investment with salience upside (downside) is expected to have a lower (higher) return in equilibrium (Bordalo et al., 2013a). Cosemans and Frehen (2021) and Cakici and Zaremba (2021) find supporting evidence of salience theory on the cross-sectional pricing of the U.S. and international equity markets, respectively. Especially, the ST effect is more pronounced for stocks with higher limits to arbitrage and during high investor sentiment periods supporting the mispricing explanation (Cosemans and Frehen, 2021). Consistent with this, Cakici and Zaremba (2021) show that the ST effect is more evidently observed where and when arbitrage is most limited: in micro firms, high idiosyncratic risk countries, and extreme market states (such as high economic uncertainty and volatilities).

The above evidence highlights that whether or not the ST would indeed explain asset pricing is dependent on to what extent the investors in a given asset market (context) are under the influence of the ST bias. The crypto market is an emerging asset class with a high level of uncertainty and limited fundamental information available to investors. Hirshleifer (2001) argues that uncertainty leaves more room for investors to follow their own subjective estimations and to ignore objective valuations. The emerging and non-mainstream nature of the crypto market create an environment that is more likely to attract investors with salience bias. For example, Cakici and Zaremba (2021) points out that retail investors are more likely to be influenced by sentiments and the resulting ST effect. Therefore, there is strong reason to conjecture that salience theory could be one of the key mechanisms that determine the pricing of cryptos and its effect would be stronger in the crypto market than in other contexts of decision making including equity markets (Chetty et al., 2009; Bordalo et al., 2013a,b, 2015; Dessaint and Matray, 2017).

To test our hypothesis, we apply the empirical asset pricing approach to the crypto market and examine if there exists a salience effect on the cross-sectional of crypto returns. The work by Liu and Tsyvinski (2021) and Liu et al. (2021) lay the foundation of using the conventional portfolio theory on this new asset class. Liu and Tsyvinski (2021) show that the crypto returns are highly skewed with greater tail exposure than the stocks. Investor attention becomes a major risk on the crypto market, as the number of new accounts opened is tightly related to the risk and return distribution of the cryptos. Furthermore, Liu et al. (2021) establish the common risk factors for the cross-sectional of crypto returns. In particular, they find the market, size, and momentum to be the most significant pricing factors in the crypto market.

Following Cosemans and Frehen (2021), we construct a relative return salience measure (ST) by the difference between the salient weighted probability with the objective probability.[5] Using the data of over four thousand coins that have a market value of greater than one million from `Coinmarketcap.com`, we study the predictability of ST on cross-sectional returns in the crypto market from January 2014 to June 2021.

We adopt single portfolio sorting to demonstrate the economic and statistical significance of the ST effect. We show that cryptos with salient upsides earn lower returns over the next month than cryptos with salient downsides. A univariate portfolio analysis indicates that the average return for the zero-cost strategy that buys high-ST cryptos ranges from -25.9% (t-value = -8.7) monthly for the equal-weighted (EW) portfolio and -32.4% (t-value = -2.3) for the value-weighted (VW) portfolio. These are more than 20 times the magnitude of those documented in the US equity market with -1.3% and -0.6% for EW and VW monthly excess

[5] The calculation of the ST measure is not a point estimate, rather it is estimating the difference between the two(subjective and objective) weighted outcomes for a given period. It is not the total return during the formation period that matters, it is the distribution and the salience of each point that matters. This makes it different from simple momentum or reversal strategies. See Section 3.2 for more details of the construction. Regarding the terminology. We use the abbreviation of 'ST' to refer to both the salience theory and the salience measure which is clearly distinguishable in most contexts. We clarify the distinction when necessary by adding measures or theory at the end of this abbreviation.

return, respectively (Cosemans and Frehen, 2021). The ST effect in the crypto market is also markedly bigger even when compared to the micro-stock results, which are the strongest documented in the international equity markets of Cakici and Zaremba (2021), where they find that the ST strategy generates -1.0% and -0.5% for EW and VW monthly excess return. Furthermore, the salience effect is comparable to the strongest factors so far documented in the context of the crypto market research. For example, Liu et al. (2021) find a VW size factor premium to be 3.4% to 4.1% per week. Our weekly findings of 3.0% VW weekly return are comparable to that magnitude. Furthermore, the monthly salience effect is much stronger in the crypto market compared to the weekly salience effect and other factors. The monthly VW return for the ST effect in the crypto market is annualized (multiplied by 12) at 388.8% while the largest weekly size effect is annualized (multiplied by 52) at 213.2%. The strong monthly effect suggests that the salience bias has a long-lasting effect in these relatively high-frequency and round-the-clock markets.

We then examine the source of the ST strategy return and its relationship with known factors in the literature. First, the salience effect cannot be explained by known risk factors. The long-short strategy generates a 3.2% alpha weekly (annualized 166.4%) and 24.6% alpha monthly (annualized 295.2%) controlling for the Liu-Tsyvinski-Wu (LTW) three-factor model (Liu et al., 2021). Second, in Fama-MacBeth regression analyses, we show that ST has significant incremental predictability of future crypto returns controlling for a list of cross-sectional determinants informed both by the ST and crypto literature (Cosemans and Frehen, 2021; Liu et al., 2021).

If salience theory is one of the first-order pricing effects in the crypto market, we would expect it to be able to explain other cross-sectional pricing patterns. For example, Bordalo et al. (2013a) show that salience theory is useful in understanding asset pricing puzzles such as the preference bias towards highly skewed assets, the growth-value puzzle and the aggregate equity premium puzzle. To explore this possibility in the crypto market, we construct an ST factor following the factor construction method of Liu et al. (2021). We show that an ST factor can potentially replace the momentum factor in the LTW three-factor model to explain other cross-sectional return strategies documented in Liu et al. (2021) and additional behavioural anomalies including the prospect theory (Barberis et al., 2016), skewness (Harvey and Siddique, 2000) and downside beta (Ang et al., 2006).[6]

Beyond the cross-sectional ST effect, we also consider the salience of crypto index return, as an asset class, compared to a list of 50 investment instruments including indices of major equity and bond, exchange rates, and commodities. We show that the mean spread between the crypto index in the upward and downward salience periods is -2.0% (t-value = -2.1) weekly. In other words, the salience of the crypto market return compared to other investment opportunities would negatively predict this asset class's future return. This confirms the salience bias also influences the return dynamic of this asset which we do not find in other traditional assets.

Related and consistent with the conjecture that salience investors are thrill-seekers, we find that the cross-sectional ST effect is stronger in the crypto market when the uncertainty is *low* in the equity market (measured by VIX) or the economy (measured by economic policy uncertainty by Baker et al. (2016)). In other words, salience investors are relatively more active in the crypto market when the alternative markets are quieter (with less volatility or uncertainty). Furthermore, when considering the effect of uncertainty in the crypto market itself as a conditional variable, we find that the cross-sectional ST effect is indeed stronger in high Bitcoin volatility periods than that in low volatility periods. This is consistent with the conclusion of Cakici and Zaremba (2021) who find that the ST effect is stronger in periods of higher volatility and uncertainty in the equity market. Importantly, This is also consistent with the general argument that uncertainty will amplify investor bias (Hirshleifer, 2001), which has found support in studies of economic uncertainty and mispricing in the US equity market by Kerestecioglu et al. (2020).

We also provide further robustness checks. In particular, exploring the relationship be-

[6]Following the equity market research convention we also refer to these cross-sectional return strategies as anomalies in our discussion

tween ST and existing factors through double sorting, correlations, and pair-wise comparison of return predictability in the Fama-Macbeth regressions. We show that ST and size factors are both important and independent from each other in the crypto market. The equity market literature, Cosemans and Frehen (2021) and especially Cakici and Zaremba (2021) show that ST is closely related to the reversal effect. In the crypto market, the momentum factor introduced Liu et al. (2021) is in fact a 'reversal' factor in the equity market's setting since it does not skip one period (week or month) for allowing the potential reversal. Our analysis shows that the ST factor dominates the momentum factor in double sorting.

Bordalo et al. (2012) point out that ST and the prospect theory of Kahneman and Tversky (1979) (KT) are similar in assuming decision-makers focus on the payoff and that the probability weights people use to make choices are different from objective probability. What is new in ST is that these weights depend on the actual payoffs and their salience (a wider context). Empirically, we show that ST dominates the KT effect, the associated skewness preference, and downside risk aversion in Fama and MacBeth (1973) regression analyses.

This study provides new evidence for both the valuation of the crypto assets and the relevance of salience theory in asset pricing. First, our study shows that the salience theory of decision-making is a good description of the crypto investors' behavior. This extends both the theoretical and empirical attempts in understanding the drivers of this market. The network effect, Sockin and Xiong (2020) predicts that there are roles for both news and investor sentiment to explain the token price fluctuations and expected returns. Similarly, Cong et al. (2021b) provide a dynamic model that demonstrates the effect of endogenous user adoption on the platform's success and token price. Speculative motives and sentiment may affect the decisions of potential users to participate on the platform. This explicitly connects investors' attention and expectation to the growth of the platform. Salience theory takes one step further in describing how investors may form their expectations given the salience payoffs that have caught their attention. Our empirical evidence not only confirms the existence of a strong ST effect in the cross-sectional and time series of cryptocurrency returns, but also shows that it is a contender for one of the risk factors that explain the cross-sectional returns. This is especially appealing given that it originates from a behavioral theory model which provides a clear foundation for the interpretation of the factor.

Second, we provide further evidence on when salience theory may be more relevant in explaining asset price. As a testing environment, the crypto market fits in very well with the condition that Cakici and Zaremba (2021), among others, identified in order to observe the ST effect: micro caps, extreme uncertainty, and potentially with less sophisticated investors. Especially, we show that the strong ST effect dominates the perspective theory and preference for skewness explanations. We also show that the ST effect is different from the short-term reversal which was difficult to disentangle in the equity market. Overall, our findings confirm that the salience effect is indeed much stronger for an asset that is harder to value and especially with less fundamental information. It highlights the important relevance of ST in understanding new and emerging asset classes (consider Sneakers as an asset class[7]).

Finally, we show that salience effects are much stronger than those documented in the equity market even by the microcaps standard. This suggests that there is a disproportionally large group of salience investors in the crypto market compared to the traditional financial market. These findings echo the importance of regulation and investor protection in this market. Salience investors are especially vulnerable as sophisticated players of this market can take advantage of their predictable biased behavior towards salience payoffs. There has been plenty of evidence including examples of crypto scams, manipulation such as pump-and-dump documented by Li et al. (2021), and attention-grabbing and potentially misleading advertisements.[8] The theory of salience thinkers provides a clear framework to understand the design of these misconducts. In particular, alongside regulations to curb

[7]Sneakers Turning Into an Asset Class - Bloomberg `https://www.bloomberg.com/news/audio/2021-02-26/sneakers-turning-into-an-asset-class-podcast`. Accessed June 27th, 2021.

[8]See for example, recently the U.K. Advertising Standard Authority (ASA) taking tougher action on misleading crypto advertisements. https://www.moneymarketing.co.uk/news/asa-bans-misleading-and-irresponsible-crypto-ads/ accessed December 15th, 2021.

scams, manipulation, and false advertising, investor education would also play an important part in reducing the impact of the salience effect in this market. For example, running awareness campaigns on social media. The initial intention for the creation of the crypto market was to distance from regulation and any institutional backing. However, tokenization become one of the vehicles for securitization. The efficiency and fairness of this market have potentially far-reaching consequences other than investment gain and loss in this market.

The rest of the paper is organized as follows. Section 2 discusses the related literature on salience theory and cryptocurrency, and the links between the two. Section 3 describes the data source and the construction of salience effect measure. Section 4 presents our main analyses of the cross-sectional salience effect. Section 5 reports several further analyses considering: the ST as a risk factor, time-series ST effect on the crypto index relative to other investments, the conditional effects of different market uncertainty on the cross-sectional ST effect, and the relationship between the ST effect and existing explanations including prospective theory, preference for skewness, size, momentum, and short-term reversal. Section 6 reports a series of robustness checks through examining the effect of alternative formations of the ST measures. We conclude the findings in Section 7.

2 Literature Review

2.1 Salience and Asset Returns

One of the axioms of the expected utility theory is the consistency of investors' risk preference. However, there has been evidence of people revealing a different preference for identical lotteries in a different context (such as a common sequence in Allais (1953)). Bordalo et al. (2012) formally introduce the effect of salience on choice under risk. Intuitively, salience theory tries to reflect the disproportional attention effect given by decision-makers to outcomes that are 'stand out' in a decision environment. This type of 'local' decision thinker can be also considered as suffering a form of 'narrow framing' or 'limited attention' bias; in this paper, we refer to this as salience bias. Importantly such a salience bias will affect a decision makers' subsequent judgments.

The salient theory is different from the standard expected utility theory most in the presence of extreme payoffs that occur with a low probability (Bordalo et al., 2012). This is partly motivated by the Kahneman and Tversky (1979) observation that extreme probabilities are more challenging to comprehend and evaluate for the human mind. It predicts that decision-makers who suffer salience bias will overweight salience outcomes, extremely good or bad, relative to an average outcome in a given state. Different from the prospective theory, salience decision makers' weight is affected by a wider context in that the outcome is compared with the average of the alternative.

The salience theory has been found applicable in different areas including asset pricing, consumer choice, and judicial decisions(Chetty et al., 2009; Bordalo et al., 2013a,b, 2015; Dessaint and Matray, 2017). Among these, the most relevant theoretical extension to the current study is by Bordalo et al. (2013a). They propose a direct application of the salience theory on asset pricing. An asset's salient payoff is defined as one most different from the average market payoff in a given state of the world. They show that under the influence of salience investors, extreme payoffs will receive disproportionate weight in evaluating assets. Investors 'overreact' to these salience payoffs in forming their expectation and therefore overvalue assets with salience upside and undervalue assets with salience downside. This intuition can be used to explain several puzzles including a preference for stocks with high positive skewness which is consistent with a large body of evidence (Barberis, 2013).

Subsequently, Cosemans and Frehen (2021) provide direct supporting evidence of salience theory on the cross-sectional pricing of the U.S. stock market. They utilize the expected 'mispricing' effects, i.e. the expected premium/discount induced by the salience thinker in the asset price, to measure the extent of the asset price that may be influenced by salience thinkers. With this salience measure (ST), they study its prediction on future cross-sectional returns. They confirm that quintile of stocks with high/positive salience measures are indeed overpriced and subsequently observed lower negative return when compared to stocks with low salience measure. Their results are robust to alternative explanations such as the simple short-term reversal which are well known to the equity literature (Jegadeesh, 1990; Subrahmanyam, 2005; Greenwood and Shleifer, 2014; Da et al., 2014). Their finding confirms that salience theory plays an important and additional role to explain cross-sectional asset pricing and it is not a repackaging of any existing phenomenon that has been documented in the literature.

Cakici and Zaremba (2021) extend Cosemans and Frehen (2021) to provide international and further evidence of the salience theory effect in 49 countries. They confirm the observations of the ST effect in the international context. More importantly, they reveal further insights regarding the conditions in which the ST effect is more prominent. They show that the ST effect as a mispricing phenomenon is more evidently observed where arbitrage is most limited: in small firms, high idiosyncratic risk countries, and extreme market states (such as high economic uncertainty and volatility).

These findings provide extra motivation for us to study ST in the crypto market since these conditions are expected to be more likely observed in the crypto markets as we will discuss in the next section.

2.2 Theory and Evidence of Crypto Pricing

The fast-growing crypto market has sparked huge academic interests in understanding the underlying economic mechanism of growth in this type of new market.[9] Especially what is the fundamental utility of the market? The early and most dominant utility is the role of crypto play as money and a means of payment.[10] Here there is a dark side of this type of platform as it can potentially and has been used as a means for money laundering and facilitating criminal activities. This economic 'utility' has brought a large part of the shadow money into

[9] Pagnotta and Buraschi (2018); Biais et al. (2020); Cong et al. (2021b) propose the "network effect" as the user adoption externality to the cryptocurrency performance. Cong et al. (2021a); Sockin and Xiong (2020) consider the price of cryptocurrency to be linked to the cost of mining the coins. Liu and Tsyvinski (2021); Liu et al. (2021) perform the return and risk analysis on the cryptocurrency market and show the uniqueness of cryptocurrency market features.

