University of Southampton

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Southampton Business School

To what extent can behavioural theories explain investor behaviour and asset return dynamics? Empirical evidence from real-world financial markets

by

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Abstract

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Behavioural finance has proposed several alternative theories of choice under risk. The thrust of the present thesis is to examine their ability to explain real-world investor behaviour and asset return dynamics. To this end, the thesis consists of three essays that analyse the patterns of returns in the emerging cryptocurrency market and the patterns of limit order submissions in the Taiwan stock market. Our findings contribute to our understanding of investor behaviour and the functioning of the cryptocurrency market.

The first essay explores to what extent prospect theory can explain returns in the cryptocurrency market. The study demonstrates that those cryptocurrencies that exhibit greater (lesser) appeal from a prospect theory perspective yield lower (higher) future returns. This outcome aligns with the theory's predictions, suggesting that cryptocurrencies with higher PT values tend to attract excess investor demand, which may lead to overpricing and subsequently result in lower future returns compared to their peers with lower PT values. The prospect theory effect is both statistically and economically meaningful, and while the effect is stronger among cryptocurrencies that have more severe arbitrage constraints, it is not confined to the micro-cap segment of the market.

The second essay investigates the extent to which salient theory can explain investor behaviour and return dynamics in the cryptocurrency market. In line with the predictions, which imply that cryptocurrencies with salient upsides (i.e., high ST values) are prone to attracting excess demand, becoming overpriced, and generating lower subsequent returns, the findings reveal that cryptocurrencies that are more (less) attractive to "salient thinkers" yield lower (higher) future returns. Although the salience effect is both statistically and economically significant, it is confined to the micro-cap segment of the market, and its magnitude is moderated by limits to arbitrage.

The third essay examines the extent to which prospect theory, salience theory, and regret theory can explain investor demand in the Taiwan stock market, and whether their predictive power varies across investor types. The findings suggest that, at the aggregate level, investor demand is consistent with the predictions of regret theory. However, when the data are disaggregated by investor type, the results exhibit heterogeneity. Specifically, the behaviour of domestic individual investors is consistent with regret theory, while that of securities investment trusts is consistent with prospect theory. Additionally, foreign investors' behaviour is consistent with both prospect theory and salience theory.

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I confirm that:

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Signature: .... Date: ....

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Chapter 1 Introduction

1.1 Background and motivation

Neoclassical economics assumes that individuals, when making decisions, exhibit rational preferences, strive to maximise their utility (or satisfaction), and utilise all relevant information (*Weintraub, 2007*). Put another way, individuals balance their preferences, constraints, and information to reach decisions, and their behaviour can be described by a theory known as 'utility theory'. This theory employs a utility function that computes the utilities of outcomes, with the outcome having the highest utility being favoured by rational decision-makers. *Von Neumann and Morgenstern* (*1944*) extended the utility theory by developing the expected utility theory (hereafter 'EUT'), which aims to account for decisions made under risk. Contrary to uncertainty, in a risky situation (or a prospect), the list of possible outcomes is often known, and their probabilities can be measured. Thus, the expected utility of a prospect (e.g., prospect A) can be calculated using the following formula:

$$v(A) = \sum_{s=1}^{S} p_s \, u(x_s) \tag{1.1}$$

where p_s is the decision weight (i.e., objective probability) of the outcome in each state $s \in S$, and $u(x_s)$ is a utility function that computes the utility of each outcome. In essence, the expected utility of a prospect is the probability-weighted average of the utilities of the possible outcomes; thus, the prospect that generates the highest expected utility should be chosen by rational decision-makers.

In addition, the risk attitude of an individual, which could be risk neutrality, risk aversion, or risk seeking, is embedded in the utility function. Risk neutrality implies that an individual only considers the expected value of a prospect and disregards the associated risk. This attitude can be captured by a linear utility function, by which the expected utility of a prospect is equal to its expected value. Risk aversion (Risk seeking) implies that an individual has a preference for avoiding (taking) risk. This attitude can be captured by a concave (convex) utility function, such as a natural logarithmic function (an exponential function), by which the expected utility of a prospect is less than (exceeds) the utility of its expected value.

Furthermore, EUT is developed based on four axioms: (1) Completeness, meaning that all prospects can be ranked based on their utilities and an individual can exhibit a preference for one over another; (2) Transitivity, meaning that if prospect A is preferred to prospect B and prospect B is preferred to prospect C, then prospect A must be also preferred to prospect C; (3) Continuity, meaning that preferences do not change abruptly as prospects change; (4) Independence, meaning that preferences should not change when prospects are equally altered. As a normative theory that illustrates how rational individuals *should* act when making decisions under risk, this theory has established itself as a key building block of mainstream finance.

However, vast theoretical and empirical research in recent decades has revealed a number of violations of EUT's axioms. To name a few examples, the presence of the common consequence and common ratio effects clearly violate the independence axiom (*Allais, 1953*; *Moskowitz, 1974*; *Slovic and Tversky, 1974*; *MacCrimmon and Larsson, 1979*), and the occurrence of preference reversals (*Loomes et al., 1989*; *Tversky and Thaler, 1990*) and cyclical choice (*Tversky, 1969*; *Loomes et al., 1991*) provide evidence against the transitivity axiom.[1] These violations stem from the fact that individuals are not fully rational and often exhibit biases when making decisions. To elaborate, behavioural biases, which come from heuristics (or mental shortcuts) used by our brain to process information (*Kahneman, 2012*), can be classified into three primary categories: cognitive biases, emotional biases, and social biases (*Nofsinger, 2017*). One illustration of cognitive biases is the framing effect (*Tversky et al., 1981*), indicating that individuals' decisions tend to vary depending on how decision problems are framed. An example of emotional bias is the status quo bias (*Samuelson and Zeckhauser, 1988*), implying that individuals have a preference for the "current state of affairs" over alternative options. The herding effect (*Scharfstein and Stein, 1990*) is a demonstration of social biases, revealing that investors follow the behaviour of others and make similar investment decisions. Such biases that impact real-world decision-making are in conflict with the core principles of mainstream finance, but they have been acknowledged and modelled by the field of behavioural finance.

More in general, the field of behavioural finance also challenges some of the assumptions and idealised conditions behind other key tenets of mainstream finance, such as the capital asset pricing model (hereafter 'CAPM') (*Sharpe, 1964*) and the efficient market hypothesis (hereafter, 'EMH') (*Fama, 1970*). For instance, investors may exhibit the cognitive bias of mental accounting (*Thaler, 1985*), leading them to consider each investment in a separate mental account, resulting in a suboptimal investment portfolio and deviating from the world postulated by CAPM. Additionally, the existence of market anomalies, such as the earnings announcement effect (*Ball and Brown, 1968*), the momentum effect (*Jegadeesh and Titman, 1993*), etc. poses a challenge to EMH. However, some of these anomalies can be explained from the perspective of behavioural finance, such as the conservatism bias (*Barberis et al., 1998*) and the disposition effect (*Odean, 1999*). Moreover, the presence of arbitrage risk,

[1] We also refer interested readers to works such as Schoemaker (*1982*), Fishburn (*1988*), and Starmer (*2000*) for a review of the axioms of EUT and its violations.

information uncertainty, and transaction costs (*Shleifer and Vishny, 1997*) also challenges the assumption of absence of limits to arbitrage made by EMH.[2]

Consequently, behavioural finance provides a more realistic and comprehensive understanding of financial decision-making in the real world. To accurately describe investor behaviour in reality, researchers have put forth several alternative theories that explicitly integrate typical behavioural biases into the modelling processes. As a result, the overall utility of a prospect being computed based on these theories becomes the sum of the products of modified weightings and utilities of outcomes, i.e., the p_s and $u(x_s)$ in *Eq. (1.1)* are replaced with their respective functions that incorporate different biases.

Among the behavioural theories of choice under risk, the most well-known theories are perhaps prospect theory (*Kahneman and Tversky, 1979*; *Tversky and Kahneman, 1992*), salience theory (*Bordalo et al., 2012*), and regret theory (*Bell, 1982*; *Loomes and Sugden, 1982*).[3] In the framework of prospect theory (hereafter 'PT'), individuals are argued to evaluate gains and losses relative to a reference point, as opposed to solely considering their final level of wealth (as outlined in EUT). Then, their risk attitude towards the outcomes can vary. For example, they are argued to be risk averse when facing gains and risk seeking when facing losses (*reflection effect*), and they experience a stronger dislike of losses compared to their enjoyment of gains (*loss aversion*). Additionally, individuals are believed to overweight small-probability events and underweight events that are more likely. To capture the tendencies described above, this theory employs a kinked utility function and an inverted S-shaped probability weighting function.

