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# Can salience theory explain investor behaviour? Real-world evidence from the cryptocurrency market☆

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ABSTRACT

Research on human attention indicates that objects that stand out from their surroundings, i.e., salient objects, attract the attention of our sensory channels and receive undue weighting in the decision-making process. In the financial realm, salience theory predicts that individuals will find assets with salient upsides (downsides) appealing (unappealing). We investigate whether this theory can explain investor behaviour in the cryptocurrency market. Consistent with the theory's predictions, using a sample of 1738 cryptocurrencies, we find that cryptocurrencies that are more (less) attractive to "salient thinkers" earn lower (higher) future returns, which indicates that they tend to be overpriced (underpriced). On average, a one cross-sectional standard-deviation increase in the salience theory value of a cryptocurrency reduces its next-week return by 0.41%. However, the salience effect is confined to the micro-cap segment of the market, and its size is moderated by limits to arbitrage.

## 1. Introduction

Conventional models of choice under risk, such as the expected utility model in economics, usually assume that people pay equal attention to all the observable information that appears in the decision frame. However, the essence of observation is attention, and human attention is a scarce resource (Berger, 1996; Eysenck, 1982; March, 1982; Simon, 1978). The literature on visual search suggests that, at any given time, only a tiny portion of the data that our visual system detects "reaches levels of processing that directly influence behaviour" (Itti & Koch, 2000). How we allocate our visual attention is likely to depend on both a top-down system that we consciously control and a "bottom-up, fast, primitive mechanism that biases [us] towards selecting stimuli based on their [*salience*]" (Itti & Koch, 2000).

Salience refers to the property by which some objects of perception stick out, and it is often caused by differences between an object and its surroundings, i.e., by its "comparative distinctiveness" (Higgins, 1996). Psychologists find that people overweight salient information when making decisions (Grether, 1980; Kahneman & Tversky, 1973). Furthermore, many financial anomalies, such as investment fashions and fads and the excess volatility of asset returns, can also be attributed to people's attention directed to salient information (Shiller, 1999).

Based on these insights, Bordalo, Gennaioli, and Shleifer (2012) develop a salience theory (hereafter 'ST') of decision-making to describe choice under risk. Their theory posits that individuals pay more attention to a lottery/investment's most salient payoffs, whose probabilities of occurrence are then overweighted in subsequent decisions. Building upon this theory, Bordalo, Gennaioli, and Shleifer (2013a) further propose a salience-based asset pricing model predicting that assets with salient upsides (i.e., high ST values) tend to attract excess demand, become overpriced and generate lower subsequent returns. We refer to this phenomenon as the ST effect. Empirical studies of this model are very limited, and they focus exclusively on the equity market. While these studies offer some evidence in support of the model (Cosemans & Frehen, 2021), they have also produced conflicting findings and have raised new questions, such as: Is the ST effect confined to the micro-cap segment? Is it mostly driven by the short-term reversal effect (see Cakici & Zaremba, 2021)? Furthermore, many questions have not yet been addressed in these studies, such as: Why has the size of the ST effect decreased over time in the US stock market and practically disappeared since 2000 (see Table 9 in Cakici & Zaremba, 2021)? Secondly, can ST account for investor behaviour in markets other than the stock market?

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To shed light on these questions, we investigate whether ST can explain investor behaviour in the cryptocurrency market, which is an economically important market (its market capitalisation reached over $2.9 trillion in December 2021) and has been attracting fast growing academic interest in recent years. The cryptocurrency market is fundamentally different from the stock market (and from conventional asset markets) in terms of investor population, drivers of value, and institutional features. These differences matter because they may lead to substantial differences in how the typical investor in the market forms a mental representation of an asset's payoffs and of their salience.

Following Cosemans and Frehen (2021), we assume that investors consider each investment in isolation (narrow framing) and extrapolate past returns into the future. This allows us to estimate the ST value of a cryptocurrency based on its recent historical return distribution. Our analysis is based on a sample of 1738 cryptocurrencies and covers the period from January 1, 2014 to June 30, 2021. We make a number of contributions to the literature. First, consistent with Bordalo et al.'s (2013a) salience-based asset pricing model, we document a negative relationship between a cryptocurrency's ST value and its future excess returns. This is an important step towards the generalisability of ST across markets and investor types. Namely, we estimate that a one cross-sectional standard-deviation increase in a cryptocurrency's ST value reduces its next-week excess return by 0.41% relative to its peers. Second, while previous studies purely focus on the cross-sectional dimension of this relationship, we also establish that a cryptocurrency's ST value predicts time-variation in its expected return. Third, we show that in the cryptocurrency market the ST effect is not subsumed by the short-term reversal effect. Fourth, we document that the ST effect is confined to the micro-cap segment of the market, which accounts for only 3% of total market capitalisation. This segment is likely populated by the least sophisticated investors (Chan, Ding, Lin, & Rossi, 2021), who are those most likely to engage in narrow framing (Liu, Wang, & Zhao, 2010) and to extrapolate past returns into the future (Da, Huang, & Jin, 2021). This finding leads us to speculate that the progressive disappearance of the ST effect in the US stock market during the past few decades has been caused by a shift in the composition of the investor population, from (naïve) retail investors to institutions (Ben-David, Franzoni, Moussawi, & Sedunov, 2021). The latter supposedly being less susceptible to biases such as narrow framing, extrapolation, and salience distortion. Lastly, we provide evidence that the magnitude of the ST effect is moderated by arbitrage constraints.

The rest of the paper is organised as follows. Section 2 reviews the related literature, and Section 3 develops our hypotheses. Section 4 describes the data. Section 5 illustrates how the ST value of a cryptocurrency is measured. Section 6 details the empirical analysis, and Section 7 concludes.

## 2. Literature review

### 2.1. The concept of salience and its applications

By nature, odd or unusual things are more likely to capture human beings' attention (Kahneman, 2012). Salience measures the extent to which an object of perception, e.g., an investment's payoff in a given state of the world, is perceived as different from the available alternatives. According to Taylor and Thompson (1982), "when one's attention is differentially directed to one portion of the environment rather than to others, the information contained in that portion will receive disproportionate weighting in subsequent judgments".

Consistent with this view, previous research shows that the salience of events or information has a significant impact on people's judgement (Grether, 1980; Hamill, Wilson, & Nisbett, 1980; Kahneman & Tversky, 1973), predictions (Bar-Hillel & Fischhoff, 1981; Nisbett & Borgida, 1975) and therefore their choices. For example, Dessaint and Matray (2017) investigate how managers react to hurricane events and find that, "even though the actual risk [of a disaster] remains unchanged", managers irrationally become more concerned about hurricane risk when their firm happens to be headquartered near a disaster area, and as such, disaster risk is perceived as more salient. Choi, Lou, and Mukherjee (2022) argue that college students' major choice tends to be affected by the distribution of a small number of superstar firms that are perceived as salient. Specifically, if an industry currently features a firm whose performance has been extraordinary in recent years, students are more likely to select majors related to this industry. In finance, many market anomalies, such as fads and overreactions, have been found to originate from the salience effect (Odean, 1998; Shiller, 1999). For example, Frydman and Wang (2020) show that, when a stock's capital gain becomes "more visually prominent" on the investor's screen (and is therefore more salient), trading decisions are more strongly affected by the disposition effect.

While the impact of salience is only partially and indirectly encapsulated by diverse effects documented in the literature, Bordalo et al. (2012) are the first to formalise an ST model that aims to describe how individuals make decisions. They argue that a "decision maker is risk-seeking when a lottery's upside is salient and risk-averse when its downside is salient". Moreover, a salient thinker typically overweights salient payoffs and underweights non-salient payoffs. Their model incorporates three key features: (1) ordering, whereby the salience of a payoff increases as the distance between the payoff and the reference point (i.e., the average payoff of alternative lotteries in this state of the world) increases; (2) diminishing sensitivity, whereby, for the same distance between the payoff and the reference point, the higher the payoff (in absolute value), the lower its salience; (3) reflection, whereby salience is independent of the sign of the distance between payoff and reference point (i.e., relative to the reference point, an $X gain is just as salient as an $X loss).

Subsequent work by the same authors explores the theoretical predictions of this ST model in the areas of consumer choice (Bordalo, Gennaioli, & Shleifer, 2013b), judicial decisions (Bordalo, Gennaioli, & Shleifer, 2015), and asset pricing (Bordalo et al., 2013a). Dertwinkel-Kalt and Köster (2020) empirically test Bordalo et al. (2012) model in a series of laboratory experiments and find that it can explain people's preference for positive skewness more successfully than prospect theory. In addition, using survey data, Dimmock, Kouwenberg, Mitchell, and Peijnenburg (2021) find that, consistent with the predictions of ST, "people display inverse-S-shaped probability weighting, overweighting low probability events" and holding under-diversified portfolios.

Cosemans and Frehen (2021) are the first to empirically test Bordalo et al.'s (2013a) salience-based asset pricing model. Using US stock market data, they find that, consistent with the model's prediction, a stock's ST value is negatively related to its future returns in the cross-section. This can be explained by investors extrapolating past returns and "overweighting salient past returns" when forming expectations about the distribution of a stock's future returns. In turn, stocks with salient upsides become attractive to salient thinkers, who then tilt their portfolios towards these stocks. Ultimately, these stocks become overpriced and earn lower future returns. In line with this argument, Hu, Xiang, and Quan (2021) find that, in the Chinese mutual fund market, funds with greater ST values attract greater net inflows of money.

However, when Cakici and Zaremba (2021) test Bordalo et al.'s (2013a) salience-based asset pricing model using data from 49 international stock markets, they conclude that the ST effect is far from robust. Among their criticisms are that the ST effect (1) is largely driven by the short-term return reversal effect, (2) is predominantly observed "following severe down markets and volatility spikes", and (3) is mostly concentrated in the micro-cap segment, which accounts for only 3% of total market cap. Moreover, their estimates suggest that, in the US, the magnitude of the ST effect has decreased over time: In the most recent period, 2000–2015, there is only little statistical evidence of such an effect.

In a contemporaneous study to ours, Cai and Zhao (2022) find that ST helps explain the cross-section of cryptocurrency returns. Our analysis transcends theirs in several ways. First, we also investigate the time-series relationship between the ST value of a cryptocurrency and its future return, i.e., we ask whether a cryptocurrency's ST value predicts time-variation in its expected return. While cross-sectional regressions focus on average returns, an appealing quality of time-series analysis is that it sheds light on changes in expected returns. Second, contrary to their findings, we show that the ST effect is confined to the micro-cap segment, which accounts for only 3% of total market capitalisation. We believe that Cai and Zhao (2022) fail to reach a similar conclusion because they examine the moderating role of cryptocurrency size only in the context of bivariate portfolio analysis, which, as is well understood, does not control for the effects of potential confounding factors. Third, we document that arbitrage constraints play an important role in moderating the magnitude of the ST effect. We argue that Cai and Zhao (2022) fail to observe this phenomenon because they investigate the role of arbitrage constraints only in the context of bivariate portfolio analysis and limit their attention to a single proxy (idiosyncratic volatility) for limits to arbitrage. Lastly, we employ multiple tests to show that the predictive power of ST is relatively stable over time and is neither driven by our methodology nor by our choice of the benchmark against which investors are believed to evaluate the salience of a cryptocurrency's payoff.

### 2.2. Nature of cryptocurrency and mechanics of the cryptocurrency market

Cryptocurrency is a type of digital currency that addresses some of the limitations of the traditional payments system based on fiat currency, namely the long settlement period, high transaction fees, the need to share personal information, and the need to hold a bank account (Maese, Avery, Naftalis, Wink, & Valdez, 2016). It is designed as a medium of exchange that can be used to pay for goods and services. Unlike other types of digital currencies which require central authorities to verify the validity of a transaction, cryptocurrencies, such as Bitcoin, employ a distributed verification mechanism (Luther & Smith, 2020).

The cryptocurrency market is different from conventional asset markets in many ways. First, there are differences in drivers of value. It is well established that the intrinsic value of traditional assets such as stocks and bonds depends on fundamentals such as cash flows, dividends, and coupon payments (Gordon & Shapiro, 1956; Miller & Modigliani, 1961). Conversely, contemporary research has demonstrated that network externalities and costs of production are among the primary drivers of value in the cryptocurrency market. For example, Cong, Li, and Wang (2021) develop a model in which cryptocurrency tokens allow users to conduct transactions on a digital marketplace, which makes them "a hybrid of money and investable assets". Two of their key insights are that the value of cryptocurrency tokens depends on the productivity of the digital marketplace and on network externalities, i.e., the greater the user base, "the easier it is for any user to find a transaction counterparty, and the more useful the tokens are". Conversely, Hayes (2017) claims that cryptocurrency is better thought of as a virtual commodity than virtual money and finds that the main determinant of its market price is its marginal cost of production, which in turn depends on electricity prices, mining efficiency, and mining difficulty. Liu, Sheng, and Wang (2021) find empirical evidence in support of the view that network externalities (e.g., user growth) affect cryptocurrency value, but unlike Hayes (2017), they find no evidence that value is affected by production factors (e.g., electricity costs).

Since the drivers of value in the cryptocurrency market are different from the typical drivers of value with which investors in conventional assets are familiar, the mental representation that investors form of a cryptocurrency's payoff and of its salience may differ from that of a stock or other traditional assets. The implication is that previous findings about ST's ability to explain investor behaviour in the equity market are not necessarily extendable to the cryptocurrency market. Rather, the latter must be studied on its own terms.

Secondly, while a stock usually trades on a single exchange or on a handful of exchanges during regular hours, there exist >200 cryptocurrency exchanges around the world, and the most popular cryptocurrencies trade on dozens of them 24/7. Hansen (2018) highlights how regulations and the amount of oversight from authorities vary widely across exchanges, as do "fee structure, trading features, […] and security and insurance measures in place". For example, she stresses that only some exchanges allow short selling and margin trading, and some do not accept fiat currency.[1]

Lastly, unlike the stock market, the cryptocurrency market is mostly populated by retail investors. A recent JPMorgan survey among 3400 institutional investors around the world reveals that only 11% of them either trade or invest in cryptocurrencies, and 78% of those who have not done that believe it is "not likely" that they will do so in the future (Graffeo, 2021).

Surveys show that cryptocurrency owners possess higher levels of digital literacy but lower levels of financial literacy than non-owners (Panos, Karkkainen, & Atkinson, 2020). Lack of financial sophistication and limited trading experience are often associated with heavier use of heuristics and exacerbation of behavioural biases (Feng & Seasholes, 2005). In particular, there is evidence that unsophisticated individual investors are more likely to extrapolate past returns into the future (Da et al., 2021) and engage in narrow framing (Liu et al., 2010), which are two of the key prerequisites on which the ST effect is based.

In conclusion, even though the cryptocurrency market shares several features of traditional markets, its unique investor population and all the above factors make it an ideal setting for extending the exploration of ST's ability to explain investor behaviour.