[10] FINMA publishes ICO guidelines (2018), https://www.finma.ch/en/news/2018/02/20180216-mm-ico-wegleitung/.

the 'public' and partly reflected the growth of these platforms. Putting this large concern aside to regulators, the most distinctive feature of these platforms is the decentralization nature and the potential of network effect which is powered by the block-train technology behind them.

Among others, Sockin and Xiong (2020) study the crypto market from the tokenization point of view of a platform/coin creator. Especially they demonstrate the importance of network effect in such decentralized platform setting: "each user's desire to join the platform grows with the number of other users on the platform and the size of their goods endowments." In a dynamic setting with overlapping generations of users, their model predicts (i) the token/coin price is positively related to the platform's user bases because of the network effect, and (ii) the expected token/coin returns are higher for platforms with weak 'fundamental' which offer lower convenience yields to users.[11]

Similarly, Cong et al. (2021b) provide a dynamic model that demonstrates the effect of endogenous user adoption on the platform's success and token price. Especially, they distinguish two motives of participation: "transaction motive" which is the real economy fundamental benefit of using the platform (e.g., payment or signing smart contracts), and "investment motive" which is the expected future token price.

Furthermore, the network effect, Sockin and Xiong (2020) predicts there are roles for both news and investor sentiment, to explain the token price fluctuations and expected returns. Speculative motives and sentiment may affect the decisions of potential users to participate on the platform. This explicitly connects investors' attention and expectation to the growth of the platform which suggests the relevance of the salience in the investment decisions.

Empirically, Liu and Tsyvinski (2021) presents a comprehensive collection of facts about the time series returns of the crypto market and tests the potential determinant factors. They show strong time-series momentum effects and proxies for investors' attention (by

[11] This latter prediction may offer an explanation for the size factor. A smaller market cap coin is a smaller market that offers less chance to match with other users for a transaction, hence a lower convenience yield and higher expected token returns.

google bitcoin search). They also find that the crypto market return can positively predict the cumulative user changes (wallet users) up to eight months. The changes of users further predict future crypto returns. These findings confirm the theoretical prediction Cong et al. (2021b) that the current crypto market return predicts future network growth.

Liu et al. (2021) study the pricing factors for cross-sectional crypto returns. They demonstrate a three-factor model with market, size, and momentum is able to explain all of the nine pricing 'anomalies', inspired by the equity market, in the crypto markets.

Although existing evidence shows investors' attention and participation can affect the dynamics of the crypto pricing, what is less explored is the reason behind the variation of investors' attention and how investors' expectations may be affected by such disproportional attentions. Salience theory takes one step further in describing how investors may form their expectations given these salience payoffs that caught their attention. We discuss this possible connection in the next section.

2.3 Salience Theory and Crypto Pricing

Existing ST and crypto literature provides two important motivations for our study. First, there is a theoretical underpinning of the salience effect. Investors' decision is context-dependent and the specific context of focus is the salience of a payoff. This will affect the expectation formation being biased due to overweighting of the salience payoff. This will lead to a predictable expected return. Investment with salience upside (downside) is expected to have a lower (higher) expected to return in equilibrium. Whether or not the ST would indeed explain asset pricing is depending on to what extent the investors in the given asset markets (contexts) are under the influence of the ST bias. Cosemans and Frehen (2021) show that the salience effect is larger during periods of high investor sentiment when unsophisticated investors are more likely to enter the market. Given the evidence in Liu and Tsyvinski (2021), among others, there is strong reason to believe that crypto market investors are more likely to be affected by sentiment and less sophisticated. This makes ST a strong contender for a theoretical explanation for understanding crypto pricing.

Second, empirically, the ST effect is confirmed in the US and international markets. It is especially stronger when arbitrage is limited and it is also very similar to the simple reversal effect in the international equity markets. The crypto market is an emerging asset class. Despite its rapid growth, the crypto market in aggregate is relatively small, highly volatile, and has high idiosyncratic volatility.[12] Investors' participation is likely depending on the 'investment' or speculative motives described in Sockin and Xiong (2020) and Cong et al. (2021b). However, the information set available to investors is limited in this new asset class and uncertainty is high. Hirshleifer (2001) argues that uncertainty leaves more room for investors to follow their own subjective estimations and to ignore objective valuations. Compared to the equity market, the crypto market is much immature and lack established fundamental, the most readily available information about a crypto asset is mainly the price and the price change. This makes it an ideal marketplace to test the effect of investors' attention to relative price changes. All of these are the conditions Cakici and Zaremba (2021) identified to have a stronger ST effect. Therefore, if salience theory is a general description of behavioral decision-making under risk, we expected that its effect would be stronger in the crypto than equity market since the crypto market is relatively new, small, and harder to value. Our central hypothesis can be summarized as follows:

Hypothesis 1 (Main). *When investors choose among the cryptos, they overweight the probability of salient payoffs which create predictable future price change. Cryptos with high salient upside will have a lower expected future return than those with a high salient downside.*

[12]The global crypto market cap is $2.88 trillion while the global equity market is $122 trillion as of 2021. This is comparable to the 3% micro-cap in their study. There is a potential reason to believe that the ST effect would be likely to present in this market given its emerging nature. Source: `https://coinmarketcap.com/` and `https://www.sifma.org/resources/research/research-quarterly-equities/`. Accessed November 15th, 2021.

3 Data and Methodology

3.1 Data Sources

We retrieve the crypto prices from `Coinmarketcap.com` following similar works (Liu and Tsyvinski, 2021; Liu et al., 2021). In our sample, the crypto daily price observations range from January 1st, 2014 to June 30th, 2021. The collected dataset contains crypto symbol as the identifier, prices on daily frequency, trading volume in dollar amount, and market capitalization of included cryptos.[13] Cryptos are traded on electric exchanges, either centralized or decentralized, twenty-four hours a day and seven days a week. There is generally no exchange close time for the crypto market. We include all calendar days with crypto transactions, and the returns are calculated using the whole day close price from 0:00:00.000 am to 23:59:59.999 pm UTC.

3.2 Salience Theory Measure

Following Bordalo et al. (2016) and Cosemans and Frehen (2021), we assume that, when choosing between cryptos, investors infer the set of future return states from the distribution of its past returns. Practically, we assume that the state space is formed by the daily returns over the past week/month in our main analysis. We measure the salience of the return (r_{is}) of crypto i on the day s by its distance from the average return across all cryptos in the market on that day ($\bar{r}_{is}$):

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

where $\theta = 0.1$ and $\bar{r}_s = \sum_i^N r_{is}/N$ with N denoting the number of cryptos available on the market.[14] The salience theory is sensitive to the asset selection set. Following Liu and Tsyvinski (2021), we use the whole universe of the cryptos with market capitalization more than \$1 million in this paper. To calculate the salience weight for each crypto, we rank the daily returns in each month in descending order of salience and plug the rank k_{is} in the

[13] The website provides the daily open, close, high, and low prices of cryptos. We use the daily close price for the return related calculations.

[14] θ is included to control the salience of a zero payoff.

following equation:

$$\omega_{is} = \frac{\delta^{k_{is}}}{\sum_j \delta^{k_{ij}} \cdot \pi_j}, \tag{2}$$

where δ captures the degree of salience distortion. When $\delta = 1$ there is no distortion and when $\delta \to 0$ there is a maximum salience distortion in that only the most salient payoff is considered by the investor. Following Bordalo et al. (2012) and Cosemans and Frehen (2021) we set $\delta = 0.7$ in our main analyses. k_{is} is the rank of salience payoff; k_{is} ranging from 1 (most salient) to S (least salient), and $\pi = 1/S$ as the scaling factor. S denotes the set of states and in this case the number of trading days within the ranking period. The salience effect is then measured by the covariance of the decision weights (ω_{is}) and the crypto return (r_{is}) over the estimation period.

$$\begin{aligned} ST_{i,t} &= Cov[\omega_{is,t}, r_{is,t}] = \sum_{s}^{S_t} \pi_{S,t}\omega_{iS,t}r_{iS,t} - \sum_{s}^{S_t} \pi_{S,t}r_{iS,t} \\ &= \mathbb{E}^{ST}[r_{iS,t}] - \bar{r}_{iS,t}, \end{aligned} \tag{3}$$

where t denotes the estimation period. This effectively measures the difference of salience-weighted and equal-weighted returns in the past month. It quantify the extend of salience thinking on distorting investors' expectation about future return compare to the objective realized past return. When $ST < 0$, it suggests that the lowest payoffs of an asset are the salient ones and the investors focus on downside risks which will lead to a positive 'risk' premium (positive expected return in next period). When $ST > 0$, it suggests that the highest payoffs of an asset are the salient ones and the investors focus on upside potential which results in a negative 'risk' premium (negative expected return in next period).

In the portfolio sorting analysis, we compute the ST parameter as specified in Eq. (3) using the daily salience measure for each crypto-week/month. We construct the quintile portfolio based on sorting the ST measure and calculate the excess portfolio return for the next period.

Table 1 presents the number of cryptos. The number of coins and tokens in the sample that satisfies all the filters increases from 100 in 2014 to 3,701 in 2021. The mean (median) market capitalization in the sample increased significantly over this period. The large difference between the mean and median suggests that there is a large outlier (notably Bitcoin). The volume increases at a much greater pace than the market capitalization. This is in line with the emerging nature and the growth of this asset class.

[Insert Table 1 about here.]

3.3 Control variables

Additional controls variables are informed by previous studies of asset pricing, salience theory, and crypto markets. These are constructed mainly from the trading price and trading volume of the cryptos. First, we control for the LTW three-factors of crypto returns Liu et al. (2021). For weekly (monthly) return analysis, we construct BETA as the daily crypto return sensitivity with respect to the equal-weighted market returns using trailing 30 (365) days of the portfolio formation period. We use the logarithm of the last day market capitalization to measure the SIZE of digital currencies within the week (month). We use the lagged one-week (month) return to capture momentum (MOM). Note that in the crypto market, there is no short-term reversal and the past return is used for momentum formation without one period skip. In addition, We use the time since crypto issue (AGE) as a measure of the maturity of the crypto.

We include additional risk and liquidity measures. IVOL measures the idiosyncratic volatility estimated the residuals from the market model which we used to estimate BETA. Amihud (2002) illiquidity (ILLIQ) is computed as the absolute daily return divided by the daily dollar trading volume, averaged over all trading days in a week (month).

To control for lottery demand as defined in Bali et al. (2011), MAX and MIN capture the maximum and minimum daily return within the portfolio formation week (month), respectively. To control for other behavioural prospect theory, loss aversion and skewness preference, we include the prospect theory (TK) value of a crypto which is constructed using a 30 (356) day window of daily returns for studying the weekly and monthly holding period.[15] Skewness (SKEW) is the skewness of daily stock returns over one month before the formation period, and idiosyncratic skewness (ISKEW) is defined as the skewness of the residuals from the market model. Coskewness (COSKEW) is defined as the coskewness of daily returns with daily market returns over a one-year window following the approach of Harvey and Siddique (2000). Downside beta (DBETA) is estimated from a regression of daily excess returns on the daily excess market return over a 30 (365) day window, using only days on which the market return was below the average daily market return during that year, as in Ang et al. (2006).

A summary of the variable construction are specified in the Appendix Table A1.[16]

4 Empirical Results: Salience and Crypto Returns

4.1 Univariate Portfolio Sorts

Table 2 presents the average returns of the single-sorted portfolios using the salience theory measure. The sample consists of actively traded cryptos with a market capitalization of over $1 million within the sample period from January 2014 to June 2021. On each week (month), the cryptos are sorted into quintiles according to the salience effect measure in the prior week (month). Each portfolio is held for one week (month). The "Equal-Weighted" and "Value-Weighted" columns report the one-week (one-month) ahead excess returns of each portfolio with equal-weighted and value-weighted, respectively. The "High - Low" row reports the portfolio average return difference between the highest sorting value portfolio and the lowest sorting value portfolio using the corresponding sorting variable.

[Insert Table 2 about here.]

Table 2 shows that cryptos with salient upsides earn lower returns over the next period than cryptos with salient downsides which is consistent with the findings in the equity market

[15] The choices of period are taking into consideration the relevance of the information to the investment horizon. In equity market, Barberis et al. (2016) use 60 monthly observations to estimate the skewness. In crypto market, Thoma (2020) uses 30 days formation to study daily returns

[16] A summary statistics and correlations of the key variables can be found in an Online Appendix Table OA1.

in Cosemans and Frehen (2021) and Cakici and Zaremba (2021). There are three additional observations from these crypto market analyses. First, the magnitude of the salience effect is economically much bigger than those in the equity markets. For example, the average return for the long-short strategy that buys high and sells low ST cryptos generate -25.9% (t-value = -8.7) monthly for the equal-weighted (EW) portfolio and -32.4% (t-value = -2.3) for the value-weighted (VW) portfolio. These are more than 20 times the magnitude of those documented in the U.S. equity market with -1.28% and -0.6% for EW and VW monthly excess return, respectively (Cosemans and Frehen, 2021). The ST effect in the crypto market is also markedly bigger even when compared to the micro-stock results, which are the strongest documented in Cakici and Zaremba (2021). They find that the ST strategy generates -1.0% and -0.52% for EW and VW monthly excess return.

Second, the salience effect is comparable to the strongest factors so far documented in the context of the crypto market research. For example, Liu et al. (2021) find a VW size factor premium to be 3.4% 4.1% per week. Our weekly findings of 3.0% VW weekly return are comparable to that magnitude. Furthermore, the monthly salience effect is much stronger in the crypto market. The monthly VW return for the ST effect in the crypto market is annualized (multiplied by 12) at 388.8% while the largest weekly size effect is annualized (multiplied by 52) at 213.2%.

Third, the EW results are much stronger than VW results which is consistent with the potential size effect suggested by Cakici and Zaremba (2021). The EV results put more weight on small size cryptos and therefore demonstrate a stronger effect. However, in a later analysis, we show that the ST effect in the crypto market is not restricted to small-cap cryptos. We study the relationship between market cap and the ST effect further in the robustness test section (Section 5.4).

Overall, Table 2 demonstrates a strong ST effect that is both statistically significant and economically large.

4.2 Crypto Risk Factor Analysis

We consider the relationship of the ST effect with existing known risk factors. Table 3 presents the alphas and details of the regression explaining the crypto excess return in quintile portfolios using the Liu-Tsyvinski-Wu three-factor model (Liu et al., 2021). The crypto market index is constructed using the equal-weighted returns of all the available coins and tokens. In weekly return analysis, the size and momentum factors follow the construction approach in Liu et al. (2021). For monthly factors, the size factor is constructed in the same manner as that of the weekly return. The monthly momentum factor is constructed using one-month lagged returns.

[Insert Table 3 about here.]

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.[17] As for the factor loading, for the weekly regressions, it shows that the ST portfolio loads positive size factor but negative momentum factor. There is no significant factor loading in the monthly regression suggesting that the ST effects are independent of existing factors. Overall, it confirms that the salience effect cannot be explained by known risk factors.[18]

4.3 Fama-MacBeth Cross-Sectional Regressions

We study the cross-sectional predictability of crypto return with and without the ST measures including a list of control variables. Table 4 reports the estimated regression coefficients and the t-statistics (in brackets) from Fama-MacBeth cross-sectional regressions for weekly returns (Panel A) and monthly returns (Panel B). Following Cosemans and Frehen (2021),

[17] To alleviate the concern about the impact of outliers, we have also tried wensorizing the raw return on [0.5%, 99.5%] and [1%, 99%], and the results remain with similar magnitude. The portfolio alphas are not driven by extreme cases.

[18] we also test the alpha including equity factors (Fama and French (1993) three-factor and Carhart (1997) momentum factor) and including both equity and LTW three-factor in a full seven-factor (Full7) model. The ST effect cannot be explained by these specifications (see Table OA2).

we include a list of cross-sectional determinants. The control variable definition is described in Section 3.1 and the Appendix Table A1.