Salience theory (hereafter 'ST'), on the other hand, argues that due to cognitive limitations, individuals tend to pay more attention to the outcomes that are salient, which is defined as the difference between an outcome and the available alternatives (in a given state of the world).[4] As a result, these salient outcomes tend to be overweighted by a salient thinker, while non-salient outcomes are underweighted. To capture these tendencies, this theory employs a weighting function that transforms the objective probability of an outcome into a subjective probability based on its salience weight. Moreover, when the highest (lowest) outcomes of a prospect stand out, i.e., the upside (downside) is salient, a salient thinker is risk-seeking (risk-averse).

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[2] Note that the present thesis focuses on the dissimilarities between mainstream finance and behavioural finance in describing individuals' decision-making, as captured by EUT and behavioural theories. For a comprehensive discussion/comparison of the key tenets of these two fields, we refer the interested reader to the works cited in this paragraph as well as other relevant works such as *Forbes* (*2009*) and *Ackert and Deaves* (*2010*).
[3] A Google Scholar search returns thousands of citations for each of these theories in the last two decades.
[4] See *Bordalo et al.'s* (*2012*) paper and Chapter 3 of the present thesis for a detailed discussion of salience and its key features.

Lastly, regret theory (hereafter 'RT') supplements EUT by considering individuals' aversion to regret, suggesting that they not only care about what they can obtain, but also about what they might have obtained if they had chosen an alternative. The key idea behind this theory is that an outcome is evaluated relative to a counterfactual benchmark. This is accomplished through its utility function, which computes the regret/rejoice value of an outcome based on the expected utilities of the outcome itself and its counterfactual. In other words, the main assumption is that decisions are made on the basis of minimising (maximising) the feeling of regret (rejoicing).

In summary, these three theories incorporate some common behavioural biases into the modelling of decision-making processes, offering a more realistic depiction of reality and improving upon EUT, which assumes a consistent risk attitude (i.e., the independence axiom) and does not account for probability distortion. As positive theories that describe how individuals *actually* behave in real life, their effectiveness is supported by ample evidence from experimental studies (e.g., *Abdellaoui et al., 2013*; *Dertwinkel-Kalt and Köster, 2020*; *Frydman and Camerer, 2016*).

However, one may be critical of such theories as the evidence outside of laboratory settings is limited, particularly in the financial markets. In short, there two main reasons why it is difficult to test these theories in the field. First, it is more complicated to construct testable models of investor behaviour in asset markets based on these theories (*Polkovnichenko, 2005*; *Kliger and Levy, 2009*; *Barberis et al., 2016*). Unlike laboratory experiments where subjects are provided with definite information about probabilities and possible payoffs, it is unclear how investors form mental representations of risk and returns in real markets. To effectively test these theories using financial data, additional assumptions about how investors gather and interpret market information are necessary. Second, the precision of empirical tests in a market environment is restricted by the available data. Unlike laboratory settings, where the subjects' investing behaviour is recorded in detail, researchers can only indirectly examine whether investors act in line with the predictions of these theories based on aggregate-level data or simulated data.

Therefore, to fill this gap, the aim of the present thesis is to use data from real-world financial markets to examine PT's, ST's, and RT's ability to explain the behaviour of investors and the dynamics of asset returns.[5] To achieve this aim, the thesis consists of three empirical studies that respectively investigate: (1) the extent to which PT can explain the dynamics of cryptocurrency returns; (2) the degree to which ST can explain the behaviour of cryptocurrency investors; and (3) whether the

[5] In the next section, we will motivate our choice of these theories. In brief, in addition to their widespread recognition, these theories have already been tested using financial markets data (e.g., *Barberis et al., 2016*; *Cosemans and Frehen, 2021*; *Ballinari and Müller, 2022*). However, the existing studies present several limitations: they focus exclusively on traditional asset markets, employ indirect tests, and do not make any distinctions among heterogeneous groups of investors.

predictions of PT, ST, and RT are directly supported by investors' order submission behaviour in the stock market, and whether there are behavioural heterogeneities across investor types.

1.2 A brief introduction to each of the three studies

This section outlines the motivation, research aim and objectives, research design, and conclusion of each of the three empirical studies.

1.2.1 Study one: Explaining cryptocurrency returns: A prospect theory perspective

This study explores the ability of PT to explain the dynamics of cryptocurrency returns. PT is perhaps the most well-known behavioural theory of choice under risk. According to Google Scholar records, the original version of PT (*Kahneman and Tversky, 1979*) and its refined version (aka cumulative PT, *Tversky and Kahneman, 1992*) have been cited tens of thousands of times. Their contribution to economic science and the field of decision-making under risk is a key reason why Daniel Kahneman was awarded the Nobel Prize in Economic Sciences in 2002.[6] This theory has been widely recognised for its ability to successfully explain choice behaviour in a diverse range of economic decisions, including consumption-saving decisions (*Koszegi and Rabin, 2009*), management and organisational behaviour (*Heidhues et al., 2014*), labour supply (*Camerer et al., 1997*), insurance decisions (*Sydnor, 2010*), and investors' preference for skewness (*Barberis and Huang, 2008*; *Bali et al., 2011*).[7]

Barberis et al. (*2016*) provide a blueprint for testing PT and conceivably other behavioural theories outside the laboratory. Their method involves measuring the PT value of an asset (e.g., a stock) based on three key assumptions, which are derived from the work of *Benartzi and Thaler* (*1995*). The assumptions are: (1) Investors engage in narrow framing, meaning they consider each investment in isolation; (2) investors extrapolate past returns into the future; (3) investors estimate the PT value of an asset based on its historical return distribution. Then, by using a sample of past (monthly) returns and *Tversky and Kahneman's* (*1992*) formulas for the value of a prospect, the PT value of an asset can be quantified. In addition, to test the ability of PT to capture investor behaviour, *Barberis et al.* (*2016*) posit the following chain of causality: If investor behaviour is consistent with the predictions of PT, then PT investors would tilt their portfolio towards (away from) assets with higher (lower) PT values. This leads to assets with higher (lower) PT values being overbought (underbought) and overpriced

[6] Amos Tversky passed away in 1996.
[7] See *Barberis's* (*2013*) paper for a more comprehensive review of PT in the field of economics.

(underpriced) in the short term, resulting in lower (higher) future returns. In summary, their arguments imply a negative relationship between the PT value and the future returns of an asset.

Using data from the US and 46 international stock markets, *Barberis et al.* (*2016*) do find evidence of a negative cross-sectional relationship between the PT values and future stock returns. Subsequently, their framework for testing PT using real-world financial market data has been extended to other financial markets, including the bond market (*Zhong and Wang, 2018*), the foreign exchange market (*Xu et al., 2020*), and the mutual fund market (*Gu and Yoo, 2021*; *Gupta et al., 2022*). These subsequent studies have found consistent evidence supporting the ability of PT to explain (investor behaviour and) the cross-section of asset returns across financial markets. This motivates the first study of the present thesis (Chapter 2), which aims to explore the extent to which PT can explain the dynamics of returns in the cryptocurrency market.

The cryptocurrency market is a rapidly emerging market that has experienced significant growth since its inception. Its total market capitalisation has increased from around $0.02 trillion at the start of 2017 to over $2.9 trillion by the end of 2021. Despite its economic significance, the determinants of the intrinsic value of cryptocurrencies remains unclear. Thus, understanding the behaviour of cryptocurrency investors and the factors that determine cryptocurrency prices and returns is important for economists and policy makers.

In this regard, several studies have attempted to identify the factors that drive the cross-section of cryptocurrency returns, such as size, liquidity, and idiosyncratic risk (*Zhang and Li, 2020*, *2021*; *Liu et al., 2022*). However, these studies typically assume rational behaviour on the part of cryptocurrency traders, which is questionable given that individual investors with limited financial knowledge are documented to be the dominant population in this market (*Graffeo, 2021*). Such investors are often thought to be more susceptible to behavioural biases relative to more sophisticated investors, such as the institutional investors. In light of this, we conjecture that PT may be a more useful framework for explaining the behaviour of investors and the dynamics of returns in this market. This is because this theory has already demonstrated its predictive ability in traditional markets dominated by institutional investors, and parts of the literature suggest that two components of PT, namely loss aversion and non-linear decision weights, provide a more accurate description of individual investor behaviour than institutional investor behaviour (*Mrkva et al., 2020*; *Baars and Goedde-Menke, 2022*). In addition, as shown by *Barberis et al.* (*2016*), the predictive power of PT is more pronounced among stocks that are more likely to be traded by individual investors.