## 3. Hypotheses development

Bordalo et al.'s (2013a) salience-based asset pricing model predicts that, in the cross-section, cryptocurrencies with higher (lower) ST values, i.e., cryptocurrencies with salient upsides (downsides), are more (less) appealing to salient thinkers, who tilt their portfolios towards (away from) these cryptocurrencies. The implication is that cryptocurrencies with high ST values become overpriced relative to cryptocurrencies with low ST values and earn lower subsequent returns. This leads us to our first testable hypothesis:

**H1**. *: In the cross section, cryptocurrencies with higher ST values earn lower average returns than cryptocurrencies with lower ST values.*

Based on an analogous rationale, we also conjecture that a cryptocurrency's ST value predicts time-variation in its expected return. Namely, we hypothesize that, as the ST value of a cryptocurrency rises (falls) over time, it becomes more (less) appealing to salient thinkers. Net buying (selling) pressure causes the cryptocurrency to become increasingly overpriced (underpriced), which leads to lower (higher) future returns. Based on this argument, we test the following hypothesis:

**H2**. *: The ST value of a cryptocurrency negatively predicts its future return in the time-series dimension.*

Since previous research (e.g., Zhang & Li, 2021; Zhang, Li, Xiong, & Wang, 2021) shows that, in the cryptocurrency market, the magnitude of some anomalies varies across size segments, we posit that a similar phenomenon arises with respect to the ST effect. The rationale is that liquidity is likely to be lower and arbitrage constraints are likely to be more severe among smaller cryptocurrencies. Furthermore, smaller cryptocurrencies are more likely to attract trades from unsophisticated investors. For example, Zaremba, Bilgin, Long, Mercik, and Szczygielski (2021) show that the daily reversal effect is more pronounced among small cryptocurrencies, which account for <10% of total market cap.

[1] For a more comprehensive discussion of the cryptocurrency market, see Benedetti and Nikbakht (2021).

These results parallel similar findings in the stock market, as Cosemans and Frehen (2021) find that the ST effect is stronger among micro-cap US stocks, and Cakici and Zaremba (2021) find evidence of an ST effect only among micro-cap stocks in their international sample. Therefore, we test the following hypothesis:

**H3.** *: The predictive power of ST is stronger among micro-cap cryptocurrencies.*

Since salience distortion is a behavioural phenomenon that does not alter cryptocurrencies' economic fundamentals, one would expect rational arbitrageurs to instantly eliminate the mispricing caused by salient thinkers. However, as noted by Shleifer and Vishny (1997) and Pontiff (2006), real-world arbitrage strategies are typically risky and costly. Therefore, arbitrageurs can eliminate price inefficiencies only when their expected profits compensate them for the costs and the risk they incur. In other words, when arbitrage constraints are more severe, the price of a cryptocurrency that is appealing/unappealing to salient thinkers is more likely to deviate substantially from its fundamentals. Based on this argument, we test the following hypothesis:

**H4.** *: The predictive power of ST is stronger among cryptocurrencies that are more difficult to arbitrage.*

## 4. Data

We collect daily prices, trading volumes, and market capitalisations of all available cryptocurrencies from *Coincodex* (in US dollars). Unlike other exchange-specific databases, *Coincodex* aggregates data from >210 cryptocurrency exchanges. As such, in our data set, the price of a cryptocurrency on a given day is the volume-weighted average of all prices reported by these exchanges on that day, and it is based on the 00:00 UTC time zone.[2]

Our data relate to the period from January 1, 2014 to June 30, 2021.[3] We retain only cryptocurrencies for which (1) >52 weeks of observations are available, (2) the time series of trading volume and market capitalisation are not missing, and (3) the daily price time series is not discontinuous. A total of 1738 cryptocurrencies survive this screening. It is worth noting that our sample includes both active and defunct cryptocurrencies, thereby lessening the potential for survivorship bias. Table 1 presents a set of average cross-sectional summary statistics by year. It reveals that the average number of active cryptocurrencies in the sample monotonically increases from 38 in 2015 to 1604 in 2021. The upward trend is particularly obvious starting from the end of 2017, since when this market has been attracting a great deal of attention from the mass media.

In our analysis, the outcome variable represents cryptocurrency returns and is measured at a weekly frequency. In using this frequency, we follow the existing literature on the behaviour of cryptocurrency returns. The rationale is that the cryptocurrency market has a relatively short history, and the use of a weekly (cf. monthly) frequency provides more observations and offers greater estimation accuracy (Li, Urquhart, Wang, & Zhang, 2021). Additionally, there is evidence that cryptocurrency returns follow a short-memory process (Grobys, Ahmed, & Sapkota, 2020). Therefore, we transform the daily time series that we collected from *Coincodex* into weekly (Friday-to-Friday) time series of log returns, trading volumes, and market capitalisations.[4] After winsorising these variables at the 1st and 99th percentiles for each week, we report in Table 1 a set of average cross-sectional summary statistics by year. The pattern of mean weekly returns reveals that, on average, cryptocurrencies delivered unusually high returns in 2017 and very poor returns in 2018. Average trading volume grew rapidly in 2017 and 2018, then fell substantially during the following two years and surged again in 2021. Average market capitalisation rose fairly steadily until 2018, after which it experienced a sizeable drop caused by the launch of a large number of new cryptocurrencies.

## 5. Salience theory value of a cryptocurrency and control variables

To compute the ST value of a cryptocurrency, we follow Cosemans and Frehen's (2021) methodology, which, in turn, builds upon Bordalo et al. (2013a) salience-based asset pricing model. The three crucial assumptions are that investors (1) engage in narrow framing (i.e., they evaluate each cryptocurrency individually rather than as part of their overall portfolio), (2) believe that a cryptocurrency's historical return distribution is representative of its future return distribution, and (3) evaluate the historical return distribution as described by ST.

Point 3 above requires making an assumption about the benchmark against which investors gauge the salience of a cryptocurrency's payoff, i.e., of its return on a given day. We employ the equal-weighted cryptocurrency market index as our default benchmark, as the equal-weighted method "preserves the ordering, diminishing sensitivity and the reflection properties of the salience function" (Cosemans & Frehen, 2021).[5]

Point 2 above requires making an assumption about the length of the historical time window on which investors focus when extrapolating past returns into the future. In our baseline analysis, we follow Cosemans and Frehen (2021) and use a one-month window. In other words, the ST value of a cryptocurrency at the end of week t-1 is computed based on the distribution of its past daily returns between week t-4 and week t-1.[6] Investors who extrapolate past returns but do not suffer from salience distortion realise that the objective probability of each of the 28 daily returns in this time window is the same, i.e., 1/28. However, salient thinkers unintentionally overweight (underweight) the probability of salient (non-salient) returns.

The salience of cryptocurrency $i$'s log return on day $s$ ($r_{i,\,s}$), where each day within the 4-week window can be thought of as a possible state of the world, is computed as:

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

[2] See Coincodex (https://coincodex.com) for detailed descriptions of the data.

[3] We obtained the historical data from Coincodex on July 13, 2021. Since trading volume data are only available from the end of 2013, our sample period starts on January 1, 2014.

[4] We assign a missing value to price and market capitalisation when trading volume is zero. This procedure omits 17% of the observations, but the results are robust to this choice. We follow Grobys and Junttila (2021) and use log returns because the distribution of simple cryptocurrency returns is highly positively skewed compared to that of conventional assets.

[5] Starting from the universe of cryptocurrencies tracked by Coincodex, we include in the construction of the market index only those cryptocurrencies for which (1) at least 14 daily observations are available, (2) the time series of trading volume and market capitalisation are not missing, and (3) the daily price time series is not discontinuous. A total of 2726 cryptocurrencies meet these criteria. As we show later, using alternative reference points (i.e., zero, the risk-free rate, the time-series mean of the cryptocurrency's own returns, the value-weighted market index return, and Bitcoin's return) does not change our conclusions.

[6] As we show later in the sensitivity tests, using alternative time window lengths (i.e., from 1 week to 52 weeks) does not alter our conclusions.

**Table 1**
Sample cryptocurrencies: Average cross-sectional summary statistics by year.

| Year | Number of active cryptocurrencies | Weekly return | | | Trading volume (in thousands of $) | | | Market cap (in millions of $) | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Mean | Mean | SD | Median | Mean | SD | Median | Mean | SD | Median |
| 2015 | 38 | −0.0045 | 0.2209 | −0.0158 | 1168.79 | 5497.98 | 5.70 | 145.29 | 674.27 | 1.12 |
| 2016 | 68 | 0.0140 | 0.2679 | −0.0016 | 1346.31 | 9812.17 | 2.75 | 142.70 | 1062.20 | 0.60 |
| 2017 | 93 | 0.0775 | 0.3134 | 0.0522 | 23,421.97 | 117,787.12 | 178.65 | 736.37 | 4205.32 | 8.22 |
| 2018 | 168 | −0.0605 | 0.2180 | −0.0638 | 45,394.26 | 248,018.97 | 223.30 | 1208.42 | 6461.28 | 13.05 |
| 2019 | 695 | −0.0202 | 0.3031 | −0.0209 | 9772.46 | 57,779.16 | 34.74 | 49.68 | 244.88 | 2.23 |
| 2020 | 1328 | 0.0011 | 0.3899 | −0.0015 | 7794.30 | 46,280.72 | 14.10 | 34.29 | 167.75 | 0.92 |
| 2021 | 1604 | 0.0175 | 0.4293 | −0.0013 | 40,160.84 | 224,344.75 | 26.67 | 197.07 | 893.74 | 2.87 |

This table reports a set of average cross-sectional summary statistics by year on the cryptocurrencies in the sample. For each year in the sample period, we compute the average cross-sectional mean, standard deviation (SD), and median of weekly log return, trading volume, and market capitalisation. Trading volume refers to a cryptocurrency's mean daily trading volume in a given week, and market cap refers to a cryptocurrency's market capitalisation at the end of a given week. The sample period is from January 2, 2015 to June 25, 2021.

where $\bar{r}_s$ is the log return of the equal-weighted cryptocurrency market index, and $\theta$ is a convenience parameter.[7] In simple terms, $\sigma(r_{is}, \bar{r}_s)$ measures the distance between cryptocurrency $i$'s payoff and the average payoff across all active cryptocurrencies on day $s$. The greater this distance, the more noticeable the payoff to salient thinkers.

Instead of relying on the objective probability of observing $r_{i,\ s}$, salient thinkers instinctively use cryptocurrency-specific decision weights that inflate (deflate) the probabilities of the most (least) salient payoffs, as follows:

$$\widetilde{\pi}_{is} = \pi_s \cdot \omega_{is} \tag{2}$$

where $\pi_s$ is the objective probability of state $s$, $\widetilde{\pi}_{is}$ is the subjective probability of observing $r_{i,\ s}$, and $\omega_{is}$ is the salience weight, which is computed according to the following formula:

$$\omega_{is} = \frac{\delta^{k_{is}}}{\sum_s \delta^{k_{is}} \cdot \pi_s}, \qquad \delta \in (0, 1] \tag{3}$$

Eq. (3) requires ranking cryptocurrency $i$'s daily returns in the interval between week t-4 and week t-1 in decreasing order of salience, where $k_{i,\ s}$ is the rank of $r_{i,\ s}$, which ranges from 1 (most salient) to $S$ (least salient).[8] $S$ represents the set of states, so that $\sum_{s=1}^{S} \pi_s = 1$. The parameter $\delta$ measures the degree of salience distortion. If $\delta = 1$, the decision-maker does not suffer from salience distortion and relies on objective probabilities. If $0 < \delta < 1$, the decision-maker overweights (underweights) the probability of salient (non-salient) returns. The lower $\delta$, the greater the degree of salience distortion. Following Bordalo et al. (2012), we set $\delta = 0.7$ in our baseline specification.

Lastly, the ST value of cryptocurrency $i$ at the end of week t-1 ($STV_{i,\ t-1}$) can be computed as the covariance between salience weights and daily log returns within the time window $T$ between week t-4 and week t-1[9]:

$$STV_{i,t-1} = cov\left[\omega_{is,T}, r_{is,T}\right] = E^{ST}\left[r_{is,T}\right] - \bar{r}_{is,T} \tag{4}$$

Eq. (4) shows that, as pointed out by Cosemans and Frehen (2021), the ST value of an asset "is equal to the difference between salience-weighted and equal-weighted past returns". In other words, the *STV* variable captures how "salient thinking" biases investors' return expectations. Cryptocurrencies with past salient upsides (downsides) cause salient thinkers to form rosy (bleak) expectations about their future returns, which in turn makes them attractive (unattractive). In the presence of limits to arbitrage, net demand (supply) for appealing (unappealing) cryptocurrencies may lead to overpricing (underpricing) and affect their future returns accordingly.

To isolate the abovementioned channel, we include in our analysis a number of well-documented factors that, according to the existing literature, help explain asset/cryptocurrency returns. All these control variables are defined in Table 2.

Table 3 presents some average cross-sectional summary statistics on cryptocurrency returns, the *STV* variable, and the set of controls.[10] All variables are winsorised at the 1st and 99th percentiles for each week, but our conclusions are robust to this choice. Panel A reports the mean and standard deviation of each variable, and Panel B presents the Pearson correlation coefficient for each pair of variables. *STV* is most highly correlated with *Skew1* (short-term skewness), *Mom* (momentum), *Max* (MAX effect), and *Rev* (short-term reversal). While Cakici and Zaremba (2021) argue that *STV* and *Rev* tend to capture similar phenomena, it is worth noting that the correlation coefficient between *STV* and *Rev* in our sample is only 0.18, which is significantly lower than that estimated by Cosemans and Frehen (2021) in the US stock market (0.65) or by Cakici and Zaremba (2021) in a sample of international stock markets (0.60).

## 6. Empirical analysis

### 6.1. Cross-sectional relationship between STV and future returns

#### 6.1.1. Portfolio analysis

We start investigating whether high-*STV* cryptocurrencies earn lower average returns than low-*STV* cryptocurrencies (*H1*) by using univariate portfolio analysis. This does not require any assumptions about the functional form of the relation between *STV* and future returns. First, at the end of each week, we sort cryptocurrencies into decile portfolios by *STV*, where decile 1 contains the lowest-*STV* cryptocurrencies and decile 10 the highest-*STV* cryptocurrencies. Next, we calculate the equal-weighted (EW) and value-weighted (VW) mean returns of each portfolio in the following week.[11] Lastly, we use the

[7] $\theta$ deals with the salience of states in which the cryptocurrency's return is zero. If $\theta$ were not added to the denominator, zero-return states would always be the most salient irrespective of the return on the market index. We set $\theta =$ 0.1 as in Bordalo et al. (2012), but as we show later, this choice has no material impact on our conclusions.

[8] In case of ties, the returns are further ranked by trading volume.

[9] If there are fewer than half non-missing return observations within the time window, the *STV* variable is assigned a missing value.

[10] Since we also study the time-series relationship between the *STV* variable and future cryptocurrency returns, in Table A1 in the Online Appendix we present a number of average time-series summary statistics on the *STV* variable and the set of controls.

[11] Since log returns are not additive across assets, we transform log cryptocurrency returns into simple returns before computing the average return of each portfolio. We then transform simple returns back into log returns, which are additive across time.