[Insert Table 4 about here.]

Panel A in Table 4 shows that ST has significant predictability of future crypto returns in all specifications. On its own, it can explain 10% of the future cross-sectional weekly returns, as indicated by the average R^2. Furthermore, the ST effect is robust to control for other firm-level risks, liquidity, lottery demand, prospective theory value, skewness preference, and downside risk measures. While the statistical significance is reduced as indicated by the t-value, the magnitude seems to be higher especially when other behavioral controls, such as TK and SKEW are added. Overall, there is a clear incremental improvement in the explanatory power when the ST is included. The average adjusted R-squared increase from 32% (column 11) to 45% (column 10) when the ST variable is added into a regression with all control variables. This represents a 39% increase in the explanatory power. The monthly results in Panel B are consistent with the weekly findings with the ST variable having higher t-values in general.

5 Further Analyses

5.1 ST Risk Factor in Crypto Market

If the ST effect captures one of the key crypto investors' trading behaviors, it may potentially help explain other return 'anomalies' in this emerging asset class. We further explore the relationship between ST and other crypto market return anomalies. We construct the ST factor in a similar manner of Liu et al. (2021). Each week we partition the cryptos into three salience groups by the ST measure: bottom 30 percent (down-salience), the middle 40 percent (non-salience), and top 30 percent (up-salience). We then form value-weighted portfolios for each of these three groups. The crypto ST factor is the return difference between the up-salience portfolio and the down-salience portfolio. Therefore the ST premium is by this construction negative. We follow Liu et al. (2021) strictly to construct the other three crypto factors: the market factor, the size factor and the momentum factor.[19]

Table 5 presents the alphas from the factor model regressions explaining the crypto excess return in the hedge portfolios (high-low) sorted by crypto characteristic variables studied in previous literature. It includes six different factor model specifications. Specifically, models 1 to 3 include the three specifications of the LTW three-factor model Liu et al. (2021). In models 4 to 6, we examine the incremental effect of the ST factor.

[Insert Table 5 about here.]

Panel A reports the analyses of the nine anomalies identified by Liu et al. (2021) and our ST strategy. It first confirms findings of Liu et al. (2021) that their three-factor models (M3) can explain all nine return anomalies in the crypto market. However, the LTW three-factor model cannot explain the ST effect as reported in Table 3. An additional ST factor when combined with the market and size factor can explain all eight out of the ten anomalies (M5). The ST factor cannot explain short-term momentum (one-week and two-week momentum effects). Finally, it seems there is a benefit of combining the ST factor with the existing three factors, as this four-factor model (M6) can explain all of the ten anomalies.

We extend our factor analyses to other anomalies. Panel B includes those insignificant anomalies in the study of Liu et al. (2021). Panel C further identifies new anomalies that are relevant to the prospect theory and skewness.

There are three observations from these analyses. First, there are some new anomalies that cannot be explained by the three-factor model (M3) when applying 5% significance. These include VOLMSSCALED, BETA (betting against beta), IDIOVOL, RETVOL, MAXRET, TK, and ISKEW. Among these, replacing the MOM factor with the ST factor (M5) will be able to explain IDIOVOL, RETVOL, TK, and ISKEW. Interestingly, when combining both MOM and ST together, it actually reduces the explanatory power to these

[19] For completeness, we also constructed equal-weighted factor returns. To be consistent with Liu et al. (2021), we report VW analyses in the paper. Analyses on EW portfolios using EW factors can be found in Online Appendix Table OA3.

anomalies (M6). The results of the M6 are more resemble to M3 (Size with momentum) then M5 (Size with ST).

Panel D summarizes the number of significant anomalies at 1% for the models. It shows that the new three-factor model with market, size, and ST is a strong contender among the different specifications. It is able to explain as much as the combined model does. It suggests that size and ST are the two key factors in the crypto markets. Momentum factors are important to explain momentum-related anomalies. When the comparison is made outside the momentum types of anomalies, the ST factor performs better. This new three-factor model in column (5) can be an alternative risk factor model in the crypto market to the existing LTW three-factor model.

5.2 The Salience of Cryptos as an Asset Class

Salience is not defined in isolation but relative to alternative investments (salient relative to the average market payoff). Comparing the salience of crypto return with other assets could help understand the extent of fund flow into a crypto asset that could be potentially driven by the salience of this new asset class.

In this section, we study the salience effect of cryptos compared to other investment opportunities. To this end consider a group of 50 investment instruments including indices of equity and bond, major exchange rates, and commodities (A list of the assets is given in Appendix Table A2). We construct the salience measure using the 50 return series and the return of the crypto market index. We expect that when the crypto market return is more salience the expected return will be lower in the following month.

Panel B Table 6 reports a summary of the crypto return in quintiles of crypto's salience measure (applying Eq. (3) to the 51 assets universe). It divides the sample into five groups according to the crypto market's weekly ST measures. It then reports the excess return of the following week.[20] It confirms that following the most downward salience period the returns

[20]This excess return is calculated by deducting the equal-weighted return of the 51 assets from the crypto market index return.

are significantly higher than those following the most upward salience. If we calculate the mean spread between the high and low ST periods, it is -2.0% and the t-value of -2.1 weekly. In other words, the salience of the crypto market return compared to other investment opportunities would negatively predict this asset class's future return.

Cong et al. (2021b) show that an investor's sentiment towards the asset can influence the average crypto market payoff. Our evidence extends this by showing that the salience of the crypto index return is a source of investor sentiment and hence affects its returns.

[Insert Table 6 about here.]

We have also considered the possible cross-sectional ST effect among this 51 asset universe.[21] It shows that the overall ST effect for these aggregated asset indexes is not significant although the sign of the high minus low is consistent with the theory.[22] The finding further confirms that the ST effect is behavioral in nature and is not observable in traditional asset markets where fundamental information is important to input of investors' decisions. In other words, the allocation of capital in the global financial market among these assets is more efficient and less influenced by the salience bias.

Nevertheless, the salience of the crypto market's return can potentially serve as an attention signal that may further exacerbate the cross-sectional ST effect. We further study if the time series salience effect of the crypto market index may affect the cross-sectional salience effects documented in previous sections. Panel C in Table 6 reports the cross-sectional ST effect in the five quintiles of sub-periods sorted by the crypto index's salience measure among the 51 assets. It shows that when the crypto as an asset class is more salience, regardless of upward or downward salience, the cross-sectional salience effects are also stronger. The cross-sectional ST effect measured by the high-low rows is highly significant in the most down

[21] In Table OA4, we report the ST effect using the 50 instruments plus the cryptos market index. It reports the excess return of the ST quintile.

[22] This is no surprise as the salience effect needs more homogeneous responses from investors to the salience return. Not many of these assets included here can have a distinct profile and clientele as cryptos have. It is also likely to expect that in those more traditional asset classes, investors are less subject to the salience bias than this new asset class. Therefore the salience effect at the asset class level is weaker compared to those in the cross-section of cryptos or stocks.

and up salience columns. Furthermore, we also see an 'unconditional' cross-sectional salience effect. For the non-salience period (Group 3), we see the strongest cross-sectional salience effect. This suggests that there are specialized crypto investors (under-diversified) who do not consider the relative movement of cryptos to other investment opportunities. And this type of investor is one of the major drivers of the salience effect in the crypto markets.[23]

5.3 Salience, Prospect Theory, and Preference for Skewness

Bordalo et al. (2013a) point out that both ST and the prospect theory of Kahneman and Tversky (1979) (KT) assume decision-makers focus on the payoff and that the probability weights people use to make choices are different from objective probability. The key difference of the salience theory of decision making from the prospect theory is that in ST these weights depend on the actual payoffs and their salience (a wider context). Bordalo et al. (2013a) shows that while in many cases the ST and KT will produce similar decision weights, the ST will produce different probability weighting when small probabilities are not attached to salient payoffs or when lotteries are correlated. It is an empirical question which one of these decision systems is a more accurate description of a given market. Thoma (2020) follow Barberis et al. (2016) and show that cryptos with a high (low) prospect theory value earn low (high) subsequent returns using monthly historical distribution analyses. Furthermore, they confirm that a high prospect theory value tends to be highly positively skewed which is more likely to distort the weighting to be different from the standard expectation model.

The ability to explain the preference for positive skewness is one of the theoretical predictions and contributions of Bordalo et al. (2013a). They show that the extent to which certain asset payoffs "stand out" relative to the market may cause – through salience – distortions in the perception of asset-specific risks and thus in asset prices, for instance helping to explain why right-skewed assets tend to be overvalued.

In this section, we study empirically the relationship among the salience effect, prospect theory, and skewness on the cross-section crypto returns. The prospect theory value is

[23] Findings in this section are also robustly documented in the monthly analyses reported in Table OA5.

constructed based on the standard approach specified for the stock returns (Barberis et al., 2016). One exception is that we select a relatively short estimation period for the formation of prospect theory value. For the weekly crypto return analysis, we use daily returns within the past one-month look-back period. This setup is in line with a more shorter investor horizon in the Crypto than in Stock markets. Given the short existence of the crypto market, using a short-term formation period also enables us to keep most of the observations in our sample period.[24] Using the daily crypto returns makes it more consistent with the estimation approach of salience theory.[25] The detailed prospect theory value construction is specified in Appendix Section B.

We compare the pair-wise cross-section predictability of these behavioral characteristics in the crypto market. Panel A of Table 7 reports the Fama-MacBeth regressions and Panel B reports pair-wise the correlation among the behavioral characteristics. It shows that ST dominates all of the other measures in explaining the cross-sectional crypto returns. This is especially for skewness-related measures and downside risk. This is consistent with the theoretical prediction of Bordalo et al. (2013a). For the KT measures, it is shown to be highly correlated with ST but negatively in this Crypto market sample.[26]

[Insert Table 7 about here.]

Overall, these findings further support the linkage of these measurements. Our study provides further evidence on the linkage between ST and the other behavioural theories. In the crypto market, the salience theory is different from the prospect theory and provides a good description of the cross-sectional crypto pricing.[27]

[24]Empirical work on stocks uses a look-back period of 60 months, and the prospect theory value is constructed using monthly stock returns (Barberis et al., 2016).

[25]In unreported empirical results, we perform the robustness checks on the length of the formation period for both weekly and monthly return analyses. The empirical conclusion remains in various formation period duration and parameter selection.

[26]We obtain similar conclusion from monthly return analysis. The results are presented in Table OA9.

[27]In Online Appendix Table OA10, we report the double sorting using ST and these alternative behavioral measures. The conclusions are consistent with the findings here. In general, ST dominates other measures in terms of the number of significant hedging returns in the quintiles of the other sorting variables. In addition, we show that the prospect theory effect is much weaker compare to ST in value-weighted portfolio

5.4 Salience and Size Effect

In the equity market, the smaller firms tend to behave differently from their larger counterparts in the context of cross-sectional return anomalies (Hong et al., 2000; Fama and French, 2008). This may be owing not only to the lower liquidity, resulting in stronger anomalies, but also a weaker information environment with fewer news watchers to start some of the trends for momentum traders to chase, resulting in weaker anomalies (Cai et al., 2021). Cakici and Zaremba (2021) show that the salience anomaly appears to be exclusively a microcap phenomenon (accounting for only 3% of the market cap).

To study the interactions between ST and the size effect, we start with an independent double sorting in Panel A of Table 8. One key observation is that these two factors are both important and independent from each other. The ST effects are stronger in the medium and large size groups (3, 4, and 5 size groups) and vice versa. This finding highlights a key difference between the crypto market and the equity market. The ST mispricing effect in the crypto market is not confined to the smallest size securities as documented in the international equity market by Cakici and Zaremba (2021). It is important to note that majority of the cryptos are relatively small in size with a median market cap of about 10 million. This is piratically considered as micro caps in the equity market.

To further study the argument of micro-cap, we replicate the size test of Cakici and Zaremba (2021) in Panel B of Table 8. Especially, we double sorted the crypto independently by ST and market cap. We then group them according to their representation of the total market cap as in Cakici and Zaremba (2021). Big cryptos refer to the largest, which account for 90% of the total market capitalization; Small cryptos refer to those constituting the next 7% of the market capitalization; and Micro cryptos are the smallest, accounting for the remaining 3% of the market.

[Insert Table 8 about here.]

analysis while stronger in the equal-weighted setting while the ST's results are similar in both weightings. This finding suggests that the KT effect is more sensitive to the weighing method.

Consistent with their findings, we show that ST effects are strongly presented in the micro size cryptos with both EW and VW (bottom 3% in capitalization but account for 87% of the number of cryptos on average). The small cryptos (middle 7% in market cap and 11% of the number of cryptos) also see a significant ST effect in the EW portfolio. The largest cryptos which account for 90% of the market cap and only have about 12 cryptos do not see a significant ST effect.

These findings confirm two further insights regarding the ST effect in the crypto market. First, although the ST effect is more prominent in the crypto market, there is still a difference in the level of ST influence on the pricing in a predictable way. The largest cryptos are more likely to have institutional investors' attention given their size and liquidity which match the size of the investment. With a higher level of relatively more sophisticated investors in these cryptos, the pricing is less influenced by the ST bias. This confirms that ST is indeed a behavioral bias that is moderated by investor sophistication. This suggests that as the market further developed, regulated, and integrated with mainstream finance. The sophisticated investors will reduce the influence of behavioral biased in this market. Second, although the mispricing phenomenon is more relevant to micro cryptos which account for 3% of the market cap, these cryptos account for about 87% of the number of cryptos. This is still economically important as the market efficiency of the small but many cryptos would be an important factor to see if cryptos can become an asset class to promote innovative finance and distribution effectively. Many of these micro cryptos may become leaders in their fields as the market further developed.

5.5 Salience, Momentum, and Reversal

The previous section suggests that ST can potentially replace the momentum factor in explaining other cross-sectional return variations. In the equity market literature, Cosemans and Frehen (2021) and especially Cakici and Zaremba (2021) show that ST is closely related to the reversal effect. In the crypto market, the momentum factor introduced by Liu et al.

(2021) is in fact a 'reversal' factor in the equity market's setting since the strategy does not skip one period (week or month) for allowing the potential reversal. The fact that the crypto momentum factor return is positive in this strategy suggests that there is not a simple reversal effect in the crypto market.

When studying the correlation of the factors, we see that the ST factor premium indeed has a high correlation with the momentum factor premium (27.8% for EV and 46.8% for VW factors).[28]

We further study the interaction between these two factors through double sorting. Panel A of Table 9 shows that the ST effect is in general stronger than the momentum/reversal effects. Controlling for momentum, the ST effect is observed in four out of five quintiles in EW and two out of five quintiles in VW while the momentum/reversal effect is weaker controlling for the ST effect. This explains why including the ST factor can explain the excess return of the momentum strategy while including the momentum factor cannot explain the excess return of the ST strategy in Table 5.

[Insert Table 9 about here.]

To further elevate the concern that ST is only a reflection of the short-term momentum/reversal effect, following Cakici and Zaremba (2021), we study if our ST results hold once most recent days (1 – 3 days) are excluded from the estimation period in the monthly setting. Table 10 reports the findings for the monthly ST results. While the magnitude and significance are getting weaker as more days are skipped between the formation and return calculation, the magnitude and significance are still strong and economically significant. This confirms that ST is different from short-term reversal or momentum effect. It also highlights the benefit of testing the ST theory in this asset class which has a different clientele and dynamic from the equity market. It allows us to identify the explanatory power of the theory more clearly.

[28]We present the risk factor correlation table in Table OA8.

[Insert Table 10 about here.]

Benedetti and Kostovetsky (2021) document that the ICO underpricing is over 170% and the price quickly reverses after the first trading day. To mitigate the concern that ICO underpricing and reversal may be the key drivers of our finding, we repeat our study by excluding the first month of observations for each crypto. The magnitude and statistical significance only reduce slightly compared to the baseline results.[29] This evidence further supports that ST is a separate price driver than that of mean-reversal or ICO underpricing.