It is also worth mentioning that, since the completion of this study in late 2021, this market has experienced a huge crash, leading to a total market capitalisation of $0.8 trillion by the end of 2022. At the time of this writing (February 2023), the total market capitalisation is estimated to be around $1 trillion. Fluctuations of this size are dramatic compared to those typically observed in traditional markets, suggesting a high degree of irrationality and bubble-like behaviour that may drive prices in this market. This highlights the importance of understanding cryptocurrency investor behaviour, which further emphasises the significance of this study.

In our analysis, we examine both the cross-sectional and time-series relationships between the PT values of cryptocurrencies and their next-week returns, using a comprehensive dataset that encompasses 1,573 cryptocurrencies and spans the period from January 1, 2014 to December 31, 2020. We begin by examining whether, in the cross-section, cryptocurrencies that have higher (lower) PT values, and are thus considered more (less) attractive from a PT perspective, earn lower (higher) future returns. We start with a univariate portfolio analysis, followed by a bivariate portfolio analysis and panel regressions that control for a large number of factors (e.g., size, momentum, short-term reversal, liquidity, maximum, etc.) that have been found to influence the cross-section of asset/cryptocurrency returns.

The results support the hypothesis that there exists a negative cross-sectional relationship between PT values and future cryptocurrency returns, as predicted by PT. In particular, after controlling for several cryptocurrency-specific factors, we estimate that a one cross-sectional standard deviation increase in a cryptocurrency's PT value reduces its next week's return by about 0.71% relative to its peers. This result is highly statistically significant and economically meaningful. For comparison, *Barberis et al.* (*2016*) estimate that a one cross-sectional standard deviation increase in the PT value of a stock reduces its next month's return by only about 0.129% in the US stock market.

We then employ panel regressions with cryptocurrency fixed effects to isolate the over-time variation in the data and examine whether, over time, as the PT value of a cryptocurrency rises (falls), its future returns tend to fall (rise). The results are consistent with our conjecture: After controlling for several cryptocurrency-specific factors, a one time-series standard deviation increase in the PT value of a cryptocurrency reduces it next week's return by about 1.34%.

In subsequent analyses, we use five proxies for the existence of limits to arbitrage (i.e., size, age, volatility, illiquidity, and idiosyncratic volatility) to demonstrate that the predictive power of PT is stronger among cryptocurrencies for which arbitrage forces are more constrained. This supports the interpretation that the empirical regularity documented in this study is behaviourally driven. Furthermore, we examine whether the relationship between PT values and future cryptocurrency returns is driven by one or more of the three components of PT (i.e., loss aversion, probability weighting, and concavity/convexity of the value function). The results show that all three components play a role in explaining why a cryptocurrency is appealing or unappealing to investors, and the data appear to indicate that the concavity/convexity component plays a somewhat bigger role than the other two. Additionally, we observe that the PT effect exists not only in the micro-cap segment but also in the medium- and large-cap segments of the market. (Note that, according to our classification, 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.) Lastly, we find that the pattern that we document is hardly reconcilable with EUT, and we find marginal evidence that the size of the PT effect is moderated by investor attention (as proxied by the weekly number of Wikipedia pageviews for "cryptocurrency" and "Bitcoin").

In summary, our findings support the hypothesis that cryptocurrencies that are more (less) attractive from a PT perspective earn lower (higher) future returns, and they are robust to the methodology used to estimate the PT value of a cryptocurrency. In addition, our analysis highlights that the PT effect is stronger among cryptocurrencies that are more difficult to arbitrage, but it is not confined to the micro-cap segment of the market. More in general, our findings provide support for PT's ability to explain investor behaviour in the cryptocurrency market.

1.2.2 Study two: Can salience theory explain investor behaviour? Real-world evidence from the cryptocurrency market

The second study explores the ability of ST to explain the behaviour of cryptocurrency investors. Although the formalisation of this theory is relatively recent, as put forward by *Bordalo et al.* (*2012*), the concept of salience was introduced much earlier (*Taylor and Thompson, 1982*). Previous literature has demonstrated that the concept of salience can help explain a variety of decisions, such as the choices made by managers after hurricane events (*Dessaint and Matray, 2017*) and the choices of college students in terms of specialisation (*Choi et al., 2022*), among others. More formal ST models have been applied to various decision-making settings, namely consumer choice (*Bordalo et al., 2013b*), judicial decisions (*Bordalo et al., 2015*), and most importantly, asset prices (*Bordalo et al., 2013a*). However, similar to most behavioural theories, while evidence in support of ST from laboratory experiments is abundant (e.g., *Dertwinkel-Kalt and Köster, 2020*; *Dimmock et al., 2021*), empirical evidence from real-world settings is scarce.

The first empirical examination of *Bordalo et al.'s* (*2013a*) salience-based asset pricing model was carried out by *Cosemans and Frehen* (*2021*). In their study, the authors utilise *Barberis et al.'s* (*2016*) framework to test the explanatory power of ST. They assume that investors engage in narrow framing and extrapolate past returns into the future, and that investors use the historical return distribution of an asset to estimate its ST value. They also posit the following chain of causality exists: If investor behaviour is consistent with the predictions of ST, then investors who are "salient thinkers" would tilt their portfolio towards (away from) assets with higher (lower) ST values. This leads to assets with higher (lower) ST values being overbought (underbought) and becoming overpriced (underpriced) in the short term, resulting in lower (higher) future returns. Using data from the US stock market, *Cosemans and Frehen* (*2021*) find evidence that supports the predictive power of ST, as they observe that stocks with higher ST values tend to earn lower future returns in the cross section. Similarly, *Hu et* al. (2023) find that, in the Chinese mutual fund market, mutual funds with higher ST values attract greater net inflows of money.

However, Cakici and Zaremba (2022), using data from 49 international stock markets, find that the ST effect is far from robust. Specifically, they find that the ST effect is largely driven by the short-term return reversal effect (i.e., the past one-month return) and is confined to the micro-cap segment (i.e., small stocks that represent only 3% of total market capitalisation). Additionally, when replicating the work of Cosemans and Frehen (2021), they find that the magnitude of the ST effect in the US stock market has shrunk over time, suggesting that its predictive power has been marginal in recent years.

To summarise, there have been limited empirical tests of Bordalo et al.'s (2013a) model, and these have been focused exclusively on the equity market. Even so, some conflicting findings have been revealed, which raises several questions about ST: Is the predictive ability of ST limited to the micro-cap segment? Is the ST effect different from the short-term reversal effect? More importantly, can ST explain investor behaviour in markets other than the equity market? These questions motivate the second study of the present thesis (Chapter 3), which extends the exploration of the extent to which ST can explain the behaviour of investors, specifically among cryptocurrency investors.

This choice is motivated by several reasons. As explained earlier, its growing economic significance, large fluctuations, and the amount of attention that it has been attracting from the mass media make this market ripe for exploration. Secondly, by testing ST's predictive ability in this unique market, our study takes an important step towards the generalisability of ST across markets and investor types. Indeed, the cryptocurrency market is fundamentally different from the stock market (and from other conventional asset markets) in terms of investor population, institutional features, and drivers of value. To elaborate, the dominant investor population in this market is represented by unsophisticated individual investors (Graffeo, 2021), who are prone to extrapolating past returns into the future (Da et al., 2021) and engaging in narrow framing (Liu et al., 2010), which are two of the behavioural biases modelled by ST. The reluctance of institutional investors to participate in the cryptocurrency market may exacerbate pricing anomalies or prevent them from being easily rectified. Additionally, the drivers of value in the cryptocurrency market, such as network externalities and costs of production, differ from those in traditional markets (Hayes, 2017; Cong et al., 2021; Liu et al., 2021). The aforementioned differences may lead the typical investor in the market to form distinct mental representations of an asset's payoffs and of their salience compared to conventional asset markets.

In our analysis, using a sample of 1,738 cryptocurrencies from January 1, 2014 to June 30, 2021, we examine the relationships between ST value and future cryptocurrency returns in the cross-sectional and time-series dimensions. We start by examining whether, in the cross-section, cryptocurrencies with higher ST values earn lower average returns compared to those with lower ST values, and vice versa. We employ both univariate and bivariate portfolio analysis as well as panel regressions with time fixed effects and find evidence supporting the predictions of ST. Specifically, our results indicate that cryptocurrencies that are more (less) attractive to "salient thinkers" earn lower (higher) future returns, indicating that they tend to be overpriced (underpriced). Additionally, we find that the size of the ST effect is both statistically and economically significant: On average, after accounting for several cryptocurrency-specific factors (e.g., size, momentum, short-term reversal, downside beta, illiquidity, PT effect, maximum effect, etc.), a one cross-sectional standard-deviation increase in the ST value of a cryptocurrency reduces its next-week return by 0.41% relative to its peers. For comparison, this ST effect is about 13 times the size of that documented in the US stock market (*Cosemans and Frehen, 2021*) and is just as economically meaningful as other documented cryptocurrency-specific effects such as downside beta, illiquidity, prospect theory, and maximum effect (*Grobys and Junttila, 2021*; *Li et al., 2021*; *Zhang and Li, 2021*; *Zhang et al., 2021*).