**Table 2**
Variable definitions.

| Variable | Definition | References |
|---|---|---|
| Return | Weekly (Friday-to-Friday) log return on a cryptocurrency in week t | Grobys & Junttila, 2021 |
| STV | Salience theory value of a cryptocurrency's historical daily return distribution from week t-4 to t-1 | Cosemans & Frehen, 2021 |
| Beta | Slope obtained by regressing a cryptocurrency's daily excess return on the cryptocurrency market excess return from week t-4 to t-1 | Liu, Liang, & Cui, 2020; Shen, Urquhart, & Wang, 2020; Liu, Tsyvinski, & Wu, 2022 |
| Size | Natural logarithm of a cryptocurrency's market capitalisation at the end of week t-1 | Elendner, Trimborn, Ong, & Lee, 2017; Li & Yi, 2019; Liu et al., 2020; Shen et al., 2020; Liu et al., 2022 |
| Mom | Cumulative return on a cryptocurrency from week t-3 to week t-2 | Liu et al., 2022 |
| Illiq | Mean of a cryptocurrency's absolute daily return divided by its daily trading volume in week t-1 | Amihud, 2002; Zhang & Li, 2021 |
| Rev | Return on a cryptocurrency in week t-1 | Li & Yi, 2019; Shen et al., 2020 |
| Lt_rev | Cumulative return on a cryptocurrency from week t-60 to week t-13 | Fama, 1998 |
| Vol | Standard deviation of a cryptocurrency's daily returns in week t-1 | Jia, Liu, & Yan, 2021 |
| Ivol | Idiosyncratic volatility of a cryptocurrency's daily returns from week t-4 to t-1 | Ang, Hodrick, Xing, & Zhang, 2006; Zhang & Li, 2020 |
| Max | Maximum of a cryptocurrency's daily returns in week t-1 | Bali, Cakici, & Whitelaw, 2011; Grobys & Junttila, 2021; Li et al., 2021 |
| Min | Negative of the minimum of a cryptocurrency's daily returns in week t-1 | Bali et al., 2011; Grobys & Junttila, 2021; Li et al., 2021 |
| PTV | Prospect theory value of a cryptocurrency's historical weekly return distribution from week t-52 to t-1 | Barberis, Mukherjee, & Wang, 2016; Chen et al., 2022 |
| Volume | Natural logarithm of a cryptocurrency's mean daily trading volume in week t-1 | Liu et al., 2022 |
| StdVolume | Natural logarithm of the standard deviation of a cryptocurrency's daily trading volume in week t-1 | Liu et al., 2022 |
| DBeta | Downside beta, i.e., slope obtained by regressing a cryptocurrency's weekly excess returns on the cryptocurrency market excess return from week t-52 to t-1. An observation is included in the regression only if the market return is less than the average weekly market return in that time interval | Ang et al., 2006; Zhang et al., 2021 |
| Skew1 | Short-term skewness, i.e., skewness of a cryptocurrency's daily returns in week t-1 | Jia et al., 2021; Liu et al., 2022 |
| Skew2 | Long-term skewness, i.e., skewness of a cryptocurrency's weekly returns from week t-52 to t-1 | Barberis et al., 2016 |
| Iskew | Idiosyncratic skewness of a cryptocurrency's weekly returns from week t-52 to t-1 | Harvey & Siddique, 2000 |
| Coskew | Coefficient on the squared market excess return when regressing a cryptocurrency's weekly excess return on the cryptocurrency market excess return and the squared market excess return from week t-52 to t-1 | Harvey & Siddique, 2000 |

resulting return time series to compute the mean excess return (over the risk-free rate) and CAPM alpha of each decile.[12]

Table 4 displays the results, where the t-statistics are based on Newey-West standard errors with a lag truncation parameter of five. A zero-cost long-short strategy that buys decile 1 (lowest *STV*) and shorts decile 10 (highest *STV*) generates economically and statistically significant mean returns of 10.80% (t-statistic = 7.60) and 9.13% (t-statistic = 5.61) per week for the EW and the VW portfolios, respectively. Since previous work suggests that the total cost of rebalancing the cryptocurrency portfolios is about 200 bps per week (Bianchi & Dickerson, 2021), the net mean returns remain practically significant. Our conclusions stay the same when we adjust returns for risk by computing the strategies' CAPM alphas. Therefore, these initial results are consistent with the hypothesis (*H1*) that cryptocurrencies with higher ST values earn lower average returns than cryptocurrencies with lower ST values.[13]

A key limitation of univariate portfolio analysis is the lack of control for the effects of other factors that happen to be correlated with *STV*.[14] To overcome this problem, we also perform bivariate dependent-sort portfolio analysis, which employs two sort variables and enables us to study the relation between *STV* and cryptocurrency returns conditional on a third factor. First, at the end of each week, we sort cryptocurrencies into quintiles based on one control variable (e.g., *Rev*). Next, within each of these quintiles, we further sort cryptocurrencies into quintiles by *STV*.[15] Lastly, the one-week-ahead return on a given *STV*-quintile is calculated by averaging across the five conditioning-factor quintiles. We repeat this procedure for each week to generate a time series of returns for each *STV*-sorted quintile.

The results (see Table A3 in the Online Appendix) show that the mean excess returns and CAPM alphas of the EW zero-cost portfolios (long the lowest-*STV* quintile and short the highest-*STV* quintile) are all positive and statistically significant at the 1% level. As for the VW zero-cost portfolios, their mean excess returns and CAPM alphas are all positive, but only 10 (out of 18) are statistically different from zero at the 5% level. In contrast to the results of the univariate analysis, the mean excess returns and CAPM alphas of the EW zero-cost portfolios are substantially larger than those of their VW counterparts, which emphasizes the need to control for the confounding effects of other factors. This pattern also suggests that the ST effect may be stronger among small cryptocurrencies.[16]

### *6.1.2. Panel regressions with time fixed effects*

Since bivariate portfolio analysis can only control for one confounding factor at a time, we also employ panel regressions to control for the effects of multiple covariates at once. Our preferred regression

[12] The weekly risk-free rate is derived from the one-month Treasury bill rate from Kenneth French's website (https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html). When estimating the CAPM alphas, we employ the cryptocurrency market index as a proxy for the market portfolio.

[13] The results are qualitatively the same if we use alternative benchmarks (i.e., zero, the risk-free rate, the time-series mean of the cryptocurrency's own returns, the value-weighted market index return, and Bitcoin's return) to calculate the *STV* variable or we divide the sample into sub-samples (i.e., a rolling-window approach that uses a fixed 2-year window that increments forward 13 weeks (3 months) for each iteration).

[14] Indeed, as Table A2 in the Online Appendix reveals, the mean values of *Mom*, *Rev*, *Skew1*, *Skew2*, and *Iskew* increase monotonically moving from decile 1 (lowest *STV*) to decile 10 (highest *STV*).

[15] Since bivariate portfolio analysis requires sorting cryptocurrencies into 25 groups (= 5 × 5) each week, a minimum of 25 cryptocurrencies must be active. The sample period in this part of the analysis is therefore reduced from March 2015 to June 2021.

[16] Since Bitcoin accounts for a large fraction of total market capitalisation, we repeat the portfolio analyses after excluding Bitcoin from the sample. Our conclusions do not change.

**Table 3**
Outcome variable and explanatory variables: Average cross-sectional summary statistics.

Panel A. Mean and standard deviation

| | Return | STV | Beta | Size | Mom | Rev | Illiq | Lt_rev | Vol | Ivol | Max | Min | PTV | Volume | StdVolume | Skew1 | Skew2 | Iskew | Coskew | DBeta |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Mean | 0.00 | 0.03 | 0.66 | 14.48 | 0.01 | 0.00 | 0.23 | −0.18 | 0.20 | 0.20 | 0.30 | 0.28 | −0.22 | 9.57 | 8.79 | 0.06 | 0.36 | 0.40 | −0.01 | 0.44 |
| Standard deviation | 0.30 | 0.16 | 1.17 | 2.82 | 0.36 | 0.30 | 1.62 | 1.47 | 0.18 | 0.15 | 0.30 | 0.27 | 0.11 | 3.92 | 3.71 | 0.65 | 0.88 | 0.86 | 2.25 | 0.86 |

Panel B. Pearson's pairwise correlation matrix

| | Return | STV | Beta | Size | Mom | Rev | Illiq | Lt_rev | Vol | Ivol | Max | Min | PTV | Volume | StdVolume | Skew1 | Skew2 | Iskew | Coskew |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| STV | −0.08 | | | | | | | | | | | | | | | | | | |
| Beta | 0.00 | −0.03 | | | | | | | | | | | | | | | | | |
| Size | −0.02 | 0.00 | −0.04 | | | | | | | | | | | | | | | | |
| Mom | 0.00 | 0.19 | −0.01 | 0.06 | | | | | | | | | | | | | | | |
| Rev | −0.26 | 0.18 | 0.00 | 0.05 | −0.23 | | | | | | | | | | | | | | |
| Illiq | 0.01 | −0.01 | 0.00 | −0.30 | −0.03 | −0.01 | | | | | | | | | | | | | |
| Lt_rev | −0.01 | −0.01 | 0.00 | 0.32 | −0.01 | 0.00 | −0.13 | | | | | | | | | | | | |
| Vol | −0.04 | 0.10 | 0.05 | −0.39 | 0.03 | 0.09 | 0.26 | −0.15 | | | | | | | | | | | |
| Ivol | −0.02 | 0.13 | 0.01 | −0.49 | 0.05 | 0.01 | 0.28 | −0.18 | 0.73 | | | | | | | | | | |
| Max | −0.10 | 0.19 | 0.04 | −0.33 | −0.02 | 0.30 | 0.21 | −0.13 | 0.92 | 0.65 | | | | | | | | | |
| Min | 0.03 | −0.02 | 0.05 | −0.37 | 0.08 | −0.15 | 0.25 | −0.13 | 0.91 | 0.67 | 0.72 | | | | | | | | |
| PTV | −0.04 | 0.03 | −0.02 | 0.60 | 0.07 | 0.08 | −0.28 | 0.49 | −0.36 | −0.46 | −0.29 | −0.34 | | | | | | | |
| Volume | −0.01 | 0.04 | −0.05 | 0.86 | 0.07 | 0.04 | −0.37 | 0.24 | −0.34 | −0.47 | −0.29 | −0.33 | 0.56 | | | | | | |
| StdVolume | −0.02 | 0.05 | −0.05 | 0.84 | 0.08 | 0.06 | −0.35 | 0.24 | −0.29 | −0.43 | −0.23 | −0.29 | 0.54 | 0.98 | | | | | |
| Skew1 | −0.05 | 0.20 | 0.00 | 0.00 | −0.03 | 0.17 | −0.02 | −0.01 | 0.06 | 0.03 | 0.30 | −0.20 | 0.01 | 0.02 | 0.04 | | | | |
| Skew2 | −0.04 | 0.07 | −0.02 | 0.05 | 0.03 | 0.04 | −0.07 | 0.22 | −0.01 | −0.02 | 0.01 | −0.03 | 0.39 | 0.06 | 0.07 | 0.04 | | | |
| Iskew | −0.04 | 0.07 | −0.02 | 0.13 | 0.04 | 0.05 | −0.07 | 0.20 | −0.05 | −0.06 | −0.02 | −0.06 | 0.42 | 0.13 | 0.13 | 0.04 | 0.76 | | |
| Coskew | −0.01 | 0.00 | 0.02 | 0.00 | 0.00 | 0.00 | 0.04 | 0.00 | −0.01 | −0.01 | −0.01 | −0.01 | 0.02 | 0.01 | 0.01 | 0.00 | 0.08 | −0.10 | |
| DBeta | 0.00 | −0.01 | 0.03 | 0.00 | 0.00 | 0.00 | −0.03 | 0.01 | −0.01 | −0.02 | −0.01 | −0.01 | 0.07 | −0.01 | −0.01 | −0.01 | −0.04 | 0.08 | −0.56 |

This table reports the time-series averages of the weekly cross-sectional summary statistics on the variables employed in the empirical analysis. Panel A displays the mean and standard deviation of each variable, and panel B displays the Pearson's pairwise correlation coefficients. *STV* is the salience theory value of a cryptocurrency's historical daily return distribution from week t-4 to t-1. The remaining variables are defined in Table 2. The sample period is from January 2, 2015 to June 25, 2021.

**Table 4**
Univariate portfolio analysis.

| | Low | STV2 | STV3 | STV4 | STV5 | STV6 | STV7 | STV8 | STV9 | High | Low-High |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Excess return | | | | | | | | | | | |
| EW | 0.1389*** | 0.0540*** | 0.0412*** | 0.0318*** | 0.0372*** | 0.0297*** | 0.0423*** | 0.0404*** | 0.0363*** | 0.0309** | 0.1080*** |
| | (8.03) | (4.39) | (3.93) | (3.19) | (3.47) | (2.99) | (3.76) | (3.48) | (2.89) | (2.54) | (7.60) |
| VW | 0.0651*** | 0.0139 | 0.0103 | 0.0157* | 0.0148 | 0.0144 | 0.0120 | 0.0050 | 0.0054 | −0.0262* | 0.0913*** |
| | (4.29) | (1.12) | (1.10) | (1.70) | (1.61) | (1.49) | (1.20) | (0.46) | (0.37) | (−1.82) | (5.61) |
| CAPM alpha | | | | | | | | | | | |
| EW | 0.1384*** | 0.0534*** | 0.0407*** | 0.0312*** | 0.0366*** | 0.0292*** | 0.0417*** | 0.0400*** | 0.0357*** | 0.0302** | 0.1082*** |
| | (7.98) | (4.34) | (3.89) | (3.15) | (3.43) | (2.95) | (3.72) | (3.44) | (2.86) | (2.49) | (7.61) |
| VW | 0.0647*** | 0.0134 | 0.0099 | 0.0154* | 0.0143 | 0.0140 | 0.0116 | 0.0047 | 0.0052 | −0.0269* | 0.0915*** |
| | (4.28) | (1.09) | (1.06) | (1.66) | (1.55) | (1.47) | (1.16) | (0.43) | (0.36) | (−1.88) | (5.60) |

This table reports the mean excess returns and CAPM alphas of *STV*-sorted portfolios, where *STV* is the salience theory value of a cryptocurrency's historical daily return distribution from week t-4 to t-1. We form the portfolios at the end of each week, and we hold them for one week. The mean excess returns and CAPM alphas of zero-cost long-short portfolios that are long decile 1 (lowest *STV*) and short decile 10 (highest *STV*) are displayed in the right-most column. We compute both equal-weighted (EW) and value-weighted (VW) mean excess returns and CAPM alphas. To calculate the CAPM alphas, we use the value-weighted cryptocurrency market index as a proxy for the market portfolio. The sample period is from January 2, 2015 to June 25, 2021. The t-statistics in parentheses are based on Newey-West standard errors with a lag truncation parameter of five. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

specification is:

$$\begin{aligned}Return_{i,t} = {} & \beta_0 + \beta_1 STV_{i,t-1} + \beta_2 Beta_{i,t-1} + \beta_3 Size_{i,t-1} + \beta_4 Mom_{i,t-1} + \beta_5 Rev_{i,t-1} \\ & + \beta_6 Illiq_{i,t-1} + \beta_7 Lt\_rev_{i,t-1} + \beta_8 Vol_{i,t-1} + \beta_9 Ivol_{i,t-1} + \beta_{10} Max_{i,t-1} \\ & + \beta_{11} Min_{i,t-1} + \beta_{12} PTV_{i,t-1} + Time\ FE + e_{i,t}\end{aligned} \tag{5}$$

where $Return_{i,\,t}$ denotes cryptocurrency *i*'s excess log return (over the risk-free rate) in week *t*, and the explanatory variables are as defined in Table 2. The inclusion of time (i.e., week) fixed effects (FE) allows us to isolate the cross-sectional variation in the data (Kropko & Kubinec, 2020). We estimate the parameters of the model by OLS. To estimate standard errors that are robust to cross-sectional and time-series dependence in the error term, we rely on double clustering, by both cryptocurrency and week (Gow, Ormazabal, & Taylor, 2010; Petersen, 2009).[17]

While Eq. (5) contains a set of 12 regressors, we start by estimating a simple linear equation with a single explanatory variable, *STV* (column 1 of Table 5), and then we gradually add an increasing number of covariates (columns 2–8). The estimates show that, regardless of the set of controls, the coefficient on *STV* is always negative and statistically significant at the 1% level, which supports *H1*. The ST effect is also economically significant: According to our preferred specification (column 8 of Table 5), a one cross-sectional standard-deviation increase in the ST value of a cryptocurrency reduces its next-week excess return by 0.41% relative to its peers.[18] Considering that the average cross-sectional standard deviation of returns is about 30% per week in our sample (see Panel A of Table 3), one may argue that the ST effect in the cryptocurrency market is not practically large. However, to put the size of this effect in perspective, we note that, in the US market, Cosemans and Frehen (2021) find that a one-standard-deviation increase in the ST value of a stock reduces its next *month*'s return by only 0.13%. The implication is that, in the cryptocurrency market, the ST effect is about 13 times the size of that in the US stock market. This is in line with our expectations, as the proportion of naïve retail investors (who are more susceptible to behavioural biases such as narrow framing, extrapolation, and salience distortion) is larger in the cryptocurrency market.