5.6 High vs. Low Uncertainty Period

Cakici and Zaremba (2021) show that the ST effect as a mispricing phenomenon is more evidently observed following the extreme market states (such as high economic uncertainty and volatility). We study if a similar mechanism is expected to be in play in the crypto markets. Following Cakici and Zaremba (2021) we partition the whole sample period into high and low uncertainty subperiods by various uncertainty measures. Especially, we select the traditional measure of financial market uncertainty, including the CBOE published VIX index and the Federal Reverse Bank published economic policy uncertainty index[30] (EUC) developed by Baker et al. (2016).

Table 11 reports the variations of the cross-sectional ST effects in the five different periods sorted by the uncertainty indexes. Specifically, it reports the average weekly ST high-low portfolio returns following the formation periods that fall into one of these five sub-periods.

[Insert Table 11 about here.]

In contrast to the equity market finding in Cakici and Zaremba (2021), we find that the ST effect is stronger (measured by high-minus-low on the ST strategy) in the crypto market when the uncertainty is low in the equity market in Panel A (VIX) or the economy in Panel B (UNC). This is consistent with the conjecture that Salience investors are thrill-seekers. They

[29] Empirical results are presented in Table OA6.

[30] `https://fred.stlouisfed.org/series/USEPUINDXD`.

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 when conditional the cross-sectional ST effect on the time series salience of the crypto asset class among the other 50 assets. When the crypto market is more salience, either up or downside, the cross-sectional salience effects are strongly presented.

We then consider the effect of uncertainty in the crypto market itself. To measure the uncertainty of the crypto market, we use the past month's volatility of daily Bitcoin returns as the crypto volatility index (BTC VOL).[31] Panel C shows that if we compare the cross-sectional ST effect in high and low BTC VOL periods, the ST effect is indeed stronger in high BTC VOL periods consistent withiteCZ21 in the global equity market. This suggests that the underlying market's uncertainty is indeed an important determinant of the ST effect.[32]

Overall, our volatility analyses suggest that the cross-sectional crypto market's ST effect is positively correlated with the uncertainty in the crypto market but negatively correlated with uncertainty in the stock market and economy. These finding further confirms that investors influenced by salience bias are likely to be risk seekers. It also highlights the potential diversification effect of cryptos as a non-fundamental investment asset class that has a different return dynamic to other traditional asset classes (Chuen et al., 2017; Hu et al., 2019).

6 Robustness Tests

6.1 Salience, Market Beta and Idiosyncratic Volatility

In this section, we study the interactions between ST and systematic and idiosyncratic risk through double sorting. Table 12 reports the weekly excess return of the crypto portfolios that are independently sorted by the ST and the two factors.

[31] The CVI (crypto vol index) was created in 2019 but we have a longer sample period than CVI. We, therefore, construct our own measurement. https://defipulse.com/crypto-volatility-index accessed November 28th, 2021.

[32] Table OA7 demonstrates the value-weighted portfolio returns under high and low uncertainty periods. We obtain the same conclusion from that of the equal-weighted portfolio returns.

[Insert Table 12 about here.]

6.1.1 Salience and Crypto Market Beta

Panel A of Table 12 reports the double sort between ST and crypto market beta. It shows that the ST effect is much stronger in the high Beta cryptos (the 4 and 5 groups). This is consistent with the salience theory in that being systematically important in the crypto market may modify the context for the salience-biased investor's subjective weighting. In other words, the historically high beta, suggesting more extreme co-movement with the average peers, will act as an amplified effect on the salience bias. By contrast, the beta cannot explain the cross-section return within the ST groups. The exception is in the lowest ST group where a higher beta earns a higher return.

6.1.2 Salience and Idiosyncratic Volatility

Cakici and Zaremba (2021) show that high average idiosyncratic risk markets observe higher ST effects which are in line with the limits of arbitrage explanation. Panel D of Table 12 reports the double sort between ST and IVOL in the crypto market. It shows that the ST effect is a different factor from the IVOL effect on cross-sectional crypto returns. The ST effects are the strongest in the middle group of the IVOL sort (2,3, and 4). This highlights the difference between the crypto market and the equity market. It suggests that high IVOL doesn't limit the 'arbitrageurs' to correct the ST mispricing and/or limit of arbitrage is less of an explanation in this market that is with no fundamental. There is most likely no arbitrageur in this market but only speculators.

6.2 Alternative Formation Periods

We study the robustness of the ST effect for different formation periods. The results are reported in Table 13. We find that the 1-week formation period produces the strongest ST effect among the 1 to 4 weeks formation periods, while 1-month formation produces the strongest ST effect among the 1 to 12 months formation periods. These findings suggest that there are salience thinkers in the crypto market with two different horizons: weekly and monthly. It also confirms that if investors are salient thinkers, due to cognitive limitations, they recall only the most recent returns and weigh less on old information. The relation between ST and future returns gradually weakens as the formation window extends.

[Insert Table 13 about here.]

6.3 Alternative Salience Effect Specification

We test the robustness of the ST measure by using a different choice on parameters θ and δ. Furthermore, we also test an alternative salience payoff function (Cosemans and Frehen, 2021) as follows:

$$\sigma(r_{is}, \bar{r}_s) = \frac{|r_{is} - \bar{r}_s|}{r_{is} + \bar{r}_s}. \tag{4}$$

The empirical results suggest that the ST effect is robust using the alternative ST calculation formula and alternative parameters.[33] Using the alternative salience payoff function, the salience effect is smaller in magnitude but remains highly statistically significant. In Table OA11, we report the robustness checks using the various parametric settings. Specifically, we alter the value of θ to be 0.05 and 0.15, and the value of δ to be 0.6 and 0.8. We obtain the salience effect to be similar in both economic and statistical significance. The cryptocurrency market salience effect is robust to the payoff function specification and parameter selection.

7 Conclusion

The introduction of Bitcoin has opened up a huge opportunity for experimenting with decentralized technology for trading and recording financial transactions. At the same time, the increasing appetite for speculation has fueled the rapid growth of the cryptocurrency market. cryptos have become a new asset class on their own just within a decade of their first existence since 2009. The important role that social media has played cannot be overstated in the development of this asset class and continued to influence the pricing. In this paper,

[33]Online Appendix Table OA11 reports the findings of these alternative specifications.

we contribute to the literature of crypto pricing by formally examining how investors' disproportional attention to salience outcomes would influence the time series and cross-sectional crypto pricing in a predictable way.

The salience theory is intuitive yet embedded with the fundamental concept of context-dependent preference. Salience thinkers cannot evaluate the distribution of outcomes objectively especially when there is a lack of other objective measures and the salience is being amplified through social media. The salience effect we have documented in this paper is the strongest in the salience theory literature so far. This is hardly a surprise given the nature of this asset which lacks fundamentals and with a retail-concentrated clientele. It confirms that salience theory is much more relevant in such emerging assets with high uncertainties. However, it is possible that once this asset market becomes more mature and mainstream (e.g. with more institutional investors involved). Other pricing mechanisms may dominate. Before then, salience theory offers a close description of the return dynamic in the crypto market.

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Table 1: Summary Statistics on Portfolio Analysis

Table 1 presents the number of cryptos, the mean and median of market capitalization, and the mean and median of trading volume in dollar amount by year. The sample consists of actively traded cryptos with market capitalization over $1 million within the sample period from January 2014 to June 2021.

Year	Counts	Market Cap ($million) Mean	Market Cap ($million) Median	Volume ($thousand) Mean	Volume ($thousand) 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 2: Salience Theory Effect: Portfolio Sorting

Table 2 presents the average returns of the single-sorted portfolios using the salience theory measure (ST). The sample consists of actively traded cryptos with market capitalization over \$1 million within the sample period from January 2014 to June 2021. On each week (month), the cryptos are sorted into quintile portfolios according to the salience effect measure in the prior week (month). Each portfolio is held for one week (month). The "Equal-Weighted" and "Value-Weighted" columns report the one-week (one-month) ahead excess returns of each portfolio with equal-weighted and value-weighted, respectively. The "High - Low" row reports the portfolio average return difference between the highest sorting value portfolio and the lowest sorting value portfolio using the corresponding sorting variable. The "t-Stat" row reports the Newey-West robust t-statistic.

	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]	[2.777]	[2.029]	[3.595]
3	0.000	0.014***	-0.010	0.084***
	[0.130]	[3.275]	[-0.601]	[3.508]
4	-0.005**	0.016***	-0.033*	0.092**
	[-2.287]	[3.312]	[-1.842]	[2.514]
5 (High)	-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 3: Risk Factor Analyses of Salience Effect Using LTW Three-Factor Model

Table 3 presents the details of the regressions explaining the crypto excess return in the ST quintile portfolios using the LTW three-factor model proposed in Liu et al. (2021). The model specification is

$$R_i - R_f = \alpha^i + \beta_1^i CMKT + \beta_2^i SIZE + \beta_3^i MOM + \epsilon_i.$$

CMKT is the value-weighted cryptocurrency return. SIZE is the size factor constructed from the market capitalization of the coins. MOM is the cumulative past crypto returns. A more detailed variable definition is in Table A1. The sample consists of actively traded cryptos with market capitalization over $1 million within the sample period from January 2014 to June 2021. ***, **, * denote significant levels at 1%, 5% and 10%.

	Panel A: Weekly Returns					
	1 (Low)	2	3	4	5 (High)	High - Low
α	0.020***	0.001	0.000	-0.005**	-0.011***	-0.032***
t(α)	[3.635]	[0.270]	[-0.082]	[-2.198]	[-3.448]	[-4.326]
β(CMKT)	0.096**	0.006	-0.051**	-0.006	0.011	-0.085
t(β(CMKT))	[1.998]	[0.250]	[-2.337]	[-0.264]	[0.376]	[-1.352]
β(SIZE)	-0.023	0.009	0.003	0.000	0.029***	0.052**
t(β(SIZE))	[-1.447]	[1.119]	[0.471]	[-0.031]	[3.037]	[2.474]
β(MOM)	0.021	0.009	-0.004	-0.001	-0.038***	-0.059**
t(β(MOM))	[1.087]	[0.866]	[-0.401]	[-0.122]	[-3.263]	[-2.302]
Adj. R^2	0.0195	0.0078	0.0165	0.0002	0.0418	0.0307

	Panel B: Monthly Returns					
	1 (Low)	2	3	4	5 (High)	High - Low
α	0.178***	0.051*	0.006	-0.028	-0.068***	-0.246***
t(α)	[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(β(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]
β(MOM)	0.024	0.029	0.040	0.016	0.035	0.011
t(β(MOM))	[0.666]	[0.912]	[1.674]	[0.592]	[1.145]	[0.230]
Adj. R^2	0.1148	0.1701	0.1669	0.0950	0.0813	0.0292

Table 4: Fama-MacBeth Cross-Sectional Regressions

Table 4 reports the estimated regression coefficients of the t-statistics (in brackets) from Fama-MacBeth cross-sectional regressions for crypto returns. The sample consists of actively traded cryptos with market capitalization over \$1 million within the sample period from January 2014 to June 2021, including 391 weeks (90 months). The Fama-MacBeth is performed using weekly returns (Panel A) and monthly returns (Panel B). ST is the salience theory measure. BETA denotes the beta with respect to the market return. SIZE is the market capitalization of cryptos. MOM denotes the lagged one-day return. VOLM is the logarithm of the trading volume. IVOL denotes the idiosyncratic volatility estimated from the market model. ILLIQ denotes the illiquidity level using the daily Amihud measure. MAX and MIN are maximum and minimum daily returns within the estimation period, respectively. TK is the prospective theory value. SKEW is the daily return skewness. COSKEW is the coskewness of the daily returns with the market returns. ISKEW is the idiosyncratic skewness of the residuals from the market model. DBETA is the downside beta estimated from the regression of the daily excess crypto return on the daily market return. The variable definition is specified in Table A1. The t-statistics reported in brackets are based on Newey and West (1987) standard error.

	Panel A: Weekly Returns										
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
ST	-0.355***	-0.354***	-0.374***	-0.434***	-0.452***	-0.320**	-0.309*	-0.433**	-0.450**	-0.554**	
	[-3.751]	[-3.861]	[-4.093]	[-4.504]	[-4.458]	[-1.993]	[-1.922]	[-2.514]	[-2.555]	[-2.564]	
BETA		-0.002	-0.002	0.000	0.000	-0.002	-0.001	0.001	0.000	0.000	-0.005
		[-0.882]	[-0.943]	[0.068]	[-0.109]	[-0.275]	[-0.100]	[0.143]	[0.053]	[0.064]	[-0.744]
SIZE		-0.002***	-0.002***	-0.004***	-0.003***	-0.003***	-0.003***	-0.002**	-0.002*	-0.001	-0.003***
		[-2.909]	[-2.813]	[-4.026]	[-3.541]	[-3.472]	[-3.130]	[-2.234]	[-1.707]	[-1.026]	[-3.585]
MOM			0.005	0.007	0.005	0.011	0.009	0.007	0.008	0.007	0.012
			[0.635]	[0.998]	[0.721]	[1.401]	[1.112]	[0.754]	[0.818]	[0.750]	[1.557]
AGE				0.001	-0.000	0.000	-0.001	-0.003	-0.006	-0.007	0.001
				[0.236]	[-0.024]	[0.120]	[-0.141]	[-0.857]	[-1.214]	[-1.353]	[0.285]
IVOL				-0.035***	-0.037***	-0.007	-0.008	0.006	0.007	-0.011	-0.036
				[-3.531]	[-3.068]	[-0.213]	[-0.221]	[0.151]	[0.183]	[-0.277]	[-1.027]
ILLIQ					116.409	174.284	218.263*	265.542	200.127	219.45	149.457
					[1.049]	[1.390]	[1.752]	[1.491]	[1.097]	[1.384]	[1.361]
MAX						0.011	0.000	-0.072	-0.081	-0.066	0.118
						[0.146]	[0.002]	[-0.793]	[-0.857]	[-0.687]	[1.636]
MIN						0.100	0.084	0.018	0.039	0.004	0.112
						[1.173]	[0.951]	[0.196]	[0.405]	[0.040]	[1.463]
TK								0.085	0.146	0.135	0.119
								[0.996]	[1.301]	[1.157]	[0.981]
SKEW									0.000	-0.000	-0.002
									[0.176]	[-0.006]	[-0.450]
COSKEW									1.821	1.870	2.050
									[0.339]	[0.341]	[0.376]
ISKEW										0.000	0.001
										[-0.061]	[0.182]
DBETA											-0.006
											[-1.225]
Intercept	-0.001	0.036***	0.041***	0.072***	0.065***	0.058***	0.057***	0.047**	0.046**	0.042*	0.059***
	[-0.148]	[2.719]	[2.864]	[4.587]	[4.141]	[3.821]	[3.342]	[2.446]	[2.192]	[1.866]	[3.958]
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										
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
ST	-2.630***	-2.685***	-2.652***	-2.529***	-2.608***	-2.054***	-1.979***	-1.803***	-1.849***	-1.803***	
	[-4.533]	[-4.617]	[-4.773]	[-4.502]	[-4.619]	[-4.324]	[-4.523]	[-4.352]	[-4.089]	[-4.104]	
BETA		0.001	-0.005	-0.022*	-0.020*	-0.046*	-0.058***	-0.051**	-0.050**	-0.040**	-0.046**
		[0.130]	[-0.420]	[-1.734]	[-1.799]	[-1.870]	[-2.720]	[-2.497]	[-2.387]	[-2.079]	[-2.476]
SIZE		0.021***	0.022***	0.027***	0.027***	0.025***	0.025***	0.025***	0.022***	0.023***	0.023***
		[6.552]	[7.812]	[7.813]	[7.931]	[8.269]	[7.927]	[5.383]	[3.825]	[3.304]	[3.384]
MOM			0.042***	0.042***	0.043***	0.036**	0.049***	0.049***	0.052***	0.055***	0.053***
			[3.061]	[2.947]	[3.034]	[2.328]	[3.023]	[3.202]	[3.395]	[3.626]	[3.716]
AGE				-0.001	-0.002	0.019	-0.003	-0.027	-0.030	-0.015	0.000
				[-0.093]	[-0.196]	[0.838]	[-0.257]	[-1.627]	[-1.534]	[-0.890]	[0.024]
IVOL				0.134***	0.143***	0.082	0.025	-0.024	-0.02	0.018	0.045
				[3.206]	[3.060]	[0.703]	[0.242]	[-0.225]	[-0.173]	[0.153]	[0.373]
ILLIQ					75.142	-76.72	6.585	359.266	449.632	548.692	422.713
					[0.378]	[-0.742]	[0.051]	[1.207]	[1.322]	[1.360]	[1.259]
MAX						0.459***	0.576***	0.632***	0.599***	0.654***	0.747***
						[3.117]	[4.420]	[5.065]	[4.603]	[4.365]	[4.957]
MIN						0.155	0.122	0.134	0.141	0.255	0.364**
						[0.855]	[0.737]	[0.869]	[0.844]	[1.325]	[2.201]
TK							0.143	0.310	0.324	0.229	0.302
							[0.611]	[0.986]	[0.979]	[0.517]	[0.687]
SKEW								-0.002	-0.004	-0.003	-0.005
								[-0.463]	[-0.283]	[-0.194]	[-0.326]
COSKEW								-0.141	-0.186	-0.497	-0.579
								[-0.227]	[-0.288]	[-0.793]	[-0.886]
ISKEW									0.008	0.005	0.005
									[0.477]	[0.320]	[0.335]
DBETA										-0.001	-0.000
										[-0.038]	[-0.014]
Intercept	0.007	-0.327***	-0.342***	-0.453***	-0.449***	-0.460***	-0.457***	-0.438***	-0.405***	-0.444***	-0.443***
	[0.502]	[-5.611]	[-6.503]	[-6.892]	[-6.963]	[-7.573]	[-7.172]	[-4.526]	[-3.678]	[-2.799]	[-2.905]
Avg. R^2	0.0614	0.1265	0.1627	0.2181	0.2338	0.3113	0.3331	0.3623	0.3732	0.3940	0.3755