We then examine whether, in the time-series dimension, the ST value of a cryptocurrency negatively predicts its future return. To do this, we employ panel regressions with cryptocurrency fixed effects, which allows us to focus on the variation of our data overtime. Our findings are in line with our hypothesis and are economically significant: After controlling for cryptocurrency-specific factors, over time, a one time-series standard-deviation increase in a cryptocurrency's ST value reduces its next-week excess return by approximately 0.69%.

Next, to test the hypothesis that the ST effect is stronger in (or confined to) the micro-cap segment of the market, we allocate cryptocurrencies to the micro-cap, small-cap, and large-cap segments using two different classifications. The first classification is based on market capitalisation, with the micro-cap (small-cap, large-cap) segment consisting of the cryptocurrencies that account for the bottom 3% (next 7%, remaining 90%) of total market capitalisation. The second classification is based on the number of active cryptocurrencies, with the micro-cap (small-cap, large-cap) segment consisting of the cryptocurrencies that account for the bottom 60% (next 20%, remaining 20%) of the total number of active cryptocurrencies. Afterwards, we re-estimate our panel regression equations with the inclusion of an interaction between ST value and *Small* (*Large*), a dummy variable that takes the value of 1 when the cryptocurrency belongs to the small-cap (large-cap) segment, and 0 otherwise, as well as the dummy variables *Small* and *Large*. In both classifications, our results indicate that the ST effect is concentrated predominantly in the micro-cap segment.

In addition, as this market anomaly caused by "salient thinkers" is likely to be driven by behavioural factors rather than economic fundamentals, we test the hypothesis that the predictive power of ST is stronger among cryptocurrencies that are more difficult to arbitrage. To do this, we use 6 proxies to measure the severity of arbitrage constraints, namely cryptocurrency age, bid-ask spread, Amihud-illiquidity ratio, idiosyncratic volatility, market capitalisation, and volatility. For each proxy, we add the proxy and an interaction between ST value and the proxy itself to our equations and re-run our panel regressions. We find evidence that the magnitude of the ST effect is moderated by the degree of limits to arbitrage: the more severe the limits to arbitrage, the larger the size of the ST effect. This moderating effect is further supported by a second test in which we construct a composite limits-to-arbitrage index instead of using six individual proxies.

Furthermore, the results of bivariate portfolio analysis (i.e., sorting based on short-term reversal effect and then ST value) and panel regressions that exclude the most-recent week (short-term reversal effect) indicate that the ST effect is not subsumed by the short-term reversal effect in the cryptocurrency market.

In summary, our findings are consistent with the predictions of ST. We observe that cryptocurrencies that are more (less) attractive to "salient thinkers" earn lower (higher) future returns. Our results are robust when alternative sub-samples of data and methodologies in the construction of the ST value of a cryptocurrency are employed. However, we find that the salience effect is confined to the micro-cap segment of the market, and its size is moderated by limits to arbitrage.

1.2.3 Study three: Behavioural theories of investor behaviour: Empirical evidence from the limit order book

The third study investigates whether investor behaviour in the stock market is consistent with the predictions of well-known behavioural theories through a novel and more direct approach. As mentioned earlier, the main challenges in empirically testing behavioural theories stem from difficulties in defining how investors form a mental representation of an asset's payoffs and risk in real markets and from the availability of data. *Barberis et al.* (*2016*) renew interest in testing behavioural theories with real-world financial market data and provide a blueprint for subsequent researchers. In particular, their methodology for measuring the behavioural theory value (i.e., PT value) of a stock can readily be extended to other markets and asset classes. This is evidenced by its application to the testing of PT in alternative markets such as the bond market (*Zhong and Wang, 2018*) and the cryptocurrency market (Chapter 2), and its extension to the testing of other behavioural theories, such as ST (*Cosemans and Frehen, 2021*; Chapter 3) and RT (*Ballinari and Müller, 2022*).

However, it is important to recall that the framework upon which these studies are based relies on several assumptions. The assumed chain of causality is that, if investor behaviour is consistent with the predictions of a behavioural theory, such as PT, investors will tilt their portfolio towards (away from) assets with higher (lower) PT values, resulting in these assets being overbought (underbought) (*Causality 1*). Subsequently, these overbought (underbought) assets will become overpriced (underpriced) in the short term (*Causality 2*), which then leads to lower (higher) future returns (*Causality 3*). Hence, the findings put forward by these studies are subject to three limitations. First, *Causality 1* is not observed and tested directly. In other words, taking PT as an example, does the assumption that investors tilt their portfolio towards (away from) assets with higher (lower) PT values *really* hold?

Second, their evidence is based on observing the patterns of asset returns, and as such, it is unable to address the question of behavioural heterogeneity. Put another way, the evidence so far focuses on aggregate investor behaviour and assumes investor behaviour is homogenous across investor types. However, this assumption is unlikely to be true, as individual and institutional investors, who operate within different sets of rules, tend to display different behavioural biases (*Shapira and Venezia, 2001*; *Gilad and Kliger, 2008*; *Liu et al., 2010*; *Devault et al., 2019*). Different types of institutional investors can also exhibit heterogeneous behaviours, with foreign and domestic institutional investors having different attitudes towards momentum and positive feedback trading (*Grinblatt and Keloharju, 2000*; *Richards, 2005*; *Phansatan et al., 2012*). Hence, the question remains of whether these theories are able to successfully predict the behaviour of different types of investors.

Third, previous studies have examined each behavioural theory individually rather than taking a holistic approach and comparing their predictive powers. We posit that the behaviour of some types of investors might be consistent with some of these behavioural theories and inconsistent with others. It is also possible that these three theories capture different traits of the same investor's behaviour. Since these theories are not necessarily mutually exclusive, and they share the feature of incorporating psychological mechanisms to explain investors' reactions to extreme outcomes, it is natural to ask whether these behavioural theories can be reconciled with one another and whether one of them is clearly superior to the others.

The above questions motivative the third study of the present thesis (Chapter 4). Specifically, this study simultaneously examines the extent to which PT, ST, and RT can explain aggregate investor demand in the Taiwan stock market, and whether the predictive power of these three theories varies across investor types.

To answer these questions, it is crucial to accurately measure investor demand for a stock and determine whether it aligns with the predictions of a behavioural theory (i.e., *Causality 1*). Following previous literature (e.g., *Barber and Odean, 2008*; *Bhattacharya et al., 2011*; *Chen et al., 2021*; *Vedova et al., 2022*), we use buy-sell order imbalance as a proxy for net investor demand for a stock. To observe the order submission behaviours of different types of investors, we use a comprehensive and unique dataset that includes the details (e.g., submission time, stock identifier, order direction, submitted price, volume, and trader identifier) of all orders submitted to the Taiwan stock exchange from May 2, 2013 to March 31, 2018. This dataset has three advantages over previous studies using other datasets. Firstly, it contains all limit orders (about 13 billion orders) submitted to the exchange during this five-year period (cf. a sub-sample of the market).[8] Secondly, the direction of each order (i.e., whether it is buyer- or seller-initiated) is identified by the exchange. Thirdly, the trader type for each order is identified by the exchange as individual investors, foreign investors, securities investment trusts, or other non-individual investors. The last two points are critical, as order direction and trader type would otherwise need to be estimated by the researcher, which can result in noisy measures (*Lee and Ready, 1991*; *Boehmer et al., 2021*).

In our analysis, we begin by conducting an indirect test to examine whether there is a negative cross-sectional relationship between the PT (ST, RT) value of a stock and its next-month return (*Barberis et al., 2016*; *Cosemans and Frehen, 2021*; *Ballinari and Müller, 2022*). To do this, we estimate panel regressions with time fixed effects that control for several factors that have been shown to have predictive power for future returns, such as beta, size, book-to-market ratio, past returns, etc. Our results show that the dynamics of stock returns in Taiwan are consistent with the predictions of RT, which suggest that stocks that are more appealing to investors with RT preferences (i.e., higher RT-value) are prone to attracting excess demand, becoming overpriced, and generating lower subsequent returns. Conversely, there is no evidence in support (or against of) the predictions of PT or ST. In other words, at the aggregate level, investors in Taiwan seem to act in line with the predictions of RT.