Our conclusions do not change when we add to the regression some additional factors that have been found to predict the cross-section of asset/cryptocurrency returns (columns 9–13 of Table 5). In particular, even though salience distortion is related to investors' preference for positive skewness, the inclusion of *Skew1*, *Skew2*, *Iskew*, and *Coskew* does not have material impacts on the sign and size of the coefficient on *STV*. This suggests that the behaviour captured by the *STV* variable goes beyond a mere preference for skewness.

To examine the economic importance of the ST effect, we compare its size to that of other effects documented in the literature on the cross-section of asset/cryptocurrency returns. In Fig. 1, which is based on the estimates in column 9 of Table 5, each point estimate and 95% confidence interval measures the impact on a cryptocurrency's next-week excess return of a one cross-sectional standard-deviation change in one of the explanatory variables. It emerges that, with the exclusion of *Rev* (short-term reversal) and *Mom* (momentum), the size of the ST effect is of the same order of magnitude as the others. Specifically, these estimates lead us to conclude that the ST effect is just as economically meaningful as the effects of *DBeta* (downside beta), *Illiq* (illiquidity), *PTV* (prospect theory), and *Max* (MAX effect), which have been documented in recent cryptocurrency studies (Chen, Lepori, Tai, & Sung, 2022; Grobys & Junttila, 2021; Li et al., 2021; Zhang et al., 2021; Zhang & Li, 2021). In turn, we believe that the ST effect represents a phenomenon that is worthy of further investigation by the academic community.

It is also worth noting that, in column 8 (cf. column 7) of Table 5, the coefficient on *STV* remains practically and statistically significant after the inclusion of *PTV*, i.e., the cryptocurrency's prospect theory value. Consistent with Chen et al.'s (2022) findings, the coefficient on *PTV* is negative and statistically significant, suggesting that cryptocurrencies with high prospect-theory values are attractive to some investors, become overpriced, and earn lower future returns. Our results support the view that ST and prospect theory are by no means mutually exclusive, as the cryptocurrency market may be populated by some investors whose behaviour is better described by ST and some others whose decisions are better modelled by prospect theory. It is also possible that these two theories capture different traits of the same investor's behaviour.

### 6.2. Time-series relationship between STV and future return

After observing that high-*STV* cryptocurrencies earn lower average returns than low-*STV* cryptocurrencies, we also want to explore whether

[17] While the Fama-MacBeth approach with Newey-West standard errors is popular in the asset pricing literature, Gow et al. (2010) demonstrate that it produces biased standard errors in the presence of serial correlation in the error term. Conversely, cluster-robust standard errors perform well. Since we find evidence of serial correlation in our model's error term based on an Arellano-Bond autocorrelation test (Arellano & Bond, 1991), we opt for panel regressions with time FE and cluster-robust standard errors.

[18] Note that the estimated coefficient on *STV* is −0.0255, and the average cross-sectional standard deviation of *STV* is 0.16. Hence, the size of the effect is −0.41% (= −0.0255 × 0.16).

**Table 5**
Panel regressions: Cross-sectional relationship between *STV* and next-week excess returns.

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) | (13) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| STV | −0.1701*** | −0.1650*** | −0.0248*** | −0.0219*** | −0.0220*** | −0.0247*** | −0.0273*** | −0.0255*** | −0.0267*** | −0.0269*** | −0.0251*** | −0.0258*** | −0.0267*** |
| | (−18.10) | (−17.30) | (−3.10) | (−2.77) | (−2.78) | (−3.18) | (−3.31) | (−3.05) | (−3.26) | (−3.27) | (−3.07) | (−3.16) | (−3.27) |
| Beta | | −0.0001 | 0.0006 | 0.0007 | 0.0007 | 0.0014 | 0.0014 | 0.0014 | 0.0015 | 0.0015 | 0.0015 | 0.0015 | 0.0015 |
| | | (−0.07) | (0.49) | (0.57) | (0.63) | (1.15) | (1.17) | (1.15) | (1.21) | (1.21) | (1.23) | (1.21) | (1.22) |
| Size | | −0.0019** | 0.0009 | 0.0011 | 0.0012 | −0.0001 | −0.0001 | 0.0006 | −0.0005 | −0.0006 | −0.0010 | −0.0007 | −0.0005 |
| | | (−2.57) | (1.19) | (1.52) | (1.63) | (−0.14) | (−0.13) | (0.87) | (−0.65) | (−0.67) | (−1.19) | (−0.89) | (−0.65) |
| Mom | | −0.0015 | −0.0990*** | −0.0991*** | −0.0992*** | −0.0977*** | −0.0975*** | −0.0963*** | −0.0962*** | −0.0962*** | −0.0957*** | −0.0959*** | −0.0962*** |
| | | (−0.42) | (−20.22) | (−20.38) | (−20.18) | (−19.80) | (−19.75) | (−19.78) | (−19.76) | (−19.77) | (−19.69) | (−19.73) | (−19.76) |
| Rev | | | −0.3495*** | −0.3495*** | −0.3493*** | −0.3480*** | −0.3518*** | −0.3504*** | −0.3501*** | −0.3515*** | −0.3499*** | −0.3499*** | −0.3501*** |
| | | | (−43.69) | (−43.49) | (−43.50) | (−43.03) | (−37.65) | (−37.53) | (−37.55) | (−35.90) | (−37.62) | (−37.61) | (−37.54) |
| Illiq | | | | 0.0012*** | 0.0011*** | 0.0012*** | 0.0012*** | 0.0012*** | 0.0012*** | 0.0012*** | 0.0012*** | 0.0012*** | 0.0012*** |
| | | | | (2.80) | (2.71) | (2.95) | (2.97) | (2.87) | (3.08) | (3.07) | (3.06) | (3.08) | (3.08) |
| Lt_rev | | | | | −0.0007 | −0.0009 | −0.0009 | 0.0011 | 0.0013 | 0.0013 | 0.0018* | 0.0015 | 0.0013 |
| | | | | | (−0.79) | (−1.12) | (−1.11) | (1.07) | (1.30) | (1.31) | (1.73) | (1.46) | (1.29) |
| Vol | | | | | | 0.0042 | −0.0696 | −0.0743* | −0.0785* | −0.0779* | −0.0791* | −0.0789* | −0.0786* |
| | | | | | | (0.35) | (−1.59) | (−1.69) | (−1.78) | (−1.76) | (−1.79) | (−1.79) | (−1.78) |
| Ivol | | | | | | −0.0523*** | −0.0508*** | −0.0633*** | −0.0599*** | −0.0599*** | −0.0527*** | −0.0565*** | −0.0599*** |
| | | | | | | (−4.14) | (−4.07) | (−4.98) | (−4.90) | (−4.90) | (−4.30) | (−4.59) | (−4.90) |
| Max | | | | | | | 0.0341** | 0.0364** | 0.0363** | 0.0408** | 0.0373** | 0.0368** | 0.0362** |
| | | | | | | | (2.07) | (2.21) | (2.19) | (2.22) | (2.26) | (2.23) | (2.19) |
| Min | | | | | | | 0.0163 | 0.0177 | 0.0184 | 0.0135 | 0.0176 | 0.0180 | 0.0184 |
| | | | | | | | (0.93) | (1.01) | (1.04) | (0.69) | (1.00) | (1.02) | (1.05) |
| PTV | | | | | | | | −0.0626*** | −0.0669*** | −0.0667*** | −0.0429** | −0.0509*** | −0.0663*** |
| | | | | | | | | (−3.35) | (−3.51) | (−3.50) | (−2.26) | (−2.62) | (−3.47) |
| Volume | | | | | | | | | −0.0018 | −0.0018 | −0.0018* | −0.0018 | −0.0018 |
| | | | | | | | | | (−1.59) | (−1.65) | (−1.66) | (−1.60) | (−1.61) |
| StdVolume | | | | | | | | | 0.0030* | 0.0031* | 0.0030* | 0.0030* | 0.0030* |
| | | | | | | | | | (1.83) | (1.89) | (1.83) | (1.84) | (1.84) |
| DBeta | | | | | | | | | 0.0014 | 0.0014 | 0.0011 | 0.0017 | 0.0005 |
| | | | | | | | | | (0.75) | (0.74) | (0.56) | (0.88) | (0.23) |
| Skew1 | | | | | | | | | | −0.0020 | | | |
| | | | | | | | | | | (−0.77) | | | |
| Skew2 | | | | | | | | | | | −0.0078*** | | |
| | | | | | | | | | | | (−4.83) | | |
| Iskew | | | | | | | | | | | | −0.0050*** | |
| | | | | | | | | | | | | (−3.07) | |
| Coskew | | | | | | | | | | | | | −0.0008 |
| | | | | | | | | | | | | | (−0.94) |
| Crypto FEs | No | No | No | No | No | No | No | No | No | No | No | No | No |
| Week FEs | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Adj. R-squared | 0.1278 | 0.1335 | 0.2255 | 0.2260 | 0.2261 | 0.2268 | 0.2269 | 0.2271 | 0.2273 | 0.2273 | 0.2276 | 0.2274 | 0.2273 |
| N | 140,914 | 135,333 | 135,333 | 134,957 | 134,722 | 134,430 | 134,430 | 134,429 | 134,298 | 134,273 | 134,294 | 134,298 | 134,298 |

This table displays the estimates generated by panel regressions with week FE and a varying set of controls. In all specifications, the dependent variable measures a cryptocurrency's one-week-ahead excess return. The t-statistics in parentheses are based on standard errors clustered by cryptocurrency and week. *STV* is the salience theory value of a cryptocurrency's historical daily return distribution from week t-4 to t-1. The remaining variables are defined in Table 2. The sample period is from January 2, 2015 to June 25, 2021. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

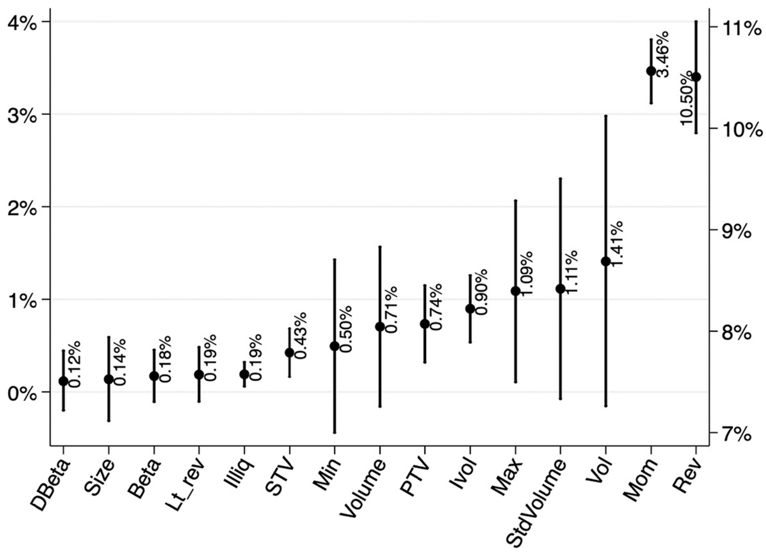


**Fig. 1.** Economic significance of the ST effect.
This figure is based on the estimates in column 9 of Table 5. Each point estimate and 95% confidence interval measures the partial effect on a cryptocurrency's next-week excess return of a one cross-sectional standard-deviation change in one of the explanatory variables in the model. All variables are as defined in Table 2. For ease of comparison, all point estimates are shown with a positive sign. For ease of presentation, the right y-axis measures the effect of *Rev*, and the left y-axis measures the effects of the remaining variables. The sample period is from January 2, 2015 to June 25, 2021. The confidence intervals are based on standard errors clustered by cryptocurrency and week.

a cryptocurrency's ST value predicts time-variation in its expected return (*H2*). Our conjecture is that, over time, as a cryptocurrency's ST value rises (falls), it becomes more and more appealing (repelling) to salient thinkers, leading to progressive overpricing (underpricing) and lowering (raising) its future return accordingly.

To isolate the time-series variation in the data and estimate the time-series relation between a cryptocurrency's ST value and its next-week excess return, we replace the week FE with cryptocurrency FE in our regression equation (see Eq. (5)) (Kropko & Kubinec, 2020). We start by estimating a simple linear regression with cryptocurrency FE and a single explanatory variable, *STV* (column 1 of Table 6). Then, we progressively include more covariates (columns 2–13). Table 6, which displays all the relevant estimates, shows that the coefficient on *STV* is always negative and statistically significant at least at the 5% level. This is consistent with our expectations and supports *H2*. According to our preferred specification (column 8 of Table 6), over time, a one time-series standard-deviation increase in a cryptocurrency's ST value reduces its next-week excess return by 0.69%.[19] In our view, this makes it an economically meaningful effect.

To examine whether this pattern is driven by our chosen outcome variable (i.e., a cryptocurrency's return in excess of the risk-free rate), we follow Madsen and Niessner (2019) and re-estimate our preferred regression equation after replacing our outcome variable with a variable that measures a cryptocurrency's abnormal excess return ($=$excess return$_{i,t} - \widehat{Beta}_{i,t} \times$ market excess return$_t$). Untabulated results reveal that our findings do not change.[20]

### 6.3. Two-dimensional relationship between STV and future returns

We next combine the cross-sectional and time-series dimensions by incorporating into our regression equation both week FE and cryptocurrency FE (see Eq. (5)) (Kropko & Kubinec, 2020). We start by estimating a simple regression equation with a single explanatory variable, *STV* (column 1 of Table 7). Then, we progressively include more covariates (columns 2–13).

Table 7 shows that, irrespective of the set of controls, the coefficient on *STV* is negative and statistically significant at least at the 5% level. The effect is also economically meaningful. According to our preferred specification (column 8 of Table 7), over time, as a cryptocurrency's ST value increases by one standard-deviation relative to the cross-sectional average ST value of the active cryptocurrencies, its next-week excess return falls by 0.44% relative to the cross-sectional average cryptocurrency excess return.[21] In what follows, to conserve space and keep the discussion focussed, we conduct all analyses using panel regressions with cryptocurrency and week FE.

### 6.4. ST effect vs. short-term reversal

Cakici and Zaremba (2021) argue that, in their sample of international stock markets, the ST effect can, to a large extent, be explained by the short-term reversal effect. Their claim is based on evidence from mean-variance spanning tests and bivariate portfolio analysis. In line with their criticism, we notice that, when *Rev* (short-term reversal) is added to our regression equations in column 3 (cf. column 2) of Tables 5, 6 and 7, the magnitude of the coefficient on *STV* experiences a substantial drop, as does its t-statistic. Nevertheless, the coefficient remains statistically significant, and its size remains economically meaningful.

Secondly, our bivariate portfolio analysis shows that, after sorting cryptocurrencies into quintiles by *Rev*, there is still a statistically significant cross-sectional relationship between *STV* and next-week excess returns. Specifically, conditional on *Rev*, a zero-cost strategy that is long quintile 1 (lowest *STV*) and short quintile 5 (highest *STV*) generates mean returns of 3.95% (t-statistic = 4.10) and 1.89% (t-statistic = 2.10) per week for the EW and the VW portfolios, respectively (see Table A3 in the Online Appendix).