Table 5: Alpha of Asset Pricing Models on Different Anomalies

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

$$R_i - R_f = \alpha^i + \beta_1^i CMKT + \epsilon_i, \quad \text{(M1)}$$
$$R_i - R_f = \alpha^i + \beta_1^i CMKT + \beta_2^i SIZE + \epsilon_i, \quad \text{(M2)}$$
$$R_i - R_f = \alpha^i + \beta_1^i CMKT + \beta_2^i SIZE + \beta_3^i MOM + \epsilon_i, \quad \text{(M3)}$$
$$R_i - R_f = \alpha^i + \beta_1^i CMKT + \beta_2^i ST + \epsilon_i, \quad \text{(M4)}$$
$$R_i - R_f = \alpha^i + \beta_1^i CMKT + \beta_2^i SIZE + \beta_3^i ST + \epsilon_i, \quad \text{(M5)}$$
$$R_i - R_f = \alpha^i + \beta_1^i CMKT + \beta_2^i SIZE + \beta_3^i MOM + \beta_4^i ST + \epsilon_i. \quad \text{(M6)}$$

The sample consists of actively traded cryptos with market capitalization over \$1 million within the sample period from January 2014 to June 2021, including 391 weeks. The analysis is based on the weekly returns on value-weighted portfolios and factor construction regimes. Panel A reports the significant anomalies in Liu et al. (2021). Panel B reports the insignificant anomalies in Liu et al. (2021). Panel C reports the behavioral anomalies, including prospective theory value, skewness, coskewness, idiosyncratic skewness, and downside beta. The t-statistics reported in brackets are based on Newey and West (1987) standard error. ***, **, * denote significant levels at 1%, 5% and 10%.

Panel A		M1	M2	M3	M4	M5	M6
ST	α	-0.030**	-0.033**	-0.033**	-0.017	-0.017	-0.018
	t(α)	[-2.247]	[-2.353]	[-2.367]	[-0.519]	[-0.515]	[-0.538]
MCAP	α	-0.127***	-0.010	-0.009	-0.128***	-0.010	-0.009
	t(α)	[-5.297]	[-1.563]	[-1.362]	[-5.334]	[-1.578]	[-1.351]
PRC	α	-0.033**	0.003	-0.015	-0.039***	-0.004	-0.014
	t(α)	[-2.438]	[0.215]	[-1.316]	[-3.139]	[-0.410]	[-1.297]
MAXDPRC	α	-0.038***	-0.012	-0.029	-0.044***	-0.019*	-0.029
	t(α)	[-2.970]	[-1.004]	[-0.652]	[-3.671]	[-1.658]	[-0.655]
MOM 1-week	α	0.042***	0.036***	0.026	0.038***	0.032***	0.027
	t(α)	[4.107]	[3.457]	[0.637]	[3.901]	[3.169]	[0.666]
MOM 2-week	α	0.043***	0.040***	0.026	0.040***	0.036***	0.026
	t(α)	[4.335]	[3.860]	[0.675]	[4.139]	[3.602]	[0.688]
MOM 3-week	α	0.027**	0.022**	-0.007	0.020**	0.014	-0.006
	t(α)	[2.503]	[1.976]	[-0.892]	[2.165]	[1.461]	[-0.855]
MOM 4-week	α	0.017	0.018***	-0.007	0.010	0.010	-0.007
	t(α)	[1.579]	[3.218]	[-0.866]	[1.100]	[1.051]	[-0.827]
PRCVOLM	α	-0.081***	-0.008**	-0.024*	-0.087***	-0.014	-0.023*
	t(α)	[-4.174]	[-2.305]	[-1.858]	[-4.679]	[-1.170]	[-1.852]
STDPRCVOL	α	-0.074***	-0.002	-0.018	-0.081***	-0.009	-0.017
	t(α)	[-3.880]	[-0.121]	[-1.486]	[-4.423]	[-0.737]	[-1.471]

Panel B		M1	M2	M3	M4	M5	M6
AGE	α	-0.014	-0.013	-0.030	-0.017	-0.016	-0.030
	t(α)	[-1.204]	[-1.073]	[-0.640]	[-1.396]	[-1.284]	[-0.642]
MOM 8-week	α	-0.004	-0.001	-0.025	-0.011	-0.010	-0.025
	t(α)	[-0.318]	[-0.073]	[-0.634]	[-1.116]	[-0.915]	[-0.649]
MOM 16-week	α	-0.014	-0.009	-0.028	-0.018	-0.013	-0.027
	t(α)	[-1.092]	[-0.646]	[-0.566]	[-1.473]	[-1.046]	[-0.562]
MOM 50-week	α	-0.030**	-0.007	-0.029	-0.036***	-0.014	-0.028
	t(α)	[-2.325]	[-0.568]	[-0.665]	[-3.001]	[-1.193]	[-0.664]
MOM 100-week	α	0.010	0.011	0.005	0.009	0.010	0.005
	t(α)	[1.081]	[1.148]	[0.478]	[0.957]	[1.010]	[0.480]
VOLM	α	-0.055***	0.010***	-0.005	-0.061***	0.004	-0.004
	t(α)	[-2.942]	[3.032]	[-0.368]	[-3.384]	[0.311]	[-0.320]
VOLMSCALED	α	-0.048***	-0.013***	-0.030***	-0.055***	-0.020**	-0.029***
	t(α)	[-3.777]	[-4.585]	[-2.958]	[-4.670]	[-2.009]	[-3.033]
BETA	α	-0.012	-0.019*	-0.024**	-0.016*	-0.024**	-0.023
	t(α)	[-1.206]	[-1.863]	[-2.294]	[-1.714]	[-2.478]	[-0.583]
BETA SQ	α	-0.010	-0.016	-0.020**	-0.014	-0.020**	-0.020
	t(α)	[-0.980]	[-1.549]	[-1.978]	[-1.455]	[-2.118]	[-0.498]
IDIOVOL	α	0.026**	0.018***	0.034***	0.029**	0.021	0.034***
	t(α)	[2.004]	[5.359]	[2.657]	[2.220]	[1.565]	[2.656]
RETVOL	α	0.041**	0.028***	0.041***	0.043***	0.030*	0.041***
	t(α)	[2.589]	[2.732]	[2.619]	[2.722]	[1.870]	[2.621]
RETSKEW	α	0.011	0.004	-0.004	0.006	-0.003	-0.003
	t(α)	[1.348]	[0.448]	[-0.527]	[0.796]	[-0.398]	[-0.462]
RETKURT	α	0.012	0.006	0.015*	0.013	0.008	0.015*
	t(α)	[1.342]	[0.694]	[1.667]	[1.528]	[0.891]	[1.662]
MAXRET	α	0.052***	0.043***	0.056***	0.052***	0.043***	0.056
	t(α)	[3.500]	[2.803]	[3.710]	[3.486]	[2.783]	[0.944]
DELAY	α	0.005	0.007	0.017	0.007	0.010	0.017
	t(α)	[0.462]	[0.663]	[1.631]	[0.685]	[0.917]	[1.617]
DAMIHUD	α	0.066***	0.018	0.034*	0.073***	0.025	0.033*
	t(α)	[3.338]	[1.014]	[1.893]	[3.780]***	[1.449]	[1.876]

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

Panel D	M1	M2	M3	M4	M5	M6
One-tail ($\|t\| >= 2.336$)	13	9	6	13	4	4
Two-tail ($\|t\| >= 2.588$)	11	8	4	13	3	3

Table 6: The Salience of Cryptos as an Asset Class among the Investment Opportunities: Weekly Returns

Table 6 reports the crypto-related measures in different salience among 51 assets, including equity indexes, credit indexes, foreign exchanges, and futures. The full list of the investment instruments is presented in Table A2. The asset return is calculated on weekly basis. The groups' number indicates the quintile portfolio in which crypto salience is among all assets. 1 represents the most down salience quintile period, and 5 represents the most up salience quintile period. Panel A lists the mean ST measure in each quintile period. Panel B has the mean, median, maximum, and minimum returns of the crypto market index in the following month. Panel C presents the single ST cross-sectional sorting results among the cryptos in each of the quintile periods. The t-statistics reported in brackets are based on Newey and West (1987) standard error.

Panel A	1 (Low)	2	3	4	5 (High)
Mean ST	-0.0127	-0.0017	0.0000	0.0017	0.0098

Panel B	1 (Low)	2	3	4	5 (High)
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%

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

Table 7: Fama-MacBeth Cross-Sectional Regressions: Behavioral Anomalies

Table 7 reports the estimated regression coefficients the *t*-statistics from Fama-MacBeth cross-sectional regressions for crypto returns (Panel A) and the correlation matrix among behavioral anomaly measures (Panel B). The sample consists of actively traded cryptos with market capitalization over $1 million within the sample period from January 2014 to June 2021. The regression is based on weekly returns with 391 different periods. The Fama-MacBeth is performed using weekly returns. ST is the salience theory measure. TK is the prospective theory value. SKEW is the daily return skewness. COSKEW is the coskewness of the daily returns with the market returns. ISKEW is the idiosyncratic skewness of the residuals from the market model. DBETA is the downside beta estimated from the regression of the daily excess crypto return on the daily market return. The variable definition is specified in Table A1. The *t*-statistics reported in brackets are based on Newey and West (1987) standard error.

Panel A	(1)	(2)	(3)	(4)	(5)
ST	-0.306***	-0.381***	-0.311***	-0.365***	-0.307***
	[-3.146]	[-3.940]	[-3.229]	[-3.857]	[-2.928]
TK	0.141**				
	[2.587]				
SKEW		-0.003			
		[-1.523]			
COSKEW			-0.830		
			[-0.196]		
ISKEW				-0.003	
				[-1.240]	
DBETA					-0.002
					[-0.629]
Intercept	0.008	0.000	0.001	0.000	0.001
	[1.478]	[0.063]	[0.251]	[0.103]	[0.187]
Avg. R^2	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 8: The Salience Effect of Crypto Market: Controlling for Size Effect

Table 8 presents the weekly portfolio returns of cryptocurrencies controlling for size effect. Panel A contains the double sorted portfolio returns on ST and market capitalization. On each week, the cryptos are sorted into 5×5 groups on ST measure and market capitalization independently. Each portfolio is held for one week. Panel B shows the average weekly returns of the single-sorted portfolios for cryptocurrencies in different size groups using the salience theory measure. "Full" columns show the portfolio returns using the full sample. "Big" includes the cryptocurrencies that cover 90% of the total market capitalization of the week, "Small" group covers the next 7% of the total market capitalization, and "Micro" captures the rest 3%. Each portfolio is held for one week. The sample consists of actively traded cryptos with market capitalization over $1 million within the sample period from January 2014 to June 2021. On the portfolio formation period, the cryptos are sorted into quintiles according to the ST measure. The row "Avg. N" tracks the average number of cryptocurrencies in each size group. The "High - Low" row reports the portfolio average return difference between the highest sorting value portfolio and the lowest sorting value portfolio using the corresponding sorting variable. The "*t*-Stat" row reports the Newey-West robust *t*-statistic.

Panel A: Double sorted by ST and Market Capitalization in quintiles

	1 (Low)	2	3	4	5 (High)	High - Low	*t*-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	-0.026***	[-3.443]
3	0.031	0.001	-0.002	-0.003	-0.003	-0.033***	[-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***	-0.019	-0.037**	-0.018***	-0.063***		
	[-4.062]	[-1.335]	[-2.351]	[-2.829]	[-5.399]		
Value-Weighted							
1 (Low)	0.160	0.061	0.057	0.058	0.048	-0.112***	[-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]
4	0.078	0.030	0.026	0.015	0.011	-0.067***	[-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				Value-weighted			
	Full	Big	Small	Micro	Full	Big	Small	Micro
Avg. N	501.6	11.8	54.3	435.5	501.6	11.8	54.3	435.5
1 (Low)	0.020***	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***	0.024***	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]	[2.325]
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 9: The Salience Effect of Crypto Market: Controlling for Momentum

Table 9 presents the average weekly returns of the double-sorted portfolios of ST measure controlling for momentum factor. The sample consists of actively traded cryptos with market capitalization over $1 million within the sample period from January 2014 to June 2021. On each week, the cryptos are sorted into 5×5 groups on ST measure and momentum factor independently. Each portfolio is held for one week. The one-week-ahead excess returns of each portfolio with equal-weighted and value-weighted construction are reported in the grid. The portfolio sorted by ST is reported in rows, and the portfolio sorted by the existing factors is reported in columns. The "High - Low" row reports the portfolio average return difference between the highest sorting value portfolio and the lowest sorting value portfolio using the corresponding sorting variable. The "t-Stat" row reports the Newey-West robust t-statistic.

	1 (Low)	2	3	4	5 (High)	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]
2	-0.006	0.003	0.008	0.006	-0.001	0.005	[0.575]
3	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]
High - Low	-0.058***	-0.048***	-0.048***	-0.052***	0.013		
	[-5.570]	[-3.877]	[-4.469]	[-5.641]	[1.495]		
Value-Weighted							
1 (Low)	0.032	0.043	0.047	0.041	0.075	0.043***	[3.157]
2	-0.011	0.008	0.015	0.022	0.023	0.033***	[3.467]
3	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]
High - Low	-0.052***	-0.035	-0.034	-0.047***	-0.028		
	[-3.580]	[-1.605]	[-1.123]	[-3.374]	[-0.874]		

Table 10: The Salience Effect of Crypto Market: Skipping Last Observations in ST Formation

Table 10 presents the average monthly returns of the single-sorted portfolios using the salience theory measure. The sample consists of actively traded cryptos with market capitalization over $1 million within the sample period from January 2014 to June 2021, including 90 different months. On each month, the cryptos are sorted into quintiles based on the ST measure. Each portfolio is held for one month. Each column reports the one-month ahead excess returns of each portfolio with equal-weighted and value-weighted. "Full", "R1D", "R2D" and "R3D" represent the construction of the ST formation period using full month observations and by removing the last 1, 2, and 3 daily observations in the formation month. The "High - Low" row reports the portfolio average return difference between the highest sorting value portfolio and the lowest sorting value portfolio using the corresponding sorting variable. The "t-Stat" row reports the Newey-West robust t-statistic.