Subsequently, we test directly whether stocks with higher PT (ST, RT) values attract greater net investor demand, both at the aggregate level and across investor types. To do this, we estimate panel regressions with time fixed effects, while controlling for factors that have been shown to have predictive power for order imbalance, such as lagged order imbalance, past returns, size, book-to-market ratio, and others. At the aggregate level, our results suggest that net investor demand is consistent with the predictions of RT, which is in line with the results from our indirect test. Conversely, our estimates are inconsistent with the predictions of PT and ST, suggesting that PT and ST fail to explain the dynamics of aggregate investor demand in the Taiwan stock market.

Upon breaking down the data by investor type, we discover significant evidence of behavioural heterogeneities. Firstly, the findings for individual investors are quite similar to those at the aggregate level (i.e., consistent with RT's predictions but inconsistent with PT's and ST's predictions). This is not surprising, as individuals account for a proportion of over 70% of the weekly transaction value on the Taiwan stock exchange. Next, we observe that foreign investors' net demand is consistent with both PT's and ST's predictions, but inconsistent with RT's predictions. Lastly, we find that investment trusts' net demand and others' net demand are consistent with PT's predictions but is inconsistent with RT's predictions. In a nutshell, our findings suggest that RT is more capable of explaining individual

[8] Note that the market orders were introduced to TWSE since 23 March 2020. Before that, investors could only submit limit orders to the market.

investors' behaviour, while PT is more successful in capturing the behaviour of non-individual investors. As for ST, it effectively captures the behaviour of foreign investors; however, it does quite poorly when applied to other investor categories. Furthermore, the economic size of these behavioural effects is larger or at least of the same order of magnitude as that of other well-known effects that have been found to influence order submission behaviour (e.g., 52-week high and past one-week return).

In summary, we find that aggregate investor demand for stocks is consistent with the predictions of RT. Nevertheless, aggregating orders across investors obscures notable behavioural heterogeneities: The behaviour of individual investors is consistent with RT's predictions, whereas the behaviour of securities investment trusts is consistent with PT's predictions, and that of foreign investors is consistent with both PT's and ST's predictions. Our results are robust when alternative methodologies in the construction of buy-sell order imbalance and the PT (RT, ST) value of a stock are employed. Additionally, our tests lead us to conclude that the results are not driven by an abnormal sub-sample of data.

1.3 Thesis structure

The rest of the thesis is organised as follows: Chapter 2 explores whether PT can explain the dynamics of cryptocurrency returns. Chapter 3 examines ST's ability to explain investor behaviour in the cryptocurrency market. Chapter 4 examines whether investor demand in the stock market is consistent with the predictions of PT, ST, and RT and sheds light on behavioural heterogeneities across investor types. Chapter 5 concludes the thesis.

Chapter 2 Explaining cryptocurrency returns: A prospect theory perspective

This chapter investigates prospect theory's ability to explain cryptocurrency returns using data concerning 1,573 cryptocurrencies over the period 2014-2020. In line with the theory's predictions, we find that cryptocurrencies that are more (less) attractive from a prospect theory perspective earn lower (higher) future returns, suggesting that they tend to be over(under)-priced. On average, a one cross-sectional standard-deviation increase in the prospect theory value of a cryptocurrency reduces its next-week return by 0.71% relative to its peers. This effect is stronger among cryptocurrencies that are more difficult to arbitrage, but it is not confined to the micro-cap segment of the market.

2.1 Introduction

The market for cryptocurrencies has grown massively over the past decade, reaching a capitalisation of over $2.9 trillion in December 2021. Given its increasing economic importance, it is imperative for economists and policy makers to understand how investor behaviour contributes to the determination of cryptocurrency prices and returns.

Under the assumption of rational traders, researchers have identified some factors (e.g., size, liquidity risk, and idiosyncratic volatility) that contribute to explaining the cross-section of expected cryptocurrency returns (*Liu et al., 2022*; *Zhang and Li, 2020; Zhang and Li, 2021*). However, there is growing evidence that investors' behaviour often deviates from that of an expected utility maximiser. For example, recent studies have documented herding behaviour (*King and Koutmos, 2021*; *Manahov, 2021*; *Yarovaya et al., 2021*), sentiment-driven behaviour (*Kraaijeveld and De Smedt, 2020*), and lottery-like demand (*Grobys and Junttila, 2021*) among cryptocurrency investors. This motivates us to investigate whether prospect theory (hereafter 'PT') can successfully describe investor behaviour in this market and consequently explain the dynamics of cryptocurrency returns.

During the past three decades, PT has emerged as the dominant alternative to the expected utility theory (hereafter 'EUT'). PT is potentially an ideal candidate for explaining cryptocurrency returns because this market, unlike conventional asset markets, is dominated by (financially naïve) individual investors (*Graffeo, 2021*), who have little trading experience compared to institutional investors. Previous research shows that less (real and perceived) experience is accompanied by a higher degree of loss aversion (*Mrkva et al., 2020*) and "more pronounced inverse-S-shaped probability weighting" (*Baars and Goedde-Menke, 2022*), which are key components of PT. Consistent with our conjecture, *Barberis et al.* (*2016)* find that, in the stock market, the predictive power of PT is stronger among stocks that tend to be traded by individual investors. Analogously, some other phenomena that can be explained by PT, such as the disposition effect (*Shapira and Venezia, 2001*), the endowment effect (*List, 2004*), and demand for lottery-like stocks (*Kumar, 2009*), are more pronounced among retail (cf. professional) investors.

Following previous studies that have successfully applied PT to explain decision-making in the stock (*Barberis et al., 2016*), bond (*Zhong and Wang*, *2018*), and foreign exchange (*Xu et al.*, *2020*) markets, we posit that investors examine each cryptocurrency in isolation (*narrow bracketing*), use its historical return distribution as a proxy for its future return distribution, and evaluate the latter as predicted by PT. This joint assumption has cross-sectional and time-series implications that can be tested empirically. Namely, we expect cryptocurrencies with higher PT values (i.e., cryptocurrencies whose past return distributions are more appealing from a PT perspective) to attract excess investor demand. These cryptocurrencies may then become overpriced and earn lower future returns than their peers with lower PT values. From a time-series perspective, we expect rising PT values to induce increasing overpricing and decreasing future returns.

To test our predictions, we analyse the returns of a sample of 1,573 cryptocurrencies in the period January 1, 2014 to December 31, 2020. The results of portfolio analyses and panel regressions support the hypothesis that there exists a negative cross-sectional relationship between PT values and future cryptocurrency returns. Specifically, after controlling for a large number of factors that influence expected returns, we find that a one cross-sectional standard-deviation increase in the PT value of a cryptocurrency reduces its next week's excess return by 0.71% relative to its peers. Consistent with a behavioural interpretation, this effect is stronger among cryptocurrencies that are more difficult to arbitrage.

Our results also suggest a negative time-series relationship between PT values and future cryptocurrency returns: As the PT value of a cryptocurrency rises by one time-series standard deviation, its next week's excess return tends to decrease by 1.34%. Both the cross-sectional and the time-series effects are highly statistically significant and economically meaningful, especially when compared with the results of previous PT studies based on conventional asset market data (e.g., *Barberis et al., 2016*).

We observe that all three components of PT (loss aversion, nonlinear probability weighting, and concavity/convexity of the value function) play roles in explaining the behaviour of cryptocurrency investors, but the concavity/convexity component has a somewhat larger effect than the other two. We also find that the PT effect exists not only for micro-cap cryptocurrencies but also for medium- and large-cap cryptocurrencies, and the effect is hardly reconcilable with the EUT. Lastly, we find marginal evidence that its size is moderated by investor attention.

Overall, our study makes two important contributions. First, we add to the literature on the determinants of cryptocurrency returns. In particular, we shed new light on investor psychology, as most of the cryptocurrency-based literature assumes that market participants act rationally (e.g., *Elendner et al., 2017*; *Liu et al., 2022*). While the dominant paradigm claims that higher returns represent compensation for bearing higher levels of non-diversifiable risk, we provide evidence that the psychological factors captured by PT also play significant roles in shaping the cross-sectional and over-time variation in cryptocurrency returns. These findings add to our understanding of how this market works and will give new impetus to the debate on the extent to which behavioural biases affect cryptocurrency investors and market dynamics. We also note that, while the number of active cryptocurrencies has grown dramatically, previous studies tend to focus only on the most popular ones. By contrast, our sample includes a wide cross-section of cryptocurrencies, which helps ensure that our results can be generalised to the whole market.