[19] Note that the estimated coefficient on *STV* is −0.0385, and the average time-series standard deviation of *STV* is 0.18. Hence, the size of the effect is −0.69% (= −0.0385 × 0.18).

[20] In a second robustness test, we measure a cryptocurrency's abnormal excess return as the difference between the cryptocurrency's excess return and the market excess return (i.e., the value of beta is constrained to be 1). Untabulated estimates show that the coefficient on *STV* is still negative, but this time it is not statistically different from zero. We regard this result as less consequential than the previous one, as cryptocurrencies with different betas are unlikely to react in the same way to market-wide news.

[21] While this description may seem wordy, it is in line with the criticism by Kropko and Kubinec (2020), who point out that a two-way FE estimator cannot simply be interpreted as providing "a single estimate of X on Y while accounting for unit-level heterogeneity and time shocks". Note that the estimated coefficient on *STV* is −0.0229. To construct a reasonable counterfactual, as recommended by Mummolo and Peterson (2018), we first regress *STV* on week and cryptocurrency FE, and then we calculate the standard deviation of the residuals, which yields a value of 0.19. Hence, the size of the effect is −0.44% (= −0.0229 × 0.19).

**Table 6**
Panel regressions: Time-series relationship between *STV* and next-week excess return.

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) | (13) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| STV | −0.1761*** | −0.1515*** | −0.0486*** | −0.0453*** | −0.0454*** | −0.0450*** | −0.0455*** | −0.0385** | −0.0398*** | −0.0401*** | −0.0380** | −0.0397** | −0.0398*** |
| | (−13.29) | (−11.14) | (−3.22) | (−2.97) | (−2.99) | (−2.95) | (−2.92) | (−2.51) | (−2.59) | (−2.62) | (−2.50) | (−2.58) | (−2.60) |
| Size | | −0.0400*** | −0.0261*** | −0.0257*** | −0.0255*** | −0.0255*** | −0.0255*** | −0.0221*** | −0.0254*** | −0.0255*** | −0.0247*** | −0.0254*** | −0.0253*** |
| | | (−7.02) | (−5.03) | (−4.93) | (−5.32) | (−5.25) | (−5.25) | (−4.37) | (−4.94) | (−4.95) | (−4.99) | (−5.01) | (−4.92) |
| Mom | | 0.0132 | −0.0644*** | −0.0641*** | −0.0642*** | −0.0642*** | −0.0641*** | −0.0649*** | −0.0652*** | −0.0651*** | −0.0646*** | −0.0651*** | −0.0653*** |
| | | (1.15) | (−4.76) | (−4.72) | (−4.64) | (−4.70) | (−4.70) | (−4.80) | (−4.83) | (−4.83) | (−4.76) | (−4.82) | (−4.85) |
| Rev | | | −0.3095*** | −0.3092*** | −0.3090*** | −0.3093*** | −0.3098*** | −0.3089*** | −0.3087*** | −0.3136*** | −0.3085*** | −0.3086*** | −0.3087*** |
| | | | (−18.43) | (−18.26) | (−18.16) | (−18.04) | (−17.28) | (−17.14) | (−17.20) | (−16.58) | (−17.28) | (−17.29) | (−17.19) |
| Illiq | | | | 0.0016*** | 0.0016*** | 0.0016*** | 0.0016*** | 0.0015*** | 0.0016*** | 0.0016*** | 0.0016*** | 0.0016*** | 0.0016*** |
| | | | | (3.52) | (3.46) | (3.40) | (3.40) | (3.13) | (3.43) | (3.43) | (3.41) | (3.43) | (3.42) |
| Lt_rev | | | | | −0.0004 | −0.0004 | −0.0004 | 0.0018 | 0.0020 | 0.0020 | 0.0024 | 0.0020 | 0.0020 |
| | | | | | (−0.13) | (−0.13) | (−0.13) | (0.45) | (0.49) | (0.49) | (0.61) | (0.51) | (0.49) |
| Vol | | | | | | 0.0280 | −0.0632 | −0.0687 | −0.0744 | −0.0729 | −0.0751 | −0.0746 | −0.0743 |
| | | | | | | (1.40) | (−1.13) | (−1.22) | (−1.32) | (−1.29) | (−1.34) | (−1.33) | (−1.32) |
| Ivol | | | | | | −0.0341* | −0.0324 | −0.0551*** | −0.0516** | −0.0513** | −0.0483** | −0.0514** | −0.0513** |
| | | | | | | (−1.65) | (−1.58) | (−2.62) | (−2.43) | (−2.42) | (−2.30) | (−2.41) | (−2.42) |
| Max | | | | | | | 0.0320 | 0.0359* | 0.0343* | 0.0507** | 0.0352* | 0.0344* | 0.0342* |
| | | | | | | | (1.60) | (1.77) | (1.69) | (2.23) | (1.75) | (1.71) | (1.68) |
| Min | | | | | | | 0.0302 | 0.0331 | 0.0334 | 0.0161 | 0.0323 | 0.0334 | 0.0335 |
| | | | | | | | (1.40) | (1.54) | (1.56) | (0.67) | (1.50) | (1.56) | (1.56) |
| PTV | | | | | | | | −0.1936* | −0.1961* | −0.1959* | −0.1634 | −0.1936* | −0.1954* |
| | | | | | | | | (−1.87) | (−1.90) | (−1.89) | (−1.46) | (−1.72) | (−1.89) |
| Volume | | | | | | | | | −0.0029 | −0.0030 | −0.0032 | −0.0029 | −0.0030 |
| | | | | | | | | | (−1.14) | (−1.17) | (−1.26) | (−1.14) | (−1.17) |
| StdVolume | | | | | | | | | 0.0062* | 0.0064** | 0.0065** | 0.0063* | 0.0063** |
| | | | | | | | | | (1.96) | (1.97) | (1.99) | (1.96) | (1.98) |
| Skew1 | | | | | | | | | | −0.0070 | | | |
| | | | | | | | | | | (−1.46) | | | |
| Skew2 | | | | | | | | | | | −0.0106 | | |
| | | | | | | | | | | | (−1.39) | | |
| Iskew | | | | | | | | | | | | −0.0011 | |
| | | | | | | | | | | | | (−0.20) | |
| Coskew | | | | | | | | | | | | | −0.0023 |
| | | | | | | | | | | | | | (−1.04) |
| Crypto FEs | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Week FEs | No | No | No | No | No | No | No | No | No | No | No | No | No |
| Adj. R-squared | 0.0010 | 0.0139 | 0.0988 | 0.0989 | 0.0987 | 0.0987 | 0.0987 | 0.1010 | 0.1014 | 0.1015 | 0.1017 | 0.1014 | 0.1014 |
| N | 140,901 | 135,321 | 135,321 | 134,945 | 134,710 | 134,416 | 134,416 | 134,415 | 134,312 | 134,287 | 134,308 | 134,312 | 134,312 |

This table displays the estimates generated by panel regressions with cryptocurrency FE and a varying set of controls. In all specifications, the dependent variable measures a cryptocurrency's one-week-ahead excess return. The t-statistics in parentheses are based on standard errors clustered by cryptocurrency and week. *STV* is the salience theory value of a cryptocurrency's historical daily return distribution from week t-4 to t-1. The remaining variables are defined in Table 2. The sample period is from January 2, 2015 to June 25, 2021. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

**Table 7**
Panel regressions: Two-dimensional relationship between *STV* and future cryptocurrency returns.

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) | (13) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| STV | −0.1905*** | −0.1565*** | −0.0222** | −0.0190** | −0.0206** | −0.0215** | −0.0246*** | −0.0229** | −0.0235*** | −0.0237*** | −0.0230** | −0.0234** | −0.0235*** |
| | (−19.75) | (−15.89) | (−2.57) | (−2.19) | (−2.36) | (−2.45) | (−2.70) | (−2.50) | (−2.59) | (−2.60) | (−2.54) | (−2.58) | (−2.59) |
| Size | | −0.0521*** | −0.0294*** | −0.0289*** | −0.0268*** | −0.0274*** | −0.0275*** | −0.0242*** | −0.0258*** | −0.0258*** | −0.0256*** | −0.0257*** | −0.0258*** |
| | | (−15.42) | (−11.93) | (−11.93) | (−10.88) | (−11.08) | (−11.15) | (−10.24) | (−10.25) | (−10.28) | (−10.18) | (−10.24) | (−10.25) |
| Mom | | 0.0050 | −0.0991*** | −0.0992*** | −0.1006*** | −0.0997*** | −0.0994*** | −0.0976*** | −0.0979*** | −0.0979*** | −0.0978*** | −0.0978*** | −0.0979*** |
| | | (1.39) | (−20.69) | (−20.98) | (−21.05) | (−20.69) | (−20.67) | (−20.35) | (−20.45) | (−20.46) | (−20.45) | (−20.48) | (−20.45) |
| Rev | | | −0.3469*** | −0.3470*** | −0.3481*** | −0.3476*** | −0.3526*** | −0.3500*** | −0.3501*** | −0.3513*** | −0.3501*** | −0.3500*** | −0.3501*** |
| | | | (−43.42) | (−43.44) | (−43.44) | (−43.03) | (−37.38) | (−37.10) | (−37.06) | (−35.41) | (−37.08) | (−37.07) | (−37.06) |
| Illiq | | | | 0.0012** | 0.0012** | 0.0012** | 0.0012** | 0.0012** | 0.0012*** | 0.0012*** | 0.0012*** | 0.0012*** | 0.0012*** |
| | | | | (2.57) | (2.49) | (2.54) | (2.55) | (2.46) | (2.62) | (2.63) | (2.63) | (2.62) | (2.62) |
| Lt_rev | | | | | −0.0053*** | −0.0056*** | −0.0056*** | −0.0022* | −0.0021 | −0.0021 | −0.0020 | −0.0021 | −0.0021 |
| | | | | | (−4.64) | (−4.77) | (−4.79) | (−1.69) | (−1.61) | (−1.58) | (−1.50) | (−1.60) | (−1.60) |
| Vol | | | | | | 0.0083 | −0.0833* | −0.0877* | −0.0905* | −0.0901* | −0.0905* | −0.0906* | −0.0905* |
| | | | | | | (0.70) | (−1.79) | (−1.87) | (−1.93) | (−1.93) | (−1.94) | (−1.94) | (−1.93) |
| Ivol | | | | | | −0.0522*** | −0.0506*** | −0.0624*** | −0.0605*** | −0.0604*** | −0.0583*** | −0.0600*** | −0.0605*** |
| | | | | | | (−3.93) | (−3.84) | (−4.76) | (−4.70) | (−4.69) | (−4.59) | (−4.67) | (−4.70) |
| Max | | | | | | | 0.0432** | 0.0458*** | 0.0445** | 0.0486** | 0.0446** | 0.0446** | 0.0445** |
| | | | | | | | (2.48) | (2.62) | (2.54) | (2.48) | (2.56) | (2.55) | (2.54) |
| Min | | | | | | | 0.0193 | 0.0210 | 0.0211 | 0.0167 | 0.0207 | 0.0210 | 0.0211 |
| | | | | | | | (1.06) | (1.15) | (1.15) | (0.84) | (1.14) | (1.15) | (1.15) |
| PTV | | | | | | | | −0.1477*** | −0.1488*** | −0.1486*** | −0.1340*** | −0.1440*** | −0.1485*** |
| | | | | | | | | (−5.60) | (−5.59) | (−5.58) | (−4.91) | (−5.22) | (−5.58) |
| Volume | | | | | | | | | −0.0024 | −0.0024 | −0.0024* | −0.0024 | −0.0024 |
| | | | | | | | | | (−1.61) | (−1.61) | (−1.65) | (−1.61) | (−1.62) |
| StdVolume | | | | | | | | | 0.0043*** | 0.0043*** | 0.0043*** | 0.0043*** | 0.0043*** |
| | | | | | | | | | (2.64) | (2.65) | (2.65) | (2.64) | (2.65) |
| Skew1 | | | | | | | | | | −0.0018 | | | |
| | | | | | | | | | | (−0.69) | | | |
| Skew2 | | | | | | | | | | | −0.0038 | | |
| | | | | | | | | | | | (−1.37) | | |
| Iskew | | | | | | | | | | | | −0.0013 | |
| | | | | | | | | | | | | (−0.50) | |
| Coskew | | | | | | | | | | | | | −0.0005 |
| | | | | | | | | | | | | | (−0.52) |
| Crypto FEs | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Week FEs | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Adj. R-squared | 0.1232 | 0.1421 | 0.2306 | 0.2312 | 0.2316 | 0.2320 | 0.2321 | 0.2327 | 0.2329 | 0.2329 | 0.2329 | 0.2329 | 0.2329 |
| N | 140,901 | 135,321 | 135,321 | 134,945 | 134,710 | 134,416 | 134,416 | 134,415 | 134,312 | 134,287 | 134,308 | 134,312 | 134,312 |

This table displays the estimates generated by panel regressions with cryptocurrency FE, week FE, and a varying set of controls. In all specifications, the dependent variable measures a cryptocurrency's one-week-ahead excess return. The t-statistics in parentheses are based on standard errors clustered by cryptocurrency and week. *STV* is the salience theory value of a cryptocurrency's historical daily return distribution from week t-4 to t-1. The remaining variables are defined in Table 2. The sample period is from January 2, 2015 to June 25, 2021. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

To shed further light on this issue, we re-calculate the *STV* variable using daily returns from week t-5 to t-2 (i.e., we skip the previous week's return) and re-estimate our panel regressions accordingly. The coefficient on *STV* remains negative and statistically significant (see Table A4 in the Online Appendix). Therefore, we conclude that, in the cryptocurrency market, the predictive power of ST cannot be fully explained by the short-term reversal effect.

### 6.5. Analysis by size segment

Since the results of our bivariate portfolio analysis suggest that the ST effect is stronger for EW (cf. VW) long-short portfolios, we want to examine further whether this effect is pervasive or limited to certain size segments of the market. We begin by following Hou, Xue, and Zhang (2020) and Cakici and Zaremba (2021) and estimating our panel regression equations by weighted least squares (WLS), where the weights are given by the market capitalisation of a cryptocurrency relative to total market capitalisation at the end of each week. The estimates show that the coefficient on *STV* gradually becomes statistically insignificant as more control variables are added to the equation (see Table A5 in the Online Appendix). This supports the results of our bivariate portfolio analysis and suggests that the ST effect is mainly driven by smaller cryptocurrencies.

However, to formally test whether the predictive power of ST is stronger among micro-cap cryptocurrencies (*H3*), we need to properly allocate cryptocurrencies to different size groups at the end of each week in the sample period. Since there is no clear consensus in the cryptocurrency literature regarding how to do this, we employ two alternative methods (see Table A6 in the Online Appendix). In the first classification, we follow Cakici and Zaremba (2021). Namely, we assume that the cryptocurrencies that account for the bottom 3% of total market capitalisation fall into the micro-cap group. The small-cap group consists of those cryptocurrencies that account for the next 7% of market capitalisation, and the large-cap group consists of those cryptocurrencies that account for the remaining 90% of total market capitalisation.

The second classification is based on the number of active cryptocurrencies. We rank all active cryptocurrencies by market capitalisation and assign the bottom 60% to the micro-cap group, the next 20% to the small-cap group, and the top 20% to the large-cap group. Based on this rule, the micro-cap group accounts for only about 0.45% of total market capitalisation in the average week.