	Equal-weighted				Value-weighted			
	Full	R1D	R2D	R3D	Full	R1D	R2D	R3D
1 (Low)	0.175***	0.121***	0.119***	0.119***	0.381***	0.233***	0.219***	0.220***
	[7.149]	[4.618]	[4.449]	[4.434]	[2.682]	[3.237]	[3.063]	[4.434]
2	0.045**	0.048***	0.050***	0.049***	0.102***	0.044***	0.050***	0.056***
	[2.029]	[2.675]	[2.837]	[3.075]	[3.595]	[3.302]	[3.839]	[3.075]
3	-0.010	0.015	0.012	0.008	0.084***	0.046***	0.041***	0.031
	[-0.601]	[0.921]	[0.733]	[0.473]	[3.508]	[3.859]	[3.991]	[0.473]
4	-0.033*	-0.023	-0.024	-0.025	0.092**	0.014	0.015	0.017
	[-1.842]	[-1.246]	[-1.482]	[-1.368]	[2.514]	[1.175]	[1.330]	[-1.368]
5 (High)	-0.084***	-0.111***	-0.106***	-0.100***	0.057**	-0.041***	-0.041***	-0.038***
	[-4.197]	[-5.766]	[-5.228]	[-4.963]	[2.227]	[-3.067]	[-3.090]	[-4.963]
High - Low	-0.259***	-0.233***	-0.226***	-0.220***	-0.324**	-0.274***	-0.260**	-0.259**
t-Stat	[-8.701]	[-7.835]	[-7.004]	[-7.321]	[-2.269]	[-2.747]	[-2.579]	[-2.549]

Table 11: The Salience Effect of Crypto Market: The Role of Market Uncertainty

Table 11 reports the average weekly returns of the single-sorted portfolios using the salience theory, with the full sample splitting into high and low uncertainty periods. The sample periods are split into the high and low uncertainty periods by the median of the uncertainty indexes: VIX (Panel A), UNC (Panel B), and the volatility of Bitcoin returns (Panel C). On each week, the assets are sorted into quintiles according to the salience effect measure in the prior week. Each portfolio is held for one week. The portfolio return is constructed in an equal-weighted manner. The "High - Low" row reports the portfolio average return difference between the quintile portfolios in high and low uncertainty periods. The "t-Stat" row reports the Newey-West robust t-statistic.

	Panel A: Uncertainty Index: VIX					
	1 (Low)	2	3	4	5 (High)	High - Low
High VIX	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 Index: UNC					
	1 (Low)	2	3	4	5 (High)	High - Low
High UNC	0.0068	-0.0002	0.0049	-0.0008	-0.0155	-0.0223
Low UNC	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 Index: BTC VOL					
	1 (Low)	2	3	4	5 (High)	High - Low
High BTC VOL	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]

Table 12: Double-sorted Portfolios on Salience Theory

Table 12 presents the average weekly returns of the double-sorted portfolios of ST measure controlling for other factors. The sample consists of actively traded cryptos with market capitalization over $1 million within the sample period from January 2014 to June 2021. On each week, the cryptos are sorted into 5×5 groups on ST measure and existing crypto risk factor independently. Each portfolio is held for one week. The one-week-ahead excess returns of each portfolio with equal-weighted and value-weighted construction are reported in the grid. The portfolio sorted by ST is reported in rows, and the portfolio sorted by the existing factors is reported in columns. The "High - Low" row reports the portfolio average return difference between the highest sorting value portfolio and the lowest sorting value portfolio using the corresponding sorting variable. The "t-Stat" row reports the Newey-West robust t-statistic. Panel A presents the portfolio returns with the control variable of market beta and Panel B by 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]
3	-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	-0.038	-0.031**	-0.049***	-0.044***		
	[-0.723]	[-1.443]	[-2.292]	[-3.835]	[-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]
3	0.015	0.009	0.005	0.020	0.013	-0.001	[0.153]
4	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	5 (High)	High - Low	*t*-Stat
			Panel B: Sorted by ST Controlling for Idiosyncratic Volatility				
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***	[-3.237]
3	0.004	0.000	0.008	-0.007	-0.012	-0.016*	[-1.745]
4	0.010	-0.003	0.001	-0.016	-0.017	-0.028***	[-2.598]
5 (High)	0.002	-0.002	-0.015	-0.021	-0.020	-0.021**	[-2.334]
ST High - Low	-0.016*	-0.025***	-0.049***	-0.042***	-0.026*		
	[-1.882]	[-4.197]	[-5.979]	[-4.542]	[1.886]		
Value-Weighted							
1 (Low)	0.018	0.044	0.065	0.051	0.063	0.045**	[2.441]
2	0.016	0.015	0.013	0.017	0.009	-0.007	[-0.742]
3	0.013	0.011	0.016	0.008	0.024	0.011	[0.487]
4	0.020	0.009	0.014	0.014	0.009	-0.011	[-0.364]
5 (High)	0.009	0.008	-0.004	-0.005	0.032	0.023	[0.387]
ST High - Low	-0.009	-0.036***	-0.069***	-0.056***	-0.031		
	[-0.880]	[-3.819]	[-6.395]	[-4.135]	[-1.078]		

Table 13: Single-sorted Portfolios on ST: Alternative Formation Periods

Table 13 presents the average weekly and monthly returns of the single-sorted portfolios using the salience theory measure. The portfolio formation period varies from one week to four weeks, with an increment of one week, and the holding period is one week in Panel A. The portfolio formation periods are one month, three months, six months, and twelve months, and the holding period is one month in Panel B. Each portfolio is held for one week. The sample consists of actively traded cryptos with market capitalization over $1 million within the sample period from January 2014 to June 2021. On the portfolio formation period, the cryptos are sorted into quintiles according to the ST measure. The "Excess" columns report the one-month ahead excess returns of each portfolio with equal-weighted and value-weighted, respectively. The "FFC4" column reports the Fama-French-Carhart four-factor alpha for the corresponding portfolio. The "LTW" column reports the Liu-Tsyvinski-Wu three-factor alpha for the corresponding portfolio. The "High - Low" row reports the portfolio average return difference between the highest sorting value portfolio and the lowest sorting value portfolio using the corresponding sorting variable. The "t-Stat" row reports the Newey-West robust t-statistic.

Panel A	Equal-weighted				Value-weighted			
Weekly Returns	1-Week	2-Week	3-Week	4-Week	1-Week	2-Week	3-Week	4-Week
1 (Low)	0.020***	0.013***	0.016***	0.010**	0.054***	0.042***	0.053***	0.032***
	[4.065]	[2.945]	[3.773]	[2.207]	[5.850]	[5.310]	[6.700]	[4.680]
2	0.000	0.007**	0.002	0.007**	0.013***	0.019***	0.014***	0.019***
	[0.162]	[2.126]	[0.670]	[2.474]	[2.777]	[3.692]	[3.159]	[4.099]
3	0.000	0.003	-0.003	0.001	0.014***	0.013***	0.013***	0.019***
	[0.130]	[1.294]	[-1.215]	[0.568]	[3.275]	[3.384]	[3.520]	[4.281]
4	-0.005**	-0.005**	-0.002	-0.005**	0.016***	0.016***	0.014***	0.005
	[-2.287]	[-2.217]	[-0.837]	[-2.104]	[3.312]	[3.402]	[3.327]	[1.135]
5 (High)	-0.014***	-0.013***	-0.009***	-0.010***	0.024**	0.022**	0.025***	0.028***
	[-4.653]	[-4.197]	[-3.173]	[-3.430]	[2.518]	[2.417]	[2.750]	[3.021]
High - Low	-0.034***	-0.026***	-0.025***	-0.020***	-0.030**	-0.020*	-0.029**	-0.004
t-Stat	[-5.223]	[-4.405]	[-4.304]	[-3.276]	[-2.226]	[-1.666]	[-2.285]	[-0.325]

Panel B	Equal-weighted				Value-weighted			
Monthly Returns	1-Month	3-Month	6-Month	12-Month	1-Month	3-Month	6-Month	12-Month
1 (Low)	0.175***	0.094***	0.058**	0.031	0.381**	0.323**	0.114***	0.105***
	[7.149]	[3.695]	[2.641]	[1.537]	[2.682]	[2.262]	[3.870]	[3.652]
2	0.045**	0.049***	0.042**	0.043**	0.102***	0.104***	0.092***	0.090***
	[2.029]	[2.752]	[2.334]	[2.216]	[3.595]	[4.292]	[3.239]	[2.953]
3	-0.010	-0.025*	0.016	0.011	0.084***	0.049***	0.062**	0.081***
	[-0.601]	[1.773]	[0.672]	[1.366]	[3.508]	[3.678]	[2.202]	[3.285]
4	-0.033*	-0.025	0.016	0.011	0.092**	0.049*	0.062**	0.081***
	[-1.842]	[-1.412]	[0.836]	[0.641]	[2.514]	[1.823]	[2.725]	[3.532]
5 (High)	-0.084***	-0.074***	-0.040**	0.006	0.057**	0.040	0.067***	0.084***
	[-4.197]	[-3.923]	[-2.001]	[0.326]	[2.227]	[1.546]	[2.993]	[3.720]
High - Low	-0.259***	-0.167***	-0.098***	-0.025	-0.324**	-0.282**	-0.048*	-0.021
t-Stat	[-8.701]	[-7.277]	[-4.657]	[-1.516]	[-2.269]	[-2.044]	[-1.891]	[-0.813]

Appendix A Supplementary Tables

Table A1: **Variable definitions**.

Variable	Definition
ST	The salience theory measure is calculated from Eq. (3) in Section 3.2. We compute the weekly (monthly) ST using a sample period of one week (one month) before the portfolio holding period.
CMKT	The cryptocurrency market return. The market return is based on equal-weighted calculation if not otherwise specified.
BETA	The estimated coefficient β_M^i in the regression $R_i - R_f = \alpha^i + \beta_M^i MKT + \epsilon_t$. The model is estimated using daily returns of the trailing 30 (365) days for the formation week (month).
SIZE	Log last day market capitalization in the portfolio formation week (month).
MOM kW	k-week momentum, as the cumulative return for the past k weeks. MOM represents the lagged one-week return, if not otherwise specified.
AGE	Time in friction of year(s) from the listing on `Coinmarketcap.com`.
IVOL	The idiosyncratic volatility is calculated as the standard deviation of the residuals from the market model $R_i - R_f = \alpha^i + \beta_M^i MKT + \epsilon_t$. The model is estimated using daily returns of the previous 30 (365) days before the formation week (month).
ILLIQ	The average absolute daily return divided by dollar volume in the portfolio formation week (month).
MAX	The maximum daily return of the crypto within the sample period.
MIN	The minimum daily return of the crypto within the sample period.
MCAP	Log last day market capitalization in the portfolio formation week (month).
PRC	Log last day price in the portfolio 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 of dollar volume in the portfolio formation week (month).
VIX	The CBOE published S&P 500 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	The prospective theory value computes as specified in Bordalo et al. (2016). The measure is calculated using daily returns from trailing 30 (365) days prior to the formation week (month).
SKEW	The daily return skewness estimated from the trailing one-month crypto returns.
COSKEW	The coskewness of the daily crypto returns over the one-month window using the approach of Harvey and Siddique (2000).
ISKEW	The idiosyncratic skewness of the residuals from the market model using trailing 30 (365) days prior to formation week (month).
DBETA	The downside beta estimated from the regression of the daily excess crypto return on the daily market return Ang et al. (2006) over the previous 30 (365) days prior to formation week (month).

Table A2: **Full list of 51 assets**.

Category	Ticker	Description
Crypto (1)	CMKT	Equal-weighted crypto market index
Equity (16)	DIA	Dow Jones Industrial Average
	EFA	iShares MSCI EAFE
	QQQ	NASDAQ 100 Index
	VWO	Vanguard Emerging Markets Stock Index
	RUI	Russell 1000 Index
	RUT	Russell 2000 Index
	RUA	Russell 3000 Index
	EEM	iShares MSCI Emerging Markets
	DAX	German Stock Index DAX 30
	NSE	India Nifty 50 Index
	CAC	France stock market index CAC 40
	NKY	NIKKEI 225 Index index
	HSI	Hang Seng Index
	EU50	EURO STOXX 50
	EU100	FTSE Euro 100 Index
	FXI	iShares China Large-Cap
Volatility (4)	VIX	VIX index future (most active)
	VXX	Barclays iPath Series VIX Short-Term Futures ETN
	VSTOXX	EURO STOXX 50 Volatility
	UVXX	ProShares Ultra VIX Short-Term Futures ETF
Forex (8)	USD	Dollar Index Future
	USD/JPY	Japanese Yen Future
	GBP/USD	British Pound Future
	EUR/USD	Euro US Dollar
	AUD/USD	Aust. Dollar
	USD/CAD	Canadian Futures
	USD/TRY	Turkish Lira
	FXE	Invesco CurrencyShares Euro Trust ETF
Commodity (10)	GDX	VanEck Gold Miners
	GOLD	Gold future (most active)
	XAU/USD	Gold Spot US Dollar
	BRENT	ICE Brent Crude (most active)
	OIL	WTI Crude (most active)
	GAS	Natural Gas (most active)
	SILVER	Silver future (most active)
	COPPER	Copper future (most active)
	CORN	Corn commodity (most active)
	WHEAT	Wheat commodity (most active)
Rate/Credit (9)	HYG	iShares iBoxx High Yield Corporate Bond
	LQD	iShares iBoxx Investment Grade Corporate Bond
	US 2 YR FUT	U.S. 2-year treasury note future (cheapest to deliver)
	US 5 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-year bond yield
Others (3)	IVR	iShares US Real Estate Index
	ARKK	ARK Innovation ETF
	INRG	iShares Global Clean Energy UCITS

Appendix B Construction of prospect theory value on cryptocurrencies

We follow the standard prospect theory value (PTV) construction process as specified in Barberis et al. (2016) for the cryptocurrencies. The formation of the prospect theory for stocks looks back to the past 60-month return on monthly basis. The crypto assets emerge in a relatively short time period. To avoid losing a major of the observations for the cryptos, we use daily returns of the crypto assets and form the prospect theory estimation period 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 formation period and find that lengthening of the PTV formation period does not alter the main conclusion 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 vary the formation period of PTV from 1-month to 1-year for monthly returns.

Besides the reason for the short time of existence of the crypto market, using daily returns and using a shorter PTV estimation period make the information formation time-frame to be more consistent with the construction of the salience effect measurement used in this paper. We describe the construction of PTV using the 1-month formation period in more detail.

We first define the functional form of the value function as in Kahneman and Tversky (1979) based on the daily crypto returns.

$$v(x) = \begin{cases} x^{\alpha} & \text{for } x \geq 0 \\ -\lambda(-x)^{\alpha} & \text{for } x < 0 \end{cases}$$

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

$$w^{+}(P) = \frac{P^{\gamma}}{(P^{\gamma} + (1-P)^{\gamma})^{1/\gamma}}, \qquad w^{-}(P) = \frac{P^{\delta}}{(P^{\delta} + (1-P)^{\delta})^{1/\delta}}$$

where γ and δ are distortion parameters, and the value 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

$$\alpha = 0.88, \quad \lambda = 2.25, \quad \gamma = 0.61, \quad \delta = 0.69.$$

In unreported empirical results, we shock the parameter selection in certain ranges (varying each of the parameters from 0.5 to 2 times its original value). The empirical conclusions are consistently the same. For the return distribution estimation, we first rank the past 30 days' crypto return in ascending order. Denote m as the number of days with a negative return, and $n = 30 - m$ as the number of days with a positive return. We assume the past 30 days of the crypto returns to have a uniform distribution, i.e., the occurring probability of each day's return is equal. The return distribution is specified as

$$\left(r_{-m}, \frac{1}{30}; r_{-m+1}, \frac{1}{30}; \ldots; r_{-1}, \frac{1}{30}; r_{1}, \frac{1}{30}, \ldots, r_{n-1}, \frac{1}{30}; r_{n}, \frac{1}{30}\right).$$

where r_i is the ranked daily crypto returns and $i \in \{-m, -m+1, \ldots, -1, 1, \ldots, n-1, n\}$. r_{-m} represents the lowest crypto returns (most negative) in the past month, and r_n represents the highest (most positive) returns.