Second, while previous empirical studies of PT (*Barberis et al., 2016*; *Zhong and Wang, 2018; Xu et al., 2020*) limit their attention to its ability to explain the cross-section of asset returns, we also explore its ability to explain the over-time variation in asset returns and document a negative time-series relationship between a cryptocurrency's PT value and its future excess return.

The rest of the paper is organised as follows. Section 2.2 reviews the related literature and develops our hypotheses. Section 2.3 describes the data, illustrates how the PT value of a cryptocurrency is constructed, and describes the control variables. Section 2.4 details and discusses the main results of the empirical analysis. Section 2.5 summarises further analyses and robustness tests, and Section 2.6 concludes.

2.2 Literature review and hypotheses development

2.2.1 Key features of the cryptocurrency market

Pioneered by electronic money such as eCash and HashCase in the 80s and 90s, the history of digital, anonymous and cryptographic currencies was largely ignored until *Nakamoto* (*2008*) proposed the first decentralised payment network known as Bitcoin (*Chohan, 2017*). The launch of Bitcoin has given fresh impetus to the development of cryptocurrency. By the end of December 2021, the total market capitalisation of the more than 5,000 active cryptocurrencies reached a record high of over $2.9 trillion. While some enthusiasts view it as a substitute for fiat money, cryptocurrency is typically regarded more as a speculative asset than a means of payment due to its excessive volatility and low consensual acceptance rate (*Yermack, 2015*; *Hairudin et al., 2020*).

The emerging cryptocurrency market is fundamentally different from conventional asset markets for a number of reasons. First, traditional assets are usually traded on a single exchange, and trading takes place only during working days. Conversely, cryptocurrencies can be traded on dozens of exchanges simultaneously and 24/7. Second, while traditional exchanges match orders based on centralised order books, in the cryptocurrency market there are no "provisions to ensure that investors receive the best price when executing trades" (*Makarov and Schoar, 2020*). As such, cross-exchange arbitrage plays a prominent role. Third, the degree of regulation and oversight from authorities varies widely across cryptocurrency exchanges. For example, only some exchanges allow short selling and margin trading, and some do not accept fiat currency (*Hansen, 2018*). Fourth, and most importantly, the cryptocurrency market is mainly populated by retail investors (*Franklin, 2020; Graffeo, 2021*), whereas conventional asset markets are currently dominated by institutional investors. For example, at the New York Stock Exchange, only about 1-2% of trading volume is generated by individual investors (*Kadan et al., 2018*; *O'Hara et al., 2019*). Specifically, the literature argues that cryptocurrency owners have limited investment experience (*Xi et al., 2020*) and possess lower (higher) levels of financial (digital) literacy than non-owners (*Panos et al., 2020*).

It is worth noting that previous research shows that loss aversion and nonlinear probability weighting, two key components of PT, are more pronounced among inexperienced individuals (*Mrkva et al., 2020*; *Baars and Goedde-Menke, 2022*). Since retail investors typically fall into this category, it is not surprising that PT has been particularly successful in describing their behaviour in traditional markets such as the stock market (*Barberis et al., 2016*). Hence, we believe that PT makes an ideal candidate for explaining the behaviour of cryptocurrency investors and the dynamics of cryptocurrency returns.

2.2.2 Prospect theory and its application to financial markets

PT (*Kahneman and Tversky, 1979*) and its subsequent refinement, cumulative PT (*Tversky and Kahneman, 1992*), incorporate into a tractable model a number of observed discrepancies between individuals' decision-making behaviour under risk and the predictions of the EUT (*Von Neumann and Morgenstern, 1944*). PT makes four key assumptions: (1) individuals think about investments in terms of gains/losses rather than terminal wealth levels. Specifically, they evaluate each possible payoff relative to a reference point, which determines whether the payoff is perceived as a loss or a gain. (2) Individuals tend to be risk averse in the domain of gains and risk seeking in the domain of losses, which is referred to as the "reflection effect". (3) Individuals are loss averse. That is, they dislike losses more than they like gains. (4) When evaluating an investment, individuals instinctively transform the objective probability of each possible outcome into a decision weight that over-weights (under-weights) low (high) probabilities, a behaviour that is referred to as nonlinear probability weighting.

Overall, PT has received widespread recognition from academics and has been shown to explain behaviour observed in the laboratory (e.g., *Abdellaoui et al., 2013*; *Kairies-Schwarz et al., 2017*; *Ruggeri et al., 2020*). Nevertheless, it has taken a surprisingly long time for PT to be applied to the analysis of real-world financial data (*Barberis, 2013*). The key reason is probably that, according to PT, a decision-maker's choice process consists of two phases, namely, an *editing* and an *evaluation* phase, and it is particularly difficult for applied researchers to get a window into the former. In the *editing* phase, the decision-maker is assumed to form a mental representation of the distribution of gains/losses that the investment entails. Next, in the *evaluation* phase, individuals are believed to compute the value (i.e., utility) of the distribution of gains/losses and choose the investment that provides the highest value. To mimic the latter phase, researchers can rely on the formulas proposed by *Tversky and Kahneman* (*1992*). However, the challenges inherent in modelling the *editing* phase have led researchers to concentrate on individual components of PT rather than attempting to test the theory as a whole.

The probability weighting component, in particular, has been the focus of many investigations. For example, *Barberis and Huang* (*2008*) derive a theoretical model showing that the probability weighting component of PT implies that "a security's own skewness can be priced". Specifically, a security with a positively skewed return distribution "can be overpriced and can earn a negative average excess return". Similarly, other studies analyse data from the US stock market, the mutual fund market, or the commodity market and find that skewness-related factors have predictive power for subsequent returns (*Harvey and Siddique, 2000*; *Bali et al., 2011*; *Fernandez-Perez et al., 2018*; *Liu, 2021*).

However, focussing on an individual component of PT can only reveal part of a broader picture. *Benartzi and Thaler* (*1995*) are the first to tackle the *editing* phase directly and apply PT, in its entirety, to real-world financial data. They assume that investors consider each asset class in isolation (*narrow bracketing*). They also assume that, in the *editing* phase, investors use the historical return distribution of each asset class as a proxy for its future return distribution. By combining these two assumptions with the assumption that investors evaluate their portfolios frequently, they are able to show that the size of the equity premium in the US is consistent with PT's predictions.

Kliger and Levy (*2009*) and *Gurevich et al.* (*2009*) analyse data from options on the S&P 500 index and on individual US stocks, respectively, and find evidence in support of PT's assumptions of loss aversion, nonlinear probability weighting, and risk aversion (seeking) in the domain of gains (losses).

Barberis et al. (*2016*) follow a similar approach to that of *Benartzi and Thaler* (*1995*) but focus on individual stocks. Using data from the US and 46 international markets, they find that, in the cross-section, stocks whose past return distributions have higher (lower) PT values, and consequently are more (less) appealing to investors, earn lower (higher) subsequent returns. This suggests that such stocks tend to be overpriced (underpriced). Subsequent investigations have extended these results to the corporate bond market (*Zhong and Wang, 2018*) and the foreign exchange market (*Xu et al., 2020*).

Based on the available literature, we find that systematic examinations of PT in the cryptocurrency market are scant. *Ababio* (*2020*) investigates co-movements between global equity market indices and a handful of PT-sorted cryptocurrencies, concluding that cryptocurrencies can help investors achieve diversification benefits. During the completion of the current study, we became aware of a contemporaneous study by *Thoma* (*2021*) that is similar in spirit to our own. However, our investigation has advantages along several dimensions. First, while his study examines only the cross-sectional relationship between cryptocurrencies' PT values and returns, we also analyse PT's time-series implications.[9] The attractive feature of time-series analysis is that it allows us to learn about the determinants of over-time variation in cryptocurrency returns. Second, we also investigate the explanatory power of PT in various size segments and sectors of the market. If its explanatory power were confined to the smallest cryptocurrencies or to a single cryptocurrency sector, its practical relevance would be inconsequential. Rather, we show very clearly that PT can successfully describe the dynamics of returns across size segments and sectors, making PT a compelling driving force in this market. Third, we also document that limits to arbitrage play a key role in shaping the PT effect. Fourth, we also examine the extent to which the size of the PT effect is moderated by the amount of uncertainty in the market, by investor attention, and by investor sentiment. Crucially, only in the case of high investor attention do we find marginal evidence of a moderating effect. Fifth, by comparing PT's predictions with those of the EUT, we also show that the former does a better job than the latter at explaining the empirical patterns that we observe in cryptocurrency returns. This is an important finding because it suggests that behavioural effects play a consequential role in this market and deserve further study.