We then re-estimate our panel regression equations with the inclusion of an interaction between *STV* and *Small* and an interaction between *STV* and *Large*, where *Small* (*Large*) is a dummy variable that takes the value of 1 when the cryptocurrency belongs to the small-cap (large-cap) group, and 0 otherwise. The results are displayed in Table 8, where the estimates in the odd (even) columns are obtained by including (excluding) Bitcoin in (from) the sample. In columns 1–4, the coefficient on *STV* is negative and statistically significant at the 1% level, indicating that, among micro-cap cryptocurrencies, there is strong evidence of a negative relationship between *STV* and future returns. Conversely, among small- and large-cap cryptocurrencies, there is no evidence of an ST effect, as the corresponding coefficients (*STV* + *STV*×*Small* and *STV* + *STV*×*Large*) are not statistically different from zero when Bitcoin is excluded. Furthermore, the coefficient on the interaction term *STV*×*Large* is positive and statistically different from zero at conventional levels, providing evidence that the ST effect is stronger among micro-cap cryptocurrencies (cf. large-cap cryptocurrencies). Therefore, the results are consistent with our expectations and supports *H3*.

The estimates displayed in Table 8 also help us shed light on the progressive disappearance of the ST effect in the US stock market during the past few decades (Cakici & Zaremba, 2021). If the ST effect is mainly driven by the behaviour of unsophisticated individual investors, like the ones who likely populate the micro-cap segment of the cryptocurrency market, then a shift in the composition of the investor population, from retail to institutional, should be accompanied by a diminishing ST effect. Indeed, while individual investors clearly dominated the US stock market until the 1970s, starting from the 1980s the share of stock market capitalisation held by retail investors has gradually decreased (Gompers & Metrick, 2001). Since the middle of the 1990s, institutions have been dominating this market (Ben-David et al., 2021). While ours is not a formal statistical test, our data are consistent with the above interpretation. We leave it to future research to explore this phenomenon in greater depth.

**Table 8**
ST effect by size segment: Micro-cap, small-cap, and large-cap.

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Allocation based on: | Market cap (3%, 7%, 90%) | Market cap (3%, 7%, 90%) | # of cryptos (60%, 20%, 20%) | # of cryptos (60%, 20%, 20%) |
| STV | −0.0343*** | −0.0346*** | −0.0352*** | −0.0353*** |
| | (−3.70) | (−3.73) | (−3.52) | (−3.53) |
| STV × Small | 0.0448 | 0.0497 | 0.0080 | 0.0098 |
| | (1.29) | (1.55) | (0.31) | (0.37) |
| STV × Large | 0.1159** | 0.1029** | 0.0814** | 0.0793** |
| | (2.49) | (2.27) | (2.18) | (2.14) |
| Small | −0.0074* | −0.0068 | −0.0238*** | −0.0234*** |
| | (−1.85) | (−1.64) | (−5.44) | (−5.36) |
| Large | −0.0025 | −0.0031 | −0.0328*** | −0.0328*** |
| | (−0.34) | (−0.42) | (−4.44) | (−4.47) |
| STV + STV × Small | 0.0105 | 0.0150 | −0.0273 | −0.0256 |
| P-value | 0.755 | 0.628 | 0.246 | 0.289 |
| STV + STV × Large | 0.0816* | 0.0683 | 0.0462 | 0.0439 |
| P-value | 0.074 | 0.122 | 0.187 | 0.203 |
| Bitcoin included | Yes | No | Yes | No |
| Crypto FEs | Yes | Yes | Yes | Yes |
| Week FEs | Yes | Yes | Yes | Yes |
| Adj. R-squared | 0.2304 | 0.2304 | 0.2307 | 0.2306 |
| N | 134,415 | 134,076 | 134,415 | 134,076 |

This table presents the estimates generated by panel regressions with cryptocurrency FE and week FE. In all specifications, the dependent variable measures a cryptocurrency's one-week-ahead excess return. In the odd (even) columns, Bitcoin is included in (excluded from) the sample. In columns 1–2, cryptocurrencies are allocated to size segments by market capitalisation: The micro-cap (small-cap, large-cap) segment consists of those cryptocurrencies that account for the bottom 3% (middle 7%, top 90%) of market capitalisation at the end of each week. In columns 3–4, they are allocated to size segments by number of active cryptocurrencies: At the end of each week, we rank all active cryptocurrencies by market capitalisation and assign the bottom 60% to the micro-cap group, the next 20% to the small-cap group, and the top 20% to the large-cap group. *STV* is the salience theory value of a cryptocurrency's historical daily return distribution from week t-4 to t-1. *Small* (*Large*) is a dummy variable that takes value of 1 if a cryptocurrency falls into the small-cap (large-cap) segment, and 0 otherwise. Each regression equation includes the following controls: *Mom*, *Rev*, *Illiq*, *Lt_rev*, *Vol*, *Ivol*, *Max*, *Min*, and *PTV*, which are defined in Table 2. The sample period is from January 2, 2015 to June 25, 2021. The t-statistics in parentheses are based on standard errors clustered by cryptocurrency and week. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

### 6.6. Is the ST effect moderated by limits to arbitrage?

We conjecture that the mispricings caused by salient thinkers cannot be fully eliminated by arbitrageurs when there are constraints that limit arbitrage activity. Thus, we expect the predictive power of ST to be stronger among cryptocurrencies that are more difficult to arbitrage (*H4*). To test this hypothesis, we follow the existing literature (Lam & Wei, 2011; Zhang, 2006) and employ six individual proxies for limits to arbitrage: Cryptocurrency age (*Age*), bid-ask spread (*BAS*), Amihud-illiquidity ratio (*Illiq*), idiosyncratic volatility (*Ivol*), market capitalisation (*Size*), and volatility (*Vol*). For each proxy, we re-estimate our preferred panel-regression specification after adding to the equation the proxy itself and an interaction between *STV* and the proxy.

Table 9 reports the results. The signs of the coefficients on the interaction terms *STV*×*Vol*, *STV*×*BAS*, and *STV*×*Ivol* are all negative, and the coefficients are statistically significant at the 1% level. Consistent with our expectations, this indicates that the ST effect has a stronger impact on the pricing of cryptocurrencies with higher volatility, higher bid-ask spread, and higher idiosyncratic volatility, which are more difficult to arbitrage. The coefficients on the interaction terms *STV*×*Size* and *STV*×*Age* have a positive sign, which is consistent with the view that information costs, and therefore arbitrage constraints, are lower for large-cap and well-established cryptocurrencies. However, they are not statistically different from zero. Lastly, in line with the belief that illiquid cryptocurrencies are harder to arbitrage, the sign of the coefficient on *STV*×*Illiq* is negative, but the coefficient itself is not statistically significant.

In a second test, we follow Stambaugh, Yu, and Yuan's (2015) approach and examine whether the predictive power of ST is stronger among cryptocurrencies that are more mispriced (i.e., either highly underpriced or highly overpriced). The rationale is that degree of mispricing and severity of limits to arbitrage are likely to go hand in hand. To measure a cryptocurrency's degree of mispricing, instead of relying on individual proxies that may be noisy, we construct an index using the control variables and the estimates that appear in column 8 of Table 7.[22] Each of these variables represents an anomaly documented in the literature. For example, the estimated coefficient on *Rev* (*Illiq*) is negative (positive), suggesting that cryptocurrencies with higher *Rev* (*Illiq*) values tend to earn lower (higher) subsequent returns, and consequently they can be thought of as being more overpriced (underpriced).

Therefore, at the end of each week, we first sort cryptocurrencies into quintiles on one of the nine anomaly variables (e.g., *Rev*). Quintile 1 (5) contains the cryptocurrencies that are most highly underpriced (overpriced). The higher the quintile in which a cryptocurrency falls, the higher the rank that we assign to it. We then repeat this procedure for each of the remaining anomaly variables and compute a cryptocurrency's composite rank as the sum of its individual ranks. The composite mispricing rank ranges from 9 (most underpriced) to 45 (most overpriced).

Subsequently, at the end of each week, we sort cryptocurrencies into quintiles by their composite rank. Next, we generate a corresponding set of dummy variables: *HighlyUnderpriced* (*Underpriced*, *Overpriced*, *HighlyOverpriced*) takes value of 1 when a cryptocurrency falls into quintile 1 (2, 4, 5), and 0 otherwise. The middle quintile, consisting of cryptocurrencies that are fairly priced relative to their peers, serves as the reference category. Lastly, we regress one-week-ahead cryptocurrency excess returns on *STV*, the set of dummies that we have just described, interactions between *STV* and these four dummies, *Size*, and cryptocurrency and week FE. Fig. 2 displays the point estimate and confidence interval of the ST effect for each of the five mispricing-based quintiles. An inverted U-shaped pattern is clearly visible. The more mispriced a cryptocurrency, in either direction, the greater the magnitude of the ST effect in absolute value. This pattern provides further evidence in support of *H4*.

Our setting also provides an opportunity for investigating the effects of arbitrage asymmetry. The literature on this topic contends that buying underpriced assets is easier than shorting overpriced ones (Lamont, 2012; Ofek, Richardson, & Whitelaw, 2004). Consistent with this argument, Stambaugh et al. (2015) find that "the negative IVOL effect among overpriced stocks is stronger than the positive effect among underpriced stocks". Following an analogous line of reasoning, one would expect the ST effect to be stronger among highly overpriced cryptocurrencies than among highly underpriced ones. Indeed, as Fig. 2 reveals, the difference in point estimates between highly overpriced and highly underpriced cryptocurrencies is negative (−0.0340), but there is not enough statistical evidence to reject the null hypothesis of no difference ($p$-value = 0.358).

### 6.7. Sensitivity analyses

An important question is whether our main results are sensitive to the sample period or to the methodology used in quantifying the ST value of a cryptocurrency. To address these concerns, we perform several sensitivity tests.[23] First, to examine the stability of the coefficient of interest, we re-estimate our preferred panel-regression specification using a rolling-window approach. Specifically, we employ a fixed 2-year window that increments forward 13 weeks (3 months) for each iteration until the end of the sample period. Panel A of Fig. 3 plots the resulting point estimates of the coefficient on *STV* and their 95% and 99% confidence intervals. The estimated coefficient on *STV* is always negative. It is not surprising that the confidence intervals are fairly wide in the early part of the sample period as the number of active cryptocurrencies was quite small. Nevertheless, the point estimate is relatively stable over time, which reassures us that the effect that we have detected is not driven by an abnormal sub-sample of data.

In a second exercise, we investigate the sensitivity of our results to the length of the historical time window on which investors are assumed to focus when forming their expectations about the future distribution of a cryptocurrency's returns. First, we re-calculate the *STV* variable using alternative window lengths, from 1 week (i.e., week t-1) to 52 weeks (i.e., from week t-52 to week t-1). Next, for each window length, we re-estimate our preferred panel-regression specification, where our original *STV* variable is replaced by its modified version. Panel B of Fig. 3 plots the resulting point estimates of the coefficient on *STV* and their confidence intervals. With the exclusion of the shortest time windows (from 1 to 3 weeks in length), the figure reveals remarkable stability in the estimated size of the ST effect. It is also worth noting that, on average, the wider the historical time window used in the construction of the *STV* variable, the smaller the estimated size of the ST effect in absolute value. This is consistent with the findings of Cosemans and Frehen (2021) and Cakici and Zaremba (2021), suggesting that salient thinkers tend to focus on the recent past when extrapolating historical returns into the future.

In a third exercise, we explore whether our main results are sensitive to the values of the parameters that govern the salience of a cryptocurrency's payoff in Eq. 1 ($\theta$) and investors' degree of salience distortion in Eq. 2 ($\delta$). First, we re-calculate the *STV* variable using alternative values for $\theta$ and $\delta$, and then we re-estimate our preferred panel-regression specification accordingly. Since varying the value of $\theta$ (in the region from 0.05 to 0.3) has no material impact on our estimates, in Panel C of Fig. 3 we only display the output generated by varying the value of $\delta$ between 0.1 and 0.9, while keeping $\theta$ constant at 0.1. What emerges is that the estimated coefficient on *STV* is always negative, but it is statistically different from zero only when $\delta$ is between 0.5 and 0.9. This result is supported by Bordalo et al. (2012) experimental results, which show that the typical degree of salience distortion ($\delta$) is about 0.7.

In a fourth exercise, we examine whether our results are sensitive to our choice of the benchmark against which investors are assumed to assess the salience of a cryptocurrency's payoff. First, we re-calculate the *STV* variable using an alternative benchmark (i.e., zero, the risk-free rate, the time-series mean of the cryptocurrency's own returns, the value-weighted market index return, and Bitcoin's return), and then we re-estimate our preferred panel-regression specification accordingly. Panel D of Fig. 3 shows that the use of alternative reference points does

[22] We exclude *Size* because, as discussed in Section 6.5, there is evidence of an ST effect only among micro-cap cryptocurrencies.

[23] Note that the exclusion of Bitcoin from the sample does not alter our conclusions.

**Table 9**
Limits to arbitrage and ST effect.

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| STV | −0.0783 | −0.0393*** | 0.0369*** | −0.0267*** | 0.0086 | 0.0329** |
| | (−1.47) | (−2.16) | (2.72) | (−2.94) | (0.55) | (1.98) |
| STV × Size | 0.0041 | | | | | |
| | (1.00) | | | | | |
| STV × Age | | 0.0001 | | | | |
| | | (0.79) | | | | |
| STV × Vol | | | −0.1107*** | | | |
| | | | (−5.41) | | | |
| STV × Illiq | | | | −0.0000 | | |
| | | | | (−0.03) | | |
| STV × BAS | | | | | −0.0839*** | |
| | | | | | (−2.59) | |
| STV × Ivol | | | | | | −0.0955*** |
| | | | | | | (−3.70) |
| Size | −0.0243*** | −0.0243*** | −0.0245*** | −0.0242*** | −0.0244*** | −0.0243*** |
| | (−10.51) | (−10.53) | (−10.71) | (−10.51) | (−10.64) | (−10.53) |
| Illiq | 0.0011** | 0.0011** | 0.0011** | 0.0011** | 0.0011** | 0.0011** |
| | (2.02) | (2.08) | (2.07) | (2.23) | (2.06) | (2.03) |
| Vol | −0.0734 | −0.0728 | −0.0756 | −0.0728 | −0.0710 | −0.0712 |
| | (−1.46) | (−1.45) | (−1.52) | (−1.45) | (−1.42) | (−1.42) |
| Ivol | −0.0547* | −0.0513* | −0.0554* | −0.0516* | −0.0540* | −0.0582* |
| | (−1.74) | (−1.66) | (−1.80) | (−1.67) | (−1.74) | (−1.89) |
| BAS | −0.0109 | −0.0141 | −0.0116 | −0.0141 | −0.0135 | −0.0095 |
| | (−0.31) | (−0.41) | (−0.33) | (−0.40) | (−0.38) | (−0.27) |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Crypto FEs | Yes | Yes | Yes | Yes | Yes | Yes |
| Week FEs | Yes | Yes | Yes | Yes | Yes | Yes |
| Adj. R-squared | 0.2353 | 0.2353 | 0.2359 | 0.2353 | 0.2354 | 0.2355 |
| N | 131,359 | 131,359 | 131,359 | 131,359 | 131,359 | 131,359 |

This table presents the estimates generated by panel regressions with cryptocurrency FE and week FE. *STV* is the salience theory value of a cryptocurrency's historical daily return distribution from week t-4 to t-1. *Age* measures the number of weeks since a cryptocurrency entered our data set. *BAS* is Novy-Marx and Velikov's (2016) measure of bid-ask spread, which is the squared root of the negative covariance between 1-day lagged and 2-day lagged cryptocurrency returns from week t-4 to week t-1. The remaining variables are as defined in Table 2. Each regression equation includes the following controls: *Mom*, *Rev*, *Lt_rev*, *Max*, *Min*, and *PTV*, which are defined in Table 2. The sample period is from January 2, 2015 to June 25, 2021. The t-statistics in parentheses are based on standard errors clustered by cryptocurrency and week. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