Combining these components, the PVT for the cryptocurrency returns is defined as

$$\begin{aligned} PTV &= \sum_{i=-m}^{-1} v(r_i)\left[w^{-}\left(\frac{m+i+1}{30}\right) - w^{-}\left(\frac{m+i}{30}\right)\right] \\ &\quad + \sum_{i=1}^{n} v(r_i)\left[w^{+}\left(\frac{n-i+1}{30}\right) - w^{+}\left(\frac{n-i}{30}\right)\right]. \end{aligned} \tag{5}$$

The construction of the PVT in our paper is similar to the empirical specification for stocks (Barberis et al., 2016) and for cryptocurrencies Thoma (2020).

Internet Appendix

Salience Theory and Cryptocurrency Returns

Abstract

We document that the salience theory of choice under risk provides a good explanation for the cross-sectional cryptocurrency returns. Investors overweigh salience payoffs, payoffs that stand out from the average of the alternatives. This leads to overpricing (underpricing) the cryptocurrencies with upward (downward) salience returns and generating negative (positive) expected returns in the subsequent period. The salience effect in the cryptocurrency market is over 20 times stronger than those observed in the equity markets. It is different from existing return anomalies documented in the cryptocurrency market and is a strong contender for a risk factor that can explain other cross-sectional strategy returns in the cryptocurrency market.

JEL Classification: G10, G11, G13, G40, G41

Keywords: Salience Theory, Asset Pricing, Behavioral Finance, Cryptocurrency, Portfolio Choice

Table OA1: Summary Statistics on Portfolio Analysis

Table OA1 presents the summary statistics of the main variables. The sample consists of actively traded cryptos with market capitalization over $1 million within the sample period from January 2017 to June 2021. All variables are used for the weekly return analysis. ST is the salience theory measure. BETA denotes the beta with respect to the market return. SIZE is the market capitalization of cryptos. MOM denotes the lagged one-day return. VOLM is the logarithm of the trading volume. IVOL denotes the idiosyncratic volatility estimated from the market model. ILLIQ denotes the illiquidity level using the daily Amihud measure. MAX and MIN are maximum and minimum daily returns within the estimation period, respectively. TK is the prospective theory value. SKEW is the daily return skewness. COSKEW is the coskewness of the daily returns with the market returns. ISKEW is the idiosyncratic skewness of the residuals from the market model. DBETA is the downside beta estimated from the regression of the daily excess crypto return on the daily market return. The variable definition is specified in Table A1.

							Panel A: Summary Statistics							
	ST	BETA	SIZE	MOM	AGE	IVOL	ILLIQ	MAX	MIN	TK	SKEW	COSKEW	ISKEW	DBETA
N	169,243	169,396	169,396	170,630	169,396	169,396	163,984	169,396	169,396	170,027	170,027	170,027	169,981	168,192
Mean	0.047	0.944	16.368	-0.015	1.594	0.545	0.000	0.236	-0.119	-0.178	0.218	0.000	0.468	0.950
Std. Dev.	0.345	1.893	1.888	0.605	1.423	1.407	0.001	1.139	1.106	0.652	1.380	0.005	0.938	1.621
							Panel B: Correlation							
ST	1.000	0.011	-0.003	0.017	0.026	0.678	0.052	0.249	-0.399	-0.308	-0.028	0.041	-0.055	-0.013
BETA		1.000	0.020	0.008	0.007	0.011	0.009	-0.005	-0.036	-0.013	0.015	-0.056	0.029	0.173
SIZE			1.000	0.147	0.131	-0.045	-0.115	0.027	0.047	0.015	0.075	-0.038	0.128	0.026
MOM				1.000	0.058	0.037	-0.008	0.046	0.020	0.015	0.116	0.031	0.179	0.012
AGE					1.000	0.011	0.041	-0.012	-0.021	-0.064	-0.040	-0.014	0.020	0.012
IVOL						1.000	0.178	0.405	-0.349	-0.217	-0.008	0.051	-0.048	-0.023
ILLIQ							1.000	0.074	-0.054	-0.010	-0.016	0.034	-0.042	-0.017
MAX								1.000	0.655	0.563	-0.024	0.056	-0.050	-0.031
MIN									1.000	0.767	-0.020	0.027	-0.018	-0.021
TK										1.000	0.239	0.007	-0.002	-0.008
SKEW											1.000	0.030	0.599	0.011
COSKEW												1.000	-0.088	-0.350
ISKEW													1.000	0.070
DBETA														1.000

Table OA2: Single-sorted Portfolios on ST: Monthly Returns

Table OA2 presents the average monthly returns of the single-sorted portfolios using the salience theory measure. The sample consists of actively traded cryptos with market capitalization over $1 million within the sample period from January 2014 to June 2021, including 90 different months. On each month, the cryptos are sorted into quintiles based on the ST measure. Each portfolio is held for one month. The "Excess" columns report the one-month ahead excess returns of each portfolio with equal-weighted and value-weighted, respectively. The "FFC4" column reports the Fama-French-Carhart four-factor alpha for the corresponding portfolio. The "LTW" column reports the Liu-Tsyvinski-Wu three-factor alpha for the corresponding portfolio. The "High - Low" row reports the portfolio average return difference between the highest sorting value portfolio and the lowest sorting value portfolio using the corresponding sorting variable. The "*t*-Stat" row reports the Newey-West robust *t*-statistic.

	Equal-weighted				Value-weighted			
	Excess	FFC4	LTW3	FULL7	Excess	FFC4	LTW3	FULL7
1 (Low)	0.175***	0.183***	0.178***	0.184***	0.381***	0.297**	0.177***	0.198***
	[7.149]	[7.028]	[5.882]	[5.707]	[2.682]	[2.043]	[2.668]	[2.821]
2	0.045**	0.039*	0.051*	0.041	0.102***	0.093***	0.100***	0.094**
	[2.029]	[1.675]	[1.932]	[1.461]	[3.595]	[3.070]	[2.719]	[2.386]
3	-0.010	-0.009	0.006	0.002	0.084***	0.076***	0.096***	0.083**
	[-0.601]	[-0.515]	[0.321]	[1.149]	[3.508]	[2.975]	[3.089]	[2.506]
4	-0.033*	-0.040**	-0.028	-0.041*	0.092**	0.069*	0.061	0.030
	[-1.842]	[-2.089]	[-1.242]	[-1.697]	[2.514]	[1.781]	[1.276]	[0.596]
5 (High)	-0.084***	-0.092***	-0.068***	-0.086***	0.057**	0.058**	0.034	0.028
	[-4.197]	[-4.428]	[-2.698]	[-3.222]	[2.227]	[2.146]	[1.038]	[0.803]
High - Low	-0.259***	-0.275***	-0.246***	-0.270***	-0.324**	-0.239	-0.143*	-0.171**
t-Stat	[-8.701]	[-8.732]	[-6.381]	[-6.645]	[-2.269]	[-1.645]	[-1.882]	[-2.129]

Table OA3: Alpha of Asset Pricing Models on Different Anomalies

Table OA3 presents the details of the regression explaining the crypto excess return in quintile portfolios using the following asset pricing model specifications.

$$R_i - R_f = \alpha^i + \beta_1^i CMKT + \epsilon_i, \quad \text{(M1)}$$
$$R_i - R_f = \alpha^i + \beta_1^i CMKT + \beta_2^i SIZE + \epsilon_i, \quad \text{(M2)}$$
$$R_i - R_f = \alpha^i + \beta_1^i CMKT + \beta_2^i SIZE + \beta_3^i MOM + \epsilon_i, \quad \text{(M3)}$$
$$R_i - R_f = \alpha^i + \beta_1^i CMKT + \beta_2^i ST + \epsilon_i, \quad \text{(M4)}$$
$$R_i - R_f = \alpha^i + \beta_1^i CMKT + \beta_2^i SIZE + \beta_3^i ST + \epsilon_i, \quad \text{(M5)}$$
$$R_i - R_f = \alpha^i + \beta_1^i CMKT + \beta_2^i SIZE + \beta_3^i MOM + \beta_4^i ST + \epsilon_i. \quad \text{(M6)}$$

The sample consists of actively traded cryptos with market capitalization over \$1 million within the sample period from January 2014 to June 2021, including 391 weeks. The analysis is based on the weekly returns on equal-weighted portfolios and factor construction regimes. Panel A reports the significant anomalies in Liu et al. (2021). Panel B reports the insignificant anomalies in Liu et al. (2021). Panel C reports the behavioral anomalies, including prospective theory value, skewness, coskewness, idiosyncratic skewness, and downside beta. The t-statistics reported in brackets are based on Newey and West (1987) standard error. ***, **, * denote significant levels at 1%, 5% and 10%.

Panel A		M1	M2	M3	M4	M5	M6
ST	α	-0.034***	-0.034***	-0.032***	-0.031	-0.031	-0.002
	t(α)	[-5.162]	[-4.951]	[-4.325]	[-1.250]	[-1.201]	[-0.615]
MCAP	α	-0.041***	-0.018	-0.034***	-0.042***	-0.037*	-0.016
	t(α)	[-8.060]	[-1.362]	[-6.490]	[-8.092]	[-1.751]	[-1.186]
PRC	α	-0.009***	-0.004	-0.007	-0.009	-0.006	-0.001
	t(α)	[-4.918]	[-0.678]	[-1.276]	[-1.603]	[-1.147]	[-0.096]
MAXDPRC	α	-0.020***	-0.016	-0.017***	-0.020***	-0.017	-0.013
	t(α)	[-3.713]	[-0.742]	[-3.012]	[-3.683]	[-0.754]	[-0.595]
MOM 1-week	α	-0.008***	-0.007***	-0.012*	-0.009	-0.009	-0.016
	t(α)	[-4.037]	[-4.332]	[-1.871]	[-1.529]	[-1.460]	[-0.817]
MOM 2-week	α	-0.005***	-0.005***	-0.012*	-0.006	-0.007	-0.006
	t(α)	[-2.628]	[-3.033]	[-1.847]	[-1.037]	[-1.165]	[-1.635]
MOM 3-week	α	-0.007***	-0.005***	-0.014**	-0.008	-0.008	-0.001
	t(α)	[-3.494]	[-3.139]	[-2.280]	[-1.270]	[-1.227]	[-0.486]
MOM 4-week	α	-0.007***	-0.001*	-0.011*	-0.008	-0.007	0.002
	t(α)	[-3.755]	[-1.817]	[-1.900]	[-1.346]	[-1.134]	[0.706]
PRCVOLM	α	-0.025***	-0.013**	-0.020***	-0.025***	-0.021***	-0.012**
	t(α)	[-4.679]	[-2.530]	[-3.557]	[-4.663]	[-3.875]	[-2.196]
STDPRCVOL	α	-0.024***	-0.011**	-0.019***	-0.024***	-0.020***	-0.011**
	t(α)	[-4.477]	[-2.185]	[-3.446]	[-4.483]	[-3.688]	[-2.130]

Panel B		M1	M2	M3	M4	M5	M6
AGE	α	0.007***	0.010	0.007	0.008	0.010	0.019
	t(α)	[3.304]	[0.411]	[1.118]	[1.301]	[1.583]	[0.745]
MOM 8-week	α	-0.006	0.000	-0.010	-0.006	-0.006	0.004
	t(α)	[-1.008]	[-0.087]	[-1.638]	[-1.087]	[-0.948]	[0.910]
MOM 16-week	α	-0.004	0.002	-0.005	-0.003	-0.002	0.009*
	t(α)	[-0.679]	[0.333]	[-0.839]	[-0.589]	[-0.389]	[1.877]
MOM 50-week	α	-0.002	0.004	-0.002	-0.002	0.000	0.007
	t(α)	[-1.087]	[0.862]	[-0.455]	[-0.336]	[-0.039]	[1.536]
MOM 100-week	α	0.002	0.008	0.001	0.001	0.003	0.010
	t(α)	[0.945]	[1.616]	[0.105]	[0.277]	[0.489]	[0.540]
VOLM	α	-0.010***	0.008*	-0.005	-0.010*	-0.006	0.011**
	t(α)	[-5.566]	[1.827]	[-0.836]	[-1.846]	[-1.172]	[2.355]
VOLMSCALED	α	-0.025***	-0.018***	-0.022***	-0.025***	-0.022***	-0.017
	t(α)	[-4.593]	[-3.236]	[-3.872]	[-4.582]	[-3.988]	[-0.747]
BETA	α	-0.012**	-0.015***	-0.014**	-0.011**	-0.016***	-0.015
	t(α)	[-2.065]	[-3.058]	[-2.352]	[-2.022]	[-2.730]	[-0.728]
BETA SQ	α	-0.007	-0.013***	-0.010*	-0.007	-0.012**	-0.012
	t(α)	[-1.418]	[-2.796]	[-1.872]	[-1.363]	[-2.163]	[-0.636]
IDIOVOL	α	-0.015***	-0.023***	-0.016***	-0.015***	-0.018***	-0.027
	t(α)	[-2.752]	[-4.206]	[-2.828]	[-2.848]	[-3.240]	[-1.229]
RETVOL	α	-0.008	-0.010*	-0.009	-0.009	-0.011*	-0.015
	t(α)	[-1.523]	[-1.773]	[-1.600]	[-1.632]	[-1.967]	[-0.696]
RETSKEW	α	0.003	0.006	0.000	0.002	0.001	0.001
	t(α)	[0.614]	[1.288]	[-0.053]	[0.352]	[0.143]	[0.112]
RETKURT	α	-0.012**	-0.010**	-0.013***	-0.013***	-0.014***	-0.014***
	t(α)	[-2.564]	[-1.975]	[-2.598]	[-2.759]	[-2.879]	[-2.729]
MAXRET	α	0.007	0.008	0.007	0.006	0.004	-0.006
	t(α)	[1.253]	[1.319]	[1.099]	[1.048]	[0.650]	[-1.105]
DELAY	α	0.000	-0.004	-0.001	-0.001	-0.003	-0.008
	t(α)	[0.025]	[-0.918]	[-0.162]	[-0.123]	[-0.613]	[-1.613]
DAMIHUD	α	0.004	-0.011**	0.001	0.004	0.001	-0.015***
	t(α)	[0.735]	[-2.371]	[0.110]	[0.724]	[0.171]	[-3.102]

Panel C		M1	M2	M3	M4	M5	M6
TK	α	0.025***	0.020***	0.023***	0.025***	0.025***	0.021***
	t(α)	[4.229]	[3.311]	[3.831]	[4.300]	[4.231]	[3.479]
SKEW	α	-0.012**	-0.016***	-0.012**	-0.012**	-0.011**	-0.018***
	t(α)	[-2.184]	[-2.847]	[-2.185]	[-2.154]	[-2.008]	[-3.245]
COSKEW	α	-0.003	-0.008*	-0.004	-0.003	-0.004	-0.010**
	t(α)	[-0.699]	[-1.780]	[-0.915]	[-0.706]	[-0.838]	[-2.057]
ISKEW	α	-0.004	-0.007	-0.006	-0.004	-0.005	-0.010*
	t(α)	[-0.774]	[-1.251]	[-1.159]	[-0.745]	[-0.860]	[-1.936]
DBETA	α	-0.003	-0.005	-0.004	-0.003	-0.005	0.003
	t(α)	[-0.508]	[-0.823]	[-0.634]	[-0.483]	[-0.831]	[0.474]

Panel D	M1	M2	M3	M4	M5	M6
One-tail ($\lvert t\rvert \geq 2.336$)	16	12	10	8	7	5
Two-tail ($\lvert t\rvert \geq 2.588$)	15	10	9	8	7	4

Table OA4: The Salience Effect among the Investment Opportunities

Table OA4 reports the average returns of the single-sorted portfolios using the salience theory measure among the investment opportunities defined in Table A2. The sample consists of weekly returns from 51 assets (including the crypto index) within the sample period from January 2014 to June 2021. On each week (month), the assets are sorted into quintiles according to the salience effect measure in the prior week (month). Each portfolio is held for one week (month). The portfolio return is constructed in an equal-weighted manner. The "High - Low" row reports the portfolio average return difference between the highest sorting value portfolio and the lowest sorting value portfolio using the corresponding sorting variable. The "t-Stat" row reports the Newey-West robust t-statistic.