2.2.3 Hypotheses development

Based on the findings of previous PT studies within conventional asset markets, we expect that investors will tilt their portfolios towards (away from) cryptocurrencies with higher (lower) PT values, resulting in overpricing (underpricing) of these cryptocurrencies and therefore lower (higher) subsequent returns. To explore this view, we test the following hypothesis:

H1. Cryptocurrencies with higher PT values earn lower subsequent returns than cryptocurrencies with lower PT values.

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[9] From an econometric perspective, we also note that, as far as we can tell, *Thoma* (*2021*) employs a pooled OLS estimator in his cross-sectional analysis. This approach does not control for common shocks that may affect all cryptocurrencies in the same time period. Conversely, by using time fixed effects, we believe we can address this issue more convincingly.

While *H1* involves making cross-sectional comparisons at the same point in time, we believe it is also meaningful to compare cryptocurrencies to themselves over time. In other words, we want to investigate whether changes in a cryptocurrency's PT value lead to over-time variation in its excess return. Based on the same arguments discussed above, we conjecture that, over time, as a cryptocurrency's PT value rises (falls) and it becomes more (less) appealing to investors, net buying (selling) pressure leads to increasing overpricing (underpricing) of the cryptocurrency and eventually lower (higher) future returns. To explore this view, we test the following hypothesis:

H2: Over time, as the PT value of a cryptocurrency rises (falls), its future excess return tends to fall (rise).

Combining the cross-sectional and the time-series dimensions of the relationship between PT values and subsequent cryptocurrency returns leads to a further testable hypothesis:

H3: Over time, as the PT value of a cryptocurrency rises (falls) relative to the cross-sectional average PT value of the active cryptocurrencies, its future return tends to fall (rise) relative to the cross-sectional average cryptocurrency return.

Lastly, if the relationship between PT values and subsequent cryptocurrency returns is driven by behavioural factors rather than by economic fundamentals, we would expect the predictive power of PT to be greater among cryptocurrencies that are more difficult to arbitrage. While, in principle, rational arbitrageurs can eliminate mispricings, *Shleifer and Vishny* (*1997*) argue that arbitrage can be costly, and mispricing only disappears if the benefits of arbitrage exceed its costs (risks). In the spirit of *Zhang* (*2006*) and *Lam and Wei* (*2011*), we consider three aspects of limits to arbitrage: (1) arbitrage risk, proxied by idiosyncratic volatility, (2) information uncertainty, proxied by cryptocurrency size, age and volatility, and (3) transaction costs, proxied by *Amihud's* (*2002*) illiquidity ratio. Specifically, we conjecture that higher arbitrage risk, higher information uncertainty, and higher transaction costs impose greater limits to arbitrage. To explore this view, we test the following hypothesis:

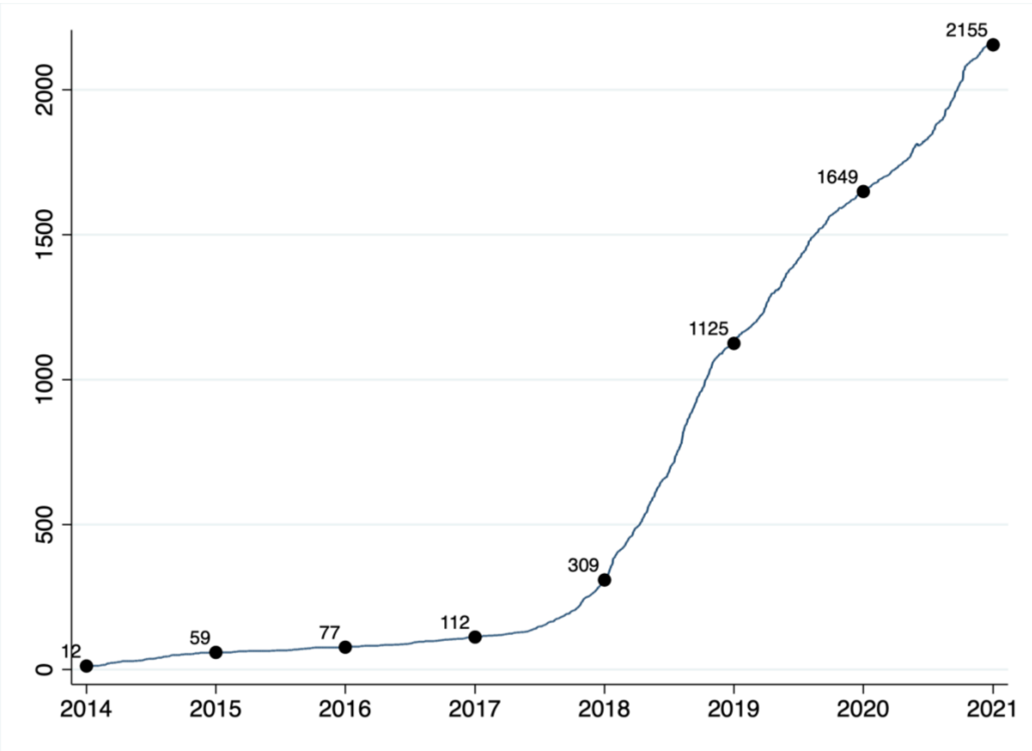
H4: The predictive power of PT is stronger among cryptocurrencies that are more difficult to arbitrage.

2.3 Data description and variables

2.3.1 Cryptocurrency prices, market capitalisation, and trading volume

We collect data for all available cryptocurrencies from *Coincodex*, which is a publicly available platform that aggregates data from more than 210 cryptocurrency exchanges and provides real-time prices as well as historical information. The price, trading volume and market capitalisation of a cryptocurrency are calculated as the volume-weighted average of all prices reported by these exchanges, the 24-hour aggregated volume on all exchanges, and its price multiplied by its circulating supply, respectively.[10] While cryptocurrencies are traded 24/7, the daily data from *Coincodex* are based on the 00:00 UTC time zone and are in US dollars. *Coincodex's* database contains both active and defunct cryptocurrencies, which mitigates survivorship bias concerns, though it is unclear whether all defunct cryptocurrencies are represented.

The sample period is from January 1, 2014 to December 31, 2020.[11] As a preliminary step, we filter out all cryptocurrencies for which (1) fewer than 15 observations are available, (2) no data about trading volume and market capitalisation are available, and (3) the time series of data is either discontinuous or not at a daily frequency. Overall, 2,304 cryptocurrencies survive this initial screening.[12] The number of active cryptocurrencies over the sample period is plotted in Figure 2.1. While there are only 12 active cryptocurrencies at the beginning of 2014, their number increases dramatically over time, especially since 2018. By the end of 2020, there are over 2,000 active cryptocurrencies in our sample.



[10] The circulating supply of a cryptocurrency refers to the number of coins that are publicly available to investors. If the supply information is unreliable or unavailable, it is treated as missing. See *Coincodex* for more details.
[11] We retrieved the historical data from *Coincodex* on January 7, 2021. Data about trading volume are available from the end of 2013; thus, the starting point of our sample period is January 1, 2014.
[12] Note that, since the construction of the PT value of a cryptocurrency requires a minimum number of observations, in practice the usable sample shrinks to 1,573 cryptocurrencies.

Figure 2.1 Number of active cryptocurrencies over time

This figure plots the number of active cryptocurrencies in our dataset between the start and the end of our sample period, which runs from January 1, 2014 to December 31, 2020. The labels along the solid line show the number of active cryptocurrencies on January 1 of each year, with the exception of the last one, which refers to December 31, 2020.

Starting from the daily time series obtained from *Coincodex*, we construct weekly (Friday-to-Friday) time series of log returns, trading volumes, and market capitalisations.[13] We choose to use weekly data because cryptocurrency returns appear to follow a short-memory process (*Grobys et al., 2020*), and previous studies on the cross-section of cryptocurrency returns typically use weekly data (e.g., *Liu et al., 2020*; *Liu et al., 2022*).

2.3.2 Prospect theory value of a cryptocurrency

To measure the PT value of a cryptocurrency at a given point in time, we follow *Barberis et al.'s* (*2016*) method. We assume that (1) investors assess each investment in isolation, (2) during the *editing* phase, they form a mental representation of each cryptocurrency based on its historical return distribution, and (3) during the *evaluation* phase, they evaluate this distribution as predicted by PT.