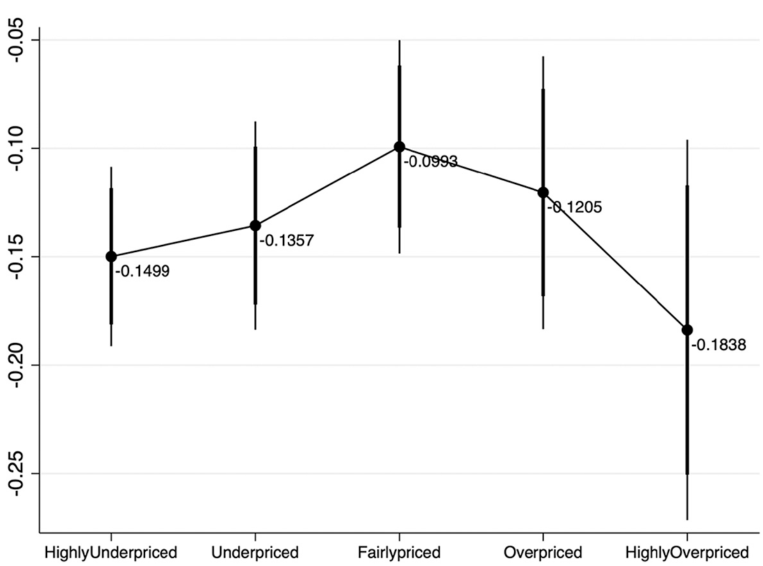


**Fig. 2.** Mispricing and ST effect.
This figure plots the point estimates and the 95% and 99% confidence intervals of the ST effect for each of five mispricing-based quintiles, namely "HighlyUnderpriced", "Underpriced", "Fairlypriced", "Overpriced", and "HighlyOverpriced". At the end of each week, we first sort cryptocurrencies into quintiles on one of the nine anomaly variables (e.g., *Rev*). Quintile 1 (5) contains the cryptocurrencies that are most highly underpriced (overpriced). The higher the quintile in which a cryptocurrency falls, the higher the rank that we assign to it. We then repeat this procedure for each of the remaining anomaly variables (*Mom, Lt_rev, Vol, Ivol, PTV, Illiq, Max, Min*) and compute a cryptocurrency's composite rank as the sum of its individual ranks. The composite mispricing rank ranges from 9 (most underpriced) to 45 (most overpriced). Subsequently, at the end of each week, we sort cryptocurrencies into quintiles by their composite rank. Next, we generate a corresponding set of dummy variables: *HighlyUnderpriced* (*Underpriced*, *Overpriced*, *HighlyOverpriced*) takes value of 1 when a cryptocurrency falls into quintile 1 (2, 4, 5), and 0 otherwise. The middle quintile, consisting of cryptocurrencies that are fairly priced relative to their peers, serves as the reference category. Lastly, we regress one-week-ahead cryptocurrency excess returns on *STV*, the set of dummies that we have just described, interactions between *STV* and these four dummies, *Size*, and cryptocurrency and week FE. The sample period is from January 2, 2015 to June 25, 2021. The confidence intervals are based on standard errors clustered by cryptocurrency and week.

not alter our conclusions.

Lastly, to investigate whether the ST effect is pervasive across cryptocurrency sectors, we re-estimate our preferred panel-regression specification individually for each sector (e.g., Proof of Stake, Privacy coins, etc). The estimated coefficient on *STV* is negative *and* statistically different from zero for 2 out of 13 sectors, which is not surprising considering that, for most sectors, the number of available cryptocurrencies and observations is very small (see Table A7 in the Online Appendix). Nevertheless, the sign of the coefficient is negative for 11 out of 13 sectors, which supports the interpretation that the ST effect is a general phenomenon that is neither confined to a single cryptocurrency sector nor driven by a specific sub-sample of data.

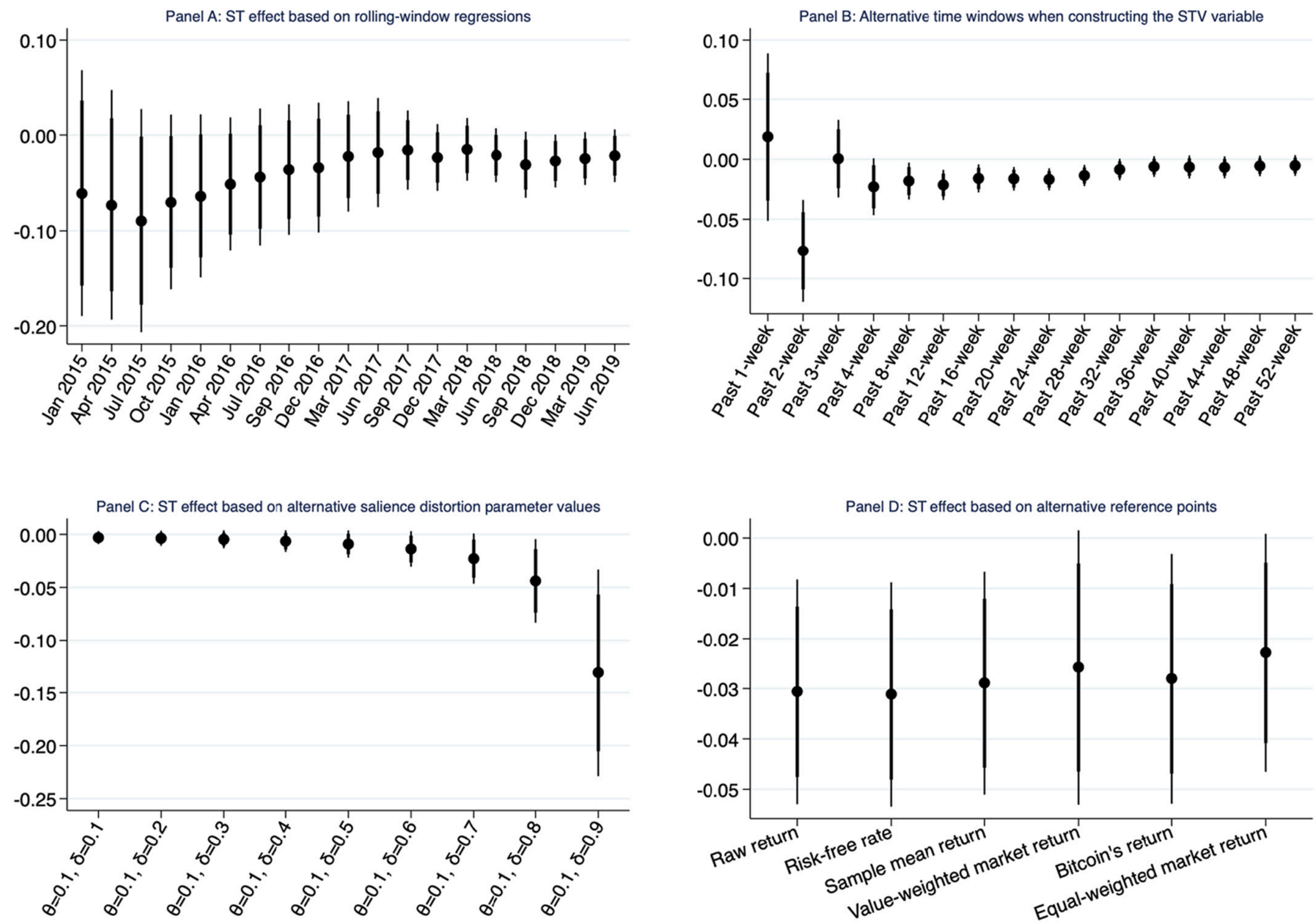


**Fig. 3.** Sensitivity tests.
This figure plots the point estimates and the 95% and 99% confidence intervals of the coefficient on *STV* from a number of sensitivity tests. All estimates are based on panel regressions with cryptocurrency FE and week FE. The dependent variable measures a cryptocurrency's one-week-ahead excess return. *STV* is the salience theory value of a cryptocurrency's historical daily return distribution. The control variables are *Size*, *Mom*, *Rev*, *Illiq*, *Lt_rev*, *Vol*, *Ivol*, *Max*, *Min,* and *PTV*, which are defined in Table 2. In Panel A, the estimates are generated by rolling-window regressions. The fixed window is 104 weeks (2 years) in length and increments forward 13 weeks (3 months) for each iteration. The labels on the x-axis refer to the start of the rolling window. For example, "Jun 2019" indicates that the last regression is based on data from the end of June 2019 to the end of June 2021. In Panel B, to construct the *STV* variable, we use historical time windows of varying length, from 1 week to 52 weeks. For example, the "Past 8-week" label on the x-axis indicates that we measure the ST value of a cryptocurrency based on its historical daily return distribution from week t-8 to t-1. In Panel C, we use alternative salience distortion parameter values when measuring a cryptocurrency's ST value. Holding $\theta$ constant at 0.1, we let $\delta$ vary between 0.1 and 0.9. In Panel D, we use alternative reference points when measuring a cryptocurrency's ST value, where the reference point refers to the benchmark against which investors are assumed to evaluate the salience of a cryptocurrency's payoffs. The "Raw return" label indicates that investors are assumed to evaluate a cryptocurrency's return against a zero-return, i.e., they simply focus on the cryptocurrency's raw return. The other reference points are the risk-free rate of return, the cryptocurrency's own sample mean return, the return on the value-weighted cryptocurrency market index, and Bitcoin's return. The sample period is from January 2, 2015 to June 25, 2021. The confidence intervals are based on standard errors clustered by cryptocurrency and week.

## 7. Conclusion

Various streams of literature suggest that objects of perception that stand out from their surroundings, i.e., salient objects, tend to attract the attention of our sensory channels. Our visual system is hardwired to detect objects that differ "in properties compared to the surrounding visual input" (Treue, 2003). And our auditory system has evolved to detect sounds that differ in intensity and spectral/temporal modulation from background noise (Kayser, Petkov, Lippert, & Logothetis, 2005).

However, only recently has the concept of salience begun to attract the interest of researchers in the fields of economics and finance. Bordalo, Gennaioli, and Shleifer (2012) propose a salience theory of decision-making according to which individuals pay more attention to an investment's most salient payoffs. In turn, this leads them to overweight the probabilities that these payoffs will occur. Bordalo et al. (2013a) take this theory a step further and predict that assets with salient upsides become overpriced because they are appealing to salient thinkers.

We test this prediction using a large data set from the cryptocurrency market. Our results provide empirical support for salience theory: We find that cryptocurrencies with salient upsides (i.e., high ST values) earn lower subsequent returns than cryptocurrencies with salient downsides (i.e., low ST values), suggesting that the former are overpriced relative to the latter. However, we detect this effect only among micro-cap cryptocurrencies, which account for a mere 3% of total market capitalisation and likely entail substantial transaction costs. While our findings are supportive of the theory and are valuable to our understanding of investor behaviour, from a practical perspective they indicate that the concrete implementation of investment strategies that try to exploit the salience bias in financial markets may be challenging for practitioners.

## CRediT authorship contribution statement

**Rongxin Chen:** Conceptualization, Data curation, Methodology, Formal analysis, Software, Visualization, Writing – original draft, Writing – review & editing. **Gabriele M. Lepori:** Conceptualization, Methodology, Formal analysis, Software, Writing – original draft, Writing – review & editing, Supervision. **Chung-Ching Tai:** Conceptualization, Methodology, Formal analysis, Writing – review & editing, Supervision. **Ming-Chien Sung:** Conceptualization, Methodology, Formal analysis, Writing – review & editing, Supervision.

## Declaration of Competing Interest

None.

## Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.irfa.2022.102419.

## References


Amihud, Y. (2002). Illiquidity and stock returns: Cross-section and time-series effects. *Journal of Financial Markets. North-Holland, 5*(1), 31–56. https://doi.org/10.1016/S1386-4181(01)00024-6

Ang, A., Hodrick, R., Xing, Y., & Zhang, X. (2006). The cross-section of volatility and expected returns. *The Journal of Finance, 61*(1), 259–299. https://doi.org/10.1111/j.1540-6261.2006.00836.x. John Wiley & Sons, Ltd.

Arellano, M., & Bond, S. (1991). Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. *Review of Economic Studies, 58*(2), 277–297. https://doi.org/10.2307/2297968. Oxford Academic.

Bali, T. G., Cakici, N., & Whitelaw, R. F. (2011). Maxing out: Stocks as lotteries and the cross-section of expected returns. *Journal of Financial Economics, 99*(2), 427–446. https://doi.org/10.1016/j.jfineco.2010.08.014. North-Holland.

Barberis, N., Mukherjee, A., & Wang, B. (2016). Prospect theory and stock returns: An empirical test. *The Review of Financial Studies, 29*(11), 3068–3107. https://doi.org/10.1093/rfs/hhw049. Elsevier BV.

Bar-Hillel, M., & Fischhoff, B. (1981). When do base rates affect predictions? *Journal of Personality and Social Psychology, 41*(4), 671–680. https://doi.org/10.1037/0022-3514.41.4.671. American Psychological Association Inc.

Ben-David, I., Franzoni, F., Moussawi, R., & Sedunov, J. (2021). The granular nature of large institutional investors. *Management Science, 67*(11), 6629–6659. https://doi.org/10.1287/MNSC.2020.3808. INFORMS.

Benedetti, H., & Nikbakht, E. (2021). Returns and network growth of digital tokens after cross-listings. *Journal of Corporate Finance. Elsevier B.V., 66*, Article 101853. https://doi.org/10.1016/j.jcorpfin.2020.101853

Berger, L. A. (1996). Mutual understanding, the state of attention, and the ground for interaction in economic systems. *Business Ethics Quarterly, 6*(1), 1–25. https://doi.org/10.2307/3857238. Cambridge University Press.

Bianchi, D., & Dickerson, A. (2021). Trading volume in cryptocurrency markets. *SSRN Electronic Journal*. https://doi.org/10.2139/SSRN.3239670. Elsevier BV.

Bordalo, P., Gennaioli, N., & Shleifer, A. (2012). Salience theory of choice under risk. *Quarterly Journal of Economics, 127*(3), 1243–1285. https://doi.org/10.1093/qje/qjs018. Oxford Academic.

Bordalo, P., Gennaioli, N., & Shleifer, A. (2013a). Salience and asset prices. *American Economic Review, 103*(3), 623–628. https://doi.org/10.1257/AER.103.3.623

Bordalo, P., Gennaioli, N., & Shleifer, A. (2013b). Salience and consumer choice. *Journal of Political Economy, 121*(5), 803–843. https://doi.org/10.1086/673885

Bordalo, P., Gennaioli, N., & Shleifer, A. (2015). Salience theory of judicial decisions. *The Journal of Legal Studies, 44*(S1), S7–S33. https://doi.org/10.1086/676007. University of Chicago Press.

Cai, C. X., & Zhao, R. (2022). Salience theory and cryptocurrency returns. *SSRN Electronic Journal*. https://doi.org/10.2139/SSRN.3983602

Cakici, N., & Zaremba, A. (2021). Salience theory and the cross-section of stock returns: International and further evidence. *Journal of Financial Economics*. https://doi.org/10.1016/J.JFINECO.2021.10.010. North-Holland.

Chan, Q., Ding, W., Lin, C., & Rossi, A. G. (2021). An inside look into cryptocurrency exchanges. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3759062. Elsevier BV.