	Weekly Returns		Monthly Returns	
	Excess Return	t-Stat	Excess Return	t-Stat
1 (Low)	0.0004	[0.276]	0.0112**	[2.013]
2	0.0017**	[1.969]	0.0076*	[1.786]
3	0.0012	[0.973]	0.0037	[0.973]
4	0.0015	[1.611]	0.0099**	[2.254]
5 (High)	0.0005	[0.327]	0.0045	[0.593]
High - Low	0.0001	[0.040]	-0.0066	[-0.711]

Table OA5: The Salience of Cryptos as an Asset Class among the Investment Opportunities: Monthly Returns

Table OA5 reports the crypto-related measures in different salience among 51 assets, including equity indexes, credit indexes, foreign exchanges, and futures. The full list of the investment instruments is presented in Table A2. The asset return is calculated on monthly basis. The groups' number indicates the quintile portfolio in which crypto salience is among all assets. 1 represents the most down salience quintile period, and 5 represents the most up salience quintile period. Panel A lists the mean ST measure in each quintile period. Panel B has the mean, median, maximum, and minimum returns of the crypto market index in the following month. Panel C presents the single ST cross-sectional sorting results among the cryptos in each of the quintile periods. The t-statistics reported in brackets are based on Newey and West (1987) standard error.

Panel A	1 (Low)	2	3	4	5 (High)
Mean ST	-0.0175	-0.009	-0.0034	0.0011	0.0102

Panel B	1 (Low)	2	3	4	5 (High)
Mean	12.69%	11.40%	2.82%	6.04%	1.01%
Maximum	66.79%	73.54%	40.25%	37.00%	53.44%
Median	12.05%	4.09%	4.60%	-6.20%	0.63%
Minimum	-32.52%	-29.96%	-31.88%	-32.97%	-24.08%

Panel C	1 (Low)	2	3	4	5 (High)
1 (Low)	0.1605***	0.0804	0.2199***	0.2497***	0.1672***
	[3.314]	[1.377]	[4.410]	[3.457]	[4.410]
2	0.0142	-0.0033	0.0392	0.1652**	0.016
	[0.378]	[-0.066]	[0.684]	[2.557]	[0.680]
3	-0.0671**	-0.0181	0.0359	0.0145	-0.0127
	[-2.261]	[-0.491]	[0.883]	[0.312]	[-0.512]
4	-0.0412	-0.0678	-0.0113	0.0075	-0.0513
	[-1.504]	[-1.248]	[-0.269]	[0.175]	[-1.572]
5 (High)	-0.1295***	-0.0651	-0.0914**	0.0234	-0.1535***
	[-3.456]	[-1.378]	[-2.574]	[0.616]	[-2.756]
High - Low	-0.2901***	-0.1455**	-0.3113***	-0.2262***	-0.3207***
t-stat	[-4.180]	[-2.552]	[-5.781]	[-3.098]	[-4.234]

Table OA6: Salience Theory Effect: Portfolio Sorting with First Month Returns after ICO Removed

Table OA6 presents the average returns of the single-sorted portfolios using the salience theory measure (ST). The sample consists of actively traded cryptos with market capitalization over $1 million within the sample period from January 2014 to June 2021. The first month returns after the ICO are removed from the sample. On each week (month), the cryptos are sorted into quintile portfolios according to the salience effect measure in the prior week (month). Each portfolio is held for one week (month). The "Equal-Weighted" and "Value-Weighted" columns report the one-week (one-month) ahead excess returns of each portfolio with equal-weighted and value-weighted, respectively. The "High - Low" row reports the portfolio average return difference between the highest sorting value portfolio and the lowest sorting value portfolio using the corresponding sorting variable. The "*t*-Stat" row reports the Newey-West robust *t*-statistic.

	Weekly Returns		Monthly Returns	
	Equal-Weighted	Value-Weighted	Equal-Weighted	Value-Weighted
1 (Low)	0.014***	0.043***	0.164***	0.365**
	[3.096]	[5.049]	[6.586]	[2.567]
2	0.001	0.013***	0.038*	0.100***
	[0.323]	[2.810]	[1.784]	[3.503]
3	-0.004	0.017***	-0.030	0.087***
	[-0.049]	[2.797]	[-0.267]	[3.562]
4	-0.004*	0.017***	-0.030*	0.087**
	[-1.738]	[3.686]	[-1.701]	[2.421]
5 (High)	-0.012***	0.023**	-0.085***	0.058**
	[-3.918]	[2.369]	[-4.249]	[2.303]
High - Low	-0.026***	-0.021**	-0.249***	-0.307**
t-Stat	[-4.133]	[-2.158]	[-8.319]	[-2.143]

Table OA7: The Salience Effect of Crypto Market: The Role of Market Uncertainty

Table OA7 reports the average weekly returns of the single-sorted portfolios using the salience theory, with the full sample splitting into high and low uncertainty periods. The sample periods are split into the high and low uncertainty periods by the median of the uncertainty indexes: VIX (Panel A), UNC (Panel B), and the volatility of Bitcoin returns (Panel C). On each week, the assets are sorted into quintiles according to the salience effect measure in the prior week. Each portfolio is held for one week. The portfolio return is constructed in a value-weighted manner. The "High - Low" row reports the portfolio average return difference between the quintile portfolios in high and low uncertainty periods. The "t-Stat" row reports the Newey-West robust t-statistic.

	Panel A: Uncertainty Index: VIX					
	1 (Low)	2	3	4	5 (High)	High - Low
High VIX	0.0342	0.0182	0.0136	0.0145	0.0393	0.0050
Low VIX	0.0743	0.0070	0.0136	0.0166	0.0088	-0.0655
High - Low	-0.0401**	0.0111	0.0000	-0.0021	0.0305	0.0705***
t-Stat	[-2.167]	[1.224]	[-0.003]	[-0.224]	[1.602]	[2.630]

	Panel B: Uncertainty Index: UNC					
	1 (Low)	2	3	4	5 (High)	High - Low
High UNC	0.0444	0.0163	0.0168	0.0228	0.0400	-0.0044
Low UNC	0.0640	0.0090	0.0103	0.0083	0.0082	-0.0558
High - Low	-0.0196	0.0073	0.0065	0.0145	0.0318*	0.0514*
t-Stat	[-1.056]	[0.800]	[0.784]	[1.542]	[1.668]	[1.908]

	Panel C: Uncertainty Index: BTC VOL					
	1 (Low)	2	3	4	5 (High)	High - Low
High BTC VOL	0.0604	0.0056	0.0143	0.0174	0.0244	-0.0360
Low BTC VOL	0.0480	0.0196	0.0128	0.0137	0.0238	-0.0242
High - Low	0.0124	-0.0140*	0.0015	0.0037	0.0006**	-0.0117***
t-Stat	[1.124]	[-1.828]	[-0.049]	[0.591]	[2.109]	[-2.692]

Table OA8: Summary Statistics for the Crypto Risk Factors

Table OA8 presents the summary statistics and pairwise correlation of the Crypto risk factors, constructed on weekly basis. CMKT, Size, and MOM are the market factor, the size factor, and the momentum following Liu et al. (2021). ST is the salience effect risk factor calculated by the difference between down-salience and up-salience portfolios.

	Equal-weighted Regime			
	CMKT	Size	MOM	ST
Mean	-0.007	0.021	0.004	-0.022
Med.	-0.004	0.018	0.005	-0.015
Max.	0.366	0.373	0.537	0.474
Min.	-0.521	-0.186	-0.416	-0.385

	CMKT	Size	MOM	ST
CMKT	1.000	-0.080	0.031	-0.044
Size		1.000	0.016	0.014
MOM			1.000	-0.278
ST				1.000

	Value-weighted Regime			
	CMKT	Size	MOM	ST
Mean	0.045	0.045	0.022	-0.012
Med.	0.014	0.021	0.024	-0.007
Max.	0.590	0.692	0.473	0.602
Min.	-0.474	-0.140	-0.444	-0.396

	CMKT	Size	MOM	ST
CMKT	1.000	0.004	-0.010	0.023
Size		1.000	-0.136	0.038
MOM			1.000	-0.468
ST				1.000

Table OA9: Fama-MacBeth Cross-Sectional Regressions: Behavioral Anomalies

Table OA9 reports the estimated regression coefficients the t-statistics from Fama-MacBeth cross-sectional regressions for crypto returns (Panel A) and the correlation matrix among behavioral anomaly measures (Panel B). The sample consists of actively traded cryptos with market capitalization over $1 million within the sample period from January 2014 to June 2021. The regression is based on monthly returns with 90 different periods. The Fama-MacBeth is performed using weekly returns. ST is the salience theory measure. TK is the prospective theory value. SKEW is the daily return skewness. COSKEW is the coskewness of the daily returns with the market returns. ISKEW is the idiosyncratic skewness of the residuals from the market model. DBETA is the downside beta estimated from the regression of the daily excess crypto return on the daily market return. The variable definition is specified in Table A1. The t-statistics reported in brackets are based on Newey and West (1987) standard error.

Panel A	(1)	(2)	(3)	(4)	(5)
ST	-2.591***	-2.601***	-2.693***	-2.561***	-2.594***
	[-4.713]	[-4.537]	[-4.711]	[-4.485]	[-4.696]
TK	0.337**				
	[2.084]				
SKEW		0.005			
		[0.836]			
COSKEW			-0.288		
			[-0.326]		
ISKEW				0.011**	
				[2.064]	
DBETA					-0.026**
					[-2.088]
Intercept	0.027	0.003	0.015	-0.005	0.035**
	[1.532]	[0.184]	[0.951]	[-0.320]	[2.000]
Avg. R^2	0.0877	0.0841	0.0929	0.0781	0.1020

Panel B	ST	TK	SKEW	COSKEW	ISKEW	DBETA
ST	1.000					
TK	-0.021	1.000				
SKEW	-0.031	0.331	1.000			
COSKEW	-0.009	-0.031	-0.137	1.000		
ISKEW	-0.025	0.018	0.109	-0.067	1.000	
DBETA	0.003	-0.093	0.003	-0.447	0.001	1.000

Table OA10: Double-sorted Portfolios on Salience Theory: Behavioral Anomalies

Table OA10 presents the average weekly returns of the double-sorted portfolios of ST measure controlling for behavioral anomaly factors. The sample consists of actively traded cryptos with market capitalization over $1 million within the sample period from January 2014 to June 2021. On each week, the cryptos are sorted into 5×5 groups on ST measure and existing crypto risk factor independently. Each portfolio is held for one week. The one-week-ahead excess returns of each portfolio with equal-weighted and value-weighted construction are reported in the grid. The table reports the difference between the highest ST and lowest ST in each of the quintile groups of the control variable. "ST, 1" row reports the high-minus-low ST portfolio difference in the lowest control value group. "ST, 5" row reports the high-minus-low ST portfolio difference in the highest control value group. The Newey-West robust t-statistic are reported in brackets. The top (bottom) table shows the portfolio return difference using the equal-weighted (value-weighted) average.

	Equal-weighted				
	TK	SKEW	COSKEW	ISKEW	DBETA
ST, 1 (Low)	-0.014	-0.045***	-0.018	-0.036***	-0.046**
	[-1.152]	[-3.474]	[-1.198]	[-2.838]	[-2.483]
ST, 2	-0.013	-0.028**	-0.033***	-0.018**	-0.020
	[-1.423]	[-2.567]	[-3.075]	[-2.092]	[-1.596]
ST, 3	-0.015**	-0.020	-0.031***	-0.034***	-0.024***
	[-2.187]	[-1.471]	[-2.848]	[-3.447]	[-2.798]
ST, 4	-0.021***	-0.016	-0.048***	-0.030*	-0.019**
	[-3.420]	[-1.217]	[-4.130]	[-1.826]	[-2.294]
ST, 5 (High)	-0.063***	-0.058***	-0.017	-0.041***	-0.037***
	[-3.724]	[-4.994]	[-0.454]	[-3.971]	[-3.023]

	Value-weighted				
	TK	SKEW	COSKEW	ISKEW	DBETA
ST, 1 (Low)	0.001	-0.033	-0.041**	-0.032	-0.017
	[0.432]	[-1.423]	[-2.287]	[-1.508]	[-0.147]
ST, 2	-0.010	-0.010	-0.046**	-0.008	-0.047**
	[-0.827]	[-0.504]	[-2.570]	[-0.414]	[-2.218]
ST, 3	-0.017**	-0.009	-0.025	-0.019	-0.036**
	[-1.973]	[-0.314]	[-1.402]	[-1.648]	[-2.429]
ST, 4	-0.028***	-0.033**	-0.056***	-0.034*	-0.023**
	[-3.729]	[-2.116]	[-3.356]	[-1.878]	[-2.209]
ST, 5 (High)	-0.067***	-0.073***	0.008	-0.053***	-0.056***
	[-3.150]	[-3.436]	[0.487]	[-2.872]	[-3.089]

Table OA11: Robustness Checks on Alternative ST Mesaures

Table OA11 presents robustness checks using alternative ST calculation approaches. The portfolio formation period is one week. Each portfolio is held for one week. The sample consists of actively traded cryptos with market capitalization over $1 million within the sample period from January 2014 to June 2021, including 391 weeks in total. The baseline empirical results are based on the first salience function (ST1) when calculating the ST measure. The first set of robustness checks is to alter the payoff function as specified in ST2.

$$\sigma(r_{is}, \bar{r}_s) = \frac{|r_{is} - \bar{r}_s|}{|r_{is}| + |\bar{r}_s| + \theta}, \tag{ST1}$$

$$\sigma(r_{is}, \bar{r}_s) = \frac{|r_{is} - \bar{r}_s|}{r_{is} + \bar{r}_s}. \tag{ST2}$$

In the next sets of robustness checks, we alter the value of θ in Eq. (1) and δ in Eq.(2). The default values for the baseline analysis are $\theta = 0.1, \delta = 0.7$. "Formula" column specifies the ST measure salience calculation formula. The next columns show the average quintile portfolio returns. The "High - Low" row reports the portfolio average return difference between the highest sorting value portfolio and the lowest sorting value portfolio using the corresponding sorting variable. The Newey-West robust t-statistics are reported in the bracket.

Model	θ	δ	Formula	1 (Low)	2	3	4	5 (High)	High - Low
M1	0.1	0.7	ST2	0.011***	0.003	0.001	-0.004	-0.008*	-0.0192***
				[5.013]	[1.454]	[0.479]	[-1.461]	[-1.701]	[-3.178]
M2	0.1	0.7	ST1	0.020***	0.000	0.000	-0.005**	-0.014***	-0.0340***
				[4.065]	[0.162]	[0.130]	[-2.287]	[-4.653]	[-5.223]
M3	0.05	0.7	ST1	0.019***	0.001	-0.001	-0.002	-0.015***	-0.0336***
				[3.986]	[0.274]	[-0.600]	[-0.972]	[-4.674]	[-5.307]
M4	0.15	0.7	ST1	0.020***	0.002	0.000	-0.005**	-0.015***	-0.0347***
				[3.915]	[0.721]	[-0.050]	[-2.109]	[-5.116]	[-5.326]
M5	0.1	0.6	ST1	0.021***	0.000	0.000	-0.005**	-0.014***	-0.0354***
				[4.312]	[0.169]	[0.057]	[-2.448]	[-4.746]	[-5.433]
M6	0.1	0.8	ST1	0.019***	0.002	0.000	-0.004*	-0.016***	-0.0354***
				[4.002]	[0.827]	[0.007]	[-1.722]	[-5.193]	[-5.223]