Chen, R., Lepori, G. M., Tai, C.-C., & Sung, M.-C. (2022). Explaining cryptocurrency returns: A prospect theory perspective. *Journal of International Financial Markets, Institutions and Money, 79*, 101599. https://doi.org/10.1016/J.INTFIN.2022.101599. North-Holland.

Choi, D., Lou, D. and Mukherjee, A. (2022) "Superstar firms and college major choice", SSRN. Available at: *https://papers.ssrn.com/sol3/papers.cfm?abstract{_}id=2845711*.

Cong, L. W., Li, Y., & Wang, N. (2021). Tokenomics: Dynamic adoption and valuation. *The Review of Financial Studies, 34*, 1105–1155. https://doi.org/10.1093/rfs/hhaa089

Cosemans, M., & Frehen, R. (2021). Salience theory and stock prices: Empirical evidence. *Journal of Financial Economics, 140*(2), 460–483. https://doi.org/10.1016/j.jfineco.2020.12.012. Elsevier B.V.

Da, Z., Huang, X., & Jin, L. J. (2021). Extrapolative beliefs in the cross-section: What can we learn from the crowds? *Journal of Financial Economics, 140*(1), 175–196. https://doi.org/10.1016/J.JFINECO.2020.10.003. North-Holland.

Dertwinkel-Kalt, M., & Köster, M. (2020). Salience and Skewness Preferences. *Journal of the European Economic Association, 18*(5), 2057–2107. https://doi.org/10.1093/JEEA/JVZ035. Oxford Academic.

Dessaint, O., & Matray, A. (2017). Do managers overreact to salient risks? Evidence from hurricane strikes. *Journal of Financial Economics, 126*(1), 97–121. https://doi.org/10.1016/J.JFINECO.2017.07.002. Elsevier B.V.

Dimmock, S. G., Kouwenberg, R., Mitchell, O. S., & Peijnenburg, K. (2021). Household portfolio Underdiversification and probability weighting: Evidence from the field. *The Review of Financial Studies, 34*(9), 4524–4563. https://doi.org/10.1093/RFS/HHAA131. Oxford Academic.

Elendner, H., Trimborn, S., Ong, B., & Lee, T. M. (2017). The cross-section of crypto-currencies as financial assets: Investing in crypto-currencies beyond bitcoin. In *Handbook of blockchain, digital finance, and inclusion, volume 1: Cryptocurrency, FinTech, InsurTech, and regulation* (pp. 145–173). Elsevier Inc.. https://doi.org/10.1016/B978-0-12-810441-5.00007-5

Eysenck, M. W. (1982). *Attention and arousal*. Berlin Heidelberg: Springer. https://doi.org/10.1007/978-3-642-68390-9

Fama, E. F. (1998). Market efficiency, long-term returns, and behavioral finance. *Journal of Financial Economics, 49*(3), 283–306. https://doi.org/10.1016/s0304-405x(98)00026-9. Elsevier.

Feng, L., & Seasholes, M. S. (2005). Do investor sophistication and trading experience eliminate behavioral biases in financial markets? *Review of Finance, 9*(3), 305–351. https://doi.org/10.1007/S10679-005-2262-0. Oxford Academic.

Frydman, C., & Wang, B. (2020). The impact of salience on investor behavior: Evidence from a natural experiment. *The Journal of Finance, 75*(1), 229–276. https://doi.org/10.1111/JOFI.12851. John Wiley & Sons, Ltd.

Gompers, P. A., & Metrick, A. (2001). Institutional investors and equity prices. *The Quarterly Journal of Economics, 116*(1), 229–259. https://doi.org/10.1162/003355301556392. Oxford Academic.

Gordon, M. J., & Shapiro, E. (1956). Capital equipment analysis: The required rate of profit. *Management Science, 3*(1), 102–110. https://doi.org/10.1287/MNSC.3.1.102. INFORMS.

Gow, I. D., Ormazabal, G., & Taylor, D. J. (2010). Correcting for cross-sectional and time-series dependence in accounting research. *Accounting Review, 85*(2), 483–512. https://doi.org/10.2308/accr.2010.85.2.483

Graffeo, E. (2021). 78% of institutional investors are not planning on investing in cryptocurrencies, though a majority say crypto is 'here to stay,'JPMorgan survey finds. *JPMorgan survey finds*. Available at: https://markets.businessinsider.com/news/currencies/cryptocurrency-news-bitcoin-price-institutional-interest-investors-jpmorgan-sentiment-bullish-2021-3 (Accessed: September 18, 2021).

Grether, D. M. (1980). Bayes rule as a descriptive model: The representativeness heuristic. *The Quarterly Journal of Economics, 95*(3), 537–557. https://doi.org/10.2307/1885092. Oxford Academic.

Grobys, K., Ahmed, S., & Sapkota, N. (2020). Technical trading rules in the cryptocurrency market. *Finance Research Letters, 32*, 101396. https://doi.org/10.1016/J.FRL.2019.101396. Elsevier.

Grobys, K., & Junttila, J. (2021). Speculation and lottery-like demand in cryptocurrency markets. *Journal of International Financial Markets, Institutions and Money, 71*, 101289. https://doi.org/10.1016/j.intfin.2021.101289. Elsevier BV.

Hamill, R., Wilson, T. D., & Nisbett, R. E. (1980). Insensitivity to sample bias: Generalizing from atypical cases. *Journal of Personality and Social Psychology, 39*(4), 578–589. https://doi.org/10.1037/0022-3514.39.4.578. American Psychological Association Inc.

Hansen, S. (2018). Guide To Top Cryptocurrency Exchanges. Available at: *https://www.forbes.com/sites/sarahhansen/2018/06/20/forbes-guide-to-cryptocurrency-exchanges/?sh=6842e6a02572*.

Harvey, C., & Siddique, A. (2000). Conditional skewness in asset pricing tests. *The Journal of Finance, 55*(3), 1263–1295. https://doi.org/10.1111/0022-1082.00247. John Wiley & Sons, Ltd.

Hayes, A. S. (2017). Cryptocurrency value formation: An empirical study leading to a cost of production model for valuing bitcoin. *Telematics and Informatics, 34*(7), 1308–1321. https://doi.org/10.1016/J.TELE.2016.05.005. Pergamon.

Higgins, E. T. (1996). Knowledge activation: Activation, accessibility, applicability, and salience. In *Handbook of basic principles* (pp. 133–168). New York: The Guilford Press.

Hou, K., Xue, C., & Zhang, L. (2020). Replicating Anomalies. *Review of Financial Studies, 33*(5), 2019–2133. https://doi.org/10.1093/rfs/hhy131. Oxford University Press.

Hu, S., Xiang, C., & Quan, X. (2021). Attention, lottery, or salience? The impact of extreme payoffs on Chinese mutual fund flows. *SSRN Electronic Journal*. https://doi.org/10.2139/SSRN.3726918. Elsevier BV.

Itti, L., & Koch, C. (2000). A saliency-based search mechanism for overt and covert shifts of visual attention. *Vision Research, 40*(10–12), 1489–1506. https://doi.org/10.1016/S0042-6989(99)00163-7. Pergamon.

Jia, Y., Liu, Y., & Yan, S. (2021). Higher moments, extreme returns, and cross–section of cryptocurrency returns. *Finance Research Letters, 39*, 101536. https://doi.org/10.1016/j.frl.2020.101536. Elsevier Ltd.

Kahneman. (2012). *Thinking, Fast and Slow*. Penguin.

Kahneman, D., & Tversky, A. (1973). On the psychology of prediction. *Psychological Review, 80*(4), 237–251. https://doi.org/10.1037/H0034747

Kayser, C., Petkov, C. I., Lippert, M., & Logothetis, N. K. (2005). Mechanisms for allocating auditory attention: An auditory saliency map. *Current Biology, 15*(21), 1943–1947. https://doi.org/10.1016/J.CUB.2005.09.040. Cell Press.

Kropko, J., & Kubinec, R. (2020). Interpretation and identification of within-unit and cross-sectional variation in panel data models. *PLoS One, 15*(4), e0231349. https://doi.org/10.1371/journal.pone.0231349. Edited by T. Al-Ameri. Public library of science.

Lam, F. Y. E. C., & Wei, K. C. J. (2011). Limits-to-arbitrage, investment frictions, and the asset growth anomaly. *Journal of Financial Economics, 102*(1), 127–149. https://doi.org/10.1016/J.JFINECO.2011.03.024. North-Holland.

Lamont, O. A. (2012). Go down fighting: Short sellers vs. firms. *The Review of Asset Pricing Studies, 2*(1), 1–30. https://doi.org/10.1093/RAPSTU/RAS003. Oxford Academic.

Li, J., & Yi, G. (2019). Toward a factor structure in crypto asset returns. *Journal of Alternative Investment, 21*(4), 56–66. https://doi.org/10.3905/jai.2019.21.4.056. Portfolio Management Research.

Li, Y., Urquhart, A., Wang, P., & Zhang, W. (2021). MAX momentum in cryptocurrency markets. *International Review of Financial Analysis, 77*, 101829. https://doi.org/10.1016/J.IRFA.2021.101829. North-Holland.

Liu, W., Liang, X., & Cui, G. (2020). Common risk factors in the returns on cryptocurrencies. *Economic Modelling, 86*, 299–305. https://doi.org/10.1016/j.econmod.2019.09.035. Elsevier B.V.

Liu, Y., Sheng, J., & Wang, W. (2021). Technology and cryptocurrency valuation: Evidence from machine learning. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3577208. Available at:.

Liu, Y., Tsyvinski, A., & Wu, X. I. (2022). Common risk factors in cryptocurrency. *The Journal of Finance*. https://doi.org/10.1111/JOFI.13119. John Wiley & Sons, Ltd.

Liu, Y. J., Wang, M. C., & Zhao, L. (2010). Narrow framing: Professions, sophistication, and experience. *Journal of Futures Markets, 30*(3), 203–229. https://doi.org/10.1002/FUT.20407. John Wiley & Sons, Ltd.

Luther, W. J., & Smith, S. S. (2020). Is bitcoin a decentralized payment mechanism? *Journal of Institutional Economics, 16*(4), 433–444. https://doi.org/10.1017/S1744137420000107. Cambridge University Press.

Madsen, J., & Niessner, M. (2019). Is investor attention for Sale? The role of advertising in financial markets. *Journal of Accounting Research, 57*(3), 763–795. https://doi.org/10.1111/1475-679X.12257. Blackwell Publishing Ltd.

Maese, V. A., Avery, A. W., Naftalis, B. A., Wink, S. P., & Valdez, Y. D. (2016). Cryptocurrency: A primer. *Banking Law Journal, 133*(8), 468–471.

March, J. G. (1982). Theories of choice and making decisions. *Society, 20*(1), 29–39. https://doi.org/10.1007/BF02694989. Springer.

Miller, M. H., & Modigliani, F. (1961). Dividend policy, growth, and the valuation of shares. *The Journal of Business, 34*(4), 411. https://doi.org/10.1086/294442. University of Chicago Press.

Mummolo, J., & Peterson, E. (2018). Improving the interpretation of fixed effects regression results. *Political Science Research and Methods, 6*(4), 829–835. https://doi.org/10.1017/psrm.2017.44. Cambridge University Press.

Nisbett, R. E., & Borgida, E. (1975). Attribution and the psychology of prediction. *Journal of Personality and Social Psychology, 32*(5), 932–943. https://doi.org/10.1037/0022-3514.32.5.932. American Psychological Association (APA).

Novy-Marx, R., & Velikov, M. (2016). A taxonomy of anomalies and their trading costs. *The Review of Financial Studies, 29*(1), 104–147. https://doi.org/10.1093/RFS/HHV063. Oxford Academic.

Odean, T. (1998). Volume, volatility, Price, and profit when all traders are above average. *The Journal of Finance, 53*(6), 1887–1934. https://doi.org/10.1111/0022-1082.00078. John Wiley & Sons, Ltd.

Ofek, E., Richardson, M., & Whitelaw, R. F. (2004). Limited arbitrage and short sales restrictions: Evidence from the options markets. *Journal of Financial Economics, 74*(2), 305–342. https://doi.org/10.1016/J.JFINECO.2003.05.008. North-Holland.

Panos, G. A., Karkkainen, T., & Atkinson, A. (2020). Financial literacy and attitudes to cryptocurrencies. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3482083. Elsevier BV.

Petersen, M. A. (2009). Estimating standard errors in finance panel data sets: Comparing approaches. *Review of Financial Studies, 22*(1), 435–480. https://doi.org/10.1093/rfs/hhn053. Oxford Academic.

Pontiff, J. (2006). Costly arbitrage and the myth of idiosyncratic risk. *Journal of Accounting and Economics. North-Holland, 42*(1–2), 35–52. https://doi.org/10.1016/J.JACCECO.2006.04.002

Shen, D., Urquhart, A., & Wang, P. (2020). A three-factor pricing model for cryptocurrencies. *Finance Research Letters, 34*, Article 101248. https://doi.org/10.1016/j.frl.2019.07.021

Shiller, R. J. (1999). Human behavior and the efficiency of the financial system. *Handbook of Macroeconomics, 1*(PART C), 1305–1340. https://doi.org/10.1016/S1574-0048(99)10033-8. Elsevier.

Shleifer, A., & Vishny, R. W. (1997). The limits of arbitrage. *Journal of Finance, 52*(1), 35–55. https://doi.org/10.1111/j.1540-6261.1997.tb03807.x. Blackwell Publishing Inc.

Simon, H. A. (1978). Rationality as process and as product of thought. *American Economic Review, 68*(2), 58–77. https://doi.org/10.1017/CBO9780511598951.005

Stambaugh, R. F., Yu, J., & Yuan, Y. (2015). Arbitrage asymmetry and the idiosyncratic volatility puzzle. *The Journal of Finance, 70*(5), 1903–1948. https://doi.org/10.1111/JOFI.12286. John Wiley & Sons, Ltd.

Taylor, S. E., & Thompson, S. C. (1982). Stalking the elusive "vividness" effect. *Psychological Review, 89*(2), 155–181. https://doi.org/10.1037/0033-295X.89.2.155

Treue, S. (2003). Visual attention: The where, what, how and why of saliency. *Current Opinion in Neurobiology, 13*(4), 428–432. https://doi.org/10.1016/S0959-4388(03)00105-3. Elsevier Current Trends.

Zaremba, A., Bilgin, M. H., Long, H., Mercik, A., & Szczygielski, J. J. (2021). Up or down? Short-term reversal, momentum, and liquidity effects in cryptocurrency markets. *International Review of Financial Analysis, 78*, 101908. https://doi.org/10.1016/J.IRFA.2021.101908. North-Holland.

Zhang, W., & Li, Y. (2020). Is idiosyncratic volatility priced in cryptocurrency markets? *Research in International Business and Finance, 54*, 101252. https://doi.org/10.1016/j.ribaf.2020.101252. Elsevier Ltd.

Zhang, W., & Li, Y. (2021). Liquidity risk and expected cryptocurrency returns. *International Journal of Finance and Economics*, ijfe.2431. https://doi.org/10.1002/ijfe.2431. John Wiley; sons ltd.

Zhang, W., Li, Y., Xiong, X., & Wang, P. (2021). Downside risk and the cross-section of cryptocurrency returns. *Journal of Banking & Finance, 133*, 106246. https://doi.org/10.1016/J.JBANKFIN.2021.106246. North-Holland.

Zhang, X. F. (2006). Information uncertainty and stock returns. *Journal of Finance, 61*(1), 105–137. https://doi.org/10.1111/j.1540-6261.2006.00831.x. John Wiley & Sons, Ltd.