Therefore, one crucial parameter that we need to specify is the number of past returns on which investors are assumed to focus during the *editing* phase. After reviewing the most common sources of information available to stock market investors during the past century, *Barberis et al.* (*2016*) assume that the typical investor forms a mental representation of a stock by means of "the distribution of its monthly returns over the previous five years." Since the cryptocurrency market emerged during the past decade, we posit that the Internet is the most likely source of information for cryptocurrency investors. Consequently, we conduct a Google search for "cryptocurrency historical return" and examine the first 100 results (see Table A1 in the Appendix A). Our conclusion is that, when accessing websites that provide information about cryptocurrencies, Internet users are usually presented with a chart that displays the performance of a cryptocurrency during the most recent 1-year period. Accordingly, we make the assumption that the typical investor forms a mental representation of a cryptocurrency based on the distribution of its weekly returns during the most recent 1-year (i.e., 52-week) period.[14]

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[13] In using log returns, we follow *Grobys and Junttila* (*2021*); compared to traditional assets, the distribution of simple returns in the cryptocurrency market is extremely right-skewed. When trading volume is zero, we assign a missing value to price and market cap, which excludes approximately 12% of the observations. The results are robust to this choice.

[14] Our assumption is supported by the anchoring heuristic (*Tversky and Kahneman, 1974*), which indicates that the first piece of information (e.g., a chart) to which individuals are exposed affects their subsequent estimates. It

It is also necessary to select the reference point against which investors are assumed to measure gains/losses, as this is one of the key ingredients of PT. In the spirit of *Barberis et al.* (*2016*), we assume that, when investors gauge the return on a given cryptocurrency, they do so relative to the return on the cryptocurrency market index.[15] As such, to compute the PT value of a cryptocurrency at the end of week t-1, for each week from t-52 to t-1, we first compute the cryptocurrency's log return in excess of the market index. Then, assuming that *m* of them are negative and *n* of them are nonnegative, we sort the excess returns in ascending order so that they range from the most negative (r_{-m}) to the most positive (r_n). Lastly, the formulas proposed by *Tversky and Kahneman* (*1992*) imply that the PT value (i.e., *PTV*) of the cryptocurrency is:

$$PTV = \sum_{i=-m}^{n} \pi_i \, v(r_i) \tag{2.1}$$

where $v(r_i)$ represents the value function, which takes the following form:

$$v(r_i) = \begin{cases} r_i^{\alpha} & \text{if } r_i \geq 0 \\ -\lambda(-r_i)^{\beta} & \text{if } r_i < 0 \end{cases} \tag{2.2}$$

and π_i represents the decision weight, which is calculated as follows:

$$\pi_i = \begin{cases} w^{+}\left(\frac{n-i+1}{52}\right) - w^{+}\left(\frac{n-i}{52}\right) & \text{for } 0 \leq i \leq n \\ w^{-}\left(\frac{m+i+1}{52}\right) - w^{-}\left(\frac{m+i}{52}\right) & \text{for } -m \leq i < 0 \end{cases} \tag{2.3}$$

with

$$w^{+}(p) = \frac{p^{\gamma}}{(p^{\gamma} + (1-p)^{\gamma})^{\frac{1}{\gamma}}}, \qquad w^{-}(p) = \frac{p^{\delta}}{(p^{\delta} + (1-p)^{\delta})^{\frac{1}{\delta}}} \tag{2.4}$$

being the probability weighting functions.[16]

Eqs. (2.2) to *(2.4)* contain five parameters, namely $\alpha, \beta, \lambda, \gamma$ and δ. We set them equal to the values that *Tversky and Kahneman* (*1992*) estimated based on their laboratory experiments: $\alpha = \beta =$

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is also supported by the status quo heuristic (*Samuelson and Zeckhauser, 1988*), according to which, when many options are available, (e.g., chart options) individuals tend to stick with the default option, which in this case is the most recent 1-year period. Figure A1 in the Appendix A shows that our results are robust to the length of the time window used in the *editing* phase.

[15] The cryptocurrency market index is constructed as the value-weighted price of the active cryptocurrencies in the sample. Table A11 in the Appendix A shows that the results are robust to the use of alternative reference points (i.e., zero, the risk-free rate, and the time-series mean of the cryptocurrency's own returns).

[16] If there are fewer than nine valid return observations in the 52-week window, the *PTV* variable is assigned a missing value.

0.88 , $\lambda = 2.25$, $\gamma = 0.61$, $\delta = 0.69$.[17] The parameters α and β measure the concavity and convexity of the value function and capture the view that investors are risk-averse for gains and risk-seeking for losses, respectively. The smaller the value of $\alpha(\beta)$, the more risk-averse(seeking) over gains (losses) is the investor. The parameter λ measures investors' loss aversion, which refers to the view that individuals are more sensitive to losses than to gains of the same magnitude (i.e., $\lambda > 1$). Lastly, γ and δ measure the intensity of probability weighting for gains and losses, respectively. Note that, while *Eq. (2.3)* assumes that the objective probability of each of the 52 most recent weekly returns is the same (i.e., 1/52), the decision weights apply a nonlinear transformation. Probability weighting captures the observation that individuals tend to overweight (underweight) small(large)-probability events, which may explain why investors are fond of lottery-type assets (*Bali et al., 2011*; *Grobys and Junttila, 2021*). Smaller values of γ and δ indicate that investors tend to overweight extreme (positive and negative, respectively) outcomes.

2.3.3 Control variables and summary statistics

We control for a set of factors that, according to the literature, contribute to the determination of asset/cryptocurrency returns. The definitions of these factors, the expected signs of their effects, and the supporting literature are presented in Table 2.1.

To mitigate the impact of outliers, we winsorise all variables at the 1st and 99th percentiles separately for each week. Table 2.2 presents a set of average cross-sectional summary statistics.[18] Panel A reports the mean and standard deviation of each variable, and Panel B presents the Pearson correlation coefficient for each pair of variables. It is worth noting that *PTV* (the PT value of a cryptocurrency) is positively correlated with *Rev*, *Lt_rev*, and *Mom*, which measure past returns, as well as *Skew1* and *Skew2*, which measure past skewness. Conversely, *PTV* is negatively correlated with *Vol* and *Ivol*, which measure the volatility of past returns. These signs are consistent with the theory, as the PT value of a gamble is expected to be increasing in its mean payoff and skewness (due to probability weighting) and decreasing in the standard deviation of its payoffs (due to loss aversion).

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[17] Subsequent studies (e.g., *Gonzalez and Wu, 1999*; *Abdellaoui*, *2000*) have confirmed the validity of these parameter estimates using more sophisticated techniques. However, since *Rieger et al.* (*2017*) find that the values of these parameters tend to vary significantly across countries, in Section 2.4.8 we repeat our analysis using a set of country-specific parameter estimates and show that the results are robust.

[18] Since we study both the cross-sectional and the time-series relationships between PT values and future cryptocurrency returns, in Table A2 in the Appendix A we also present a number of average time-series summary statistics.

Table 2.1 Variable descriptions

Variable name	Definition	Sign of the expected effect	Reference
PTV	Prospect theory value of cryptocurrency *i*'s historical weekly return distribution from week t-52 to t-1	-	*Barberis et al., 2016*
Beta	Slope from the regression of cryptocurrency *i*'s weekly excess return on the cryptocurrency market excess return from week t-52 to t-1	+	*Liu et al., 2022*
Size	Natural logarithm of cryptocurrency *i*'s market capitalisation at the end of week t-1	-	*Elendner et al., 2017*
Mom	Cryptocurrency *i*'s cumulative return from week t-3 to t-2	+	*Liu et al., 2022*
Illiq	Mean of cryptocurrency *i*'s absolute daily return divided by its daily trading volume in week t-1	+	*Zhang and Li, 2021*
Rev	Cryptocurrency *i*'s return in week t-1	-	*Li and Yi, 2019*
Lt_Rev	Cryptocurrency *i*'s cumulative return from week t-60 to t-13	-	*Fama, 1998*
Vol	Standard deviation of cryptocurrency *i*'s daily returns in week t-1	+	*Jia* et al., *2021*
Ivol	Idiosyncratic volatility of cryptocurrency *i*'s daily returns in week t-1	+	*Zhang and Li, 2020*
Volume	Natural logarithm of cryptocurrency *i*'s mean daily trading volume in week t-1	-	*Liu et al., 2022*
StdVolume	Natural logarithm of the standard deviation of cryptocurrency *i*'s daily trading volume in week t-1	-	*Liu et al., 2022*
Max	Maximum value of cryptocurrency *i*'s daily returns in week t-1	-	*Grobys and Junttila, 2021*
Min	Negative of the minimum value of cryptocurrency *i*'s daily returns in week t-1	-	*Grobys and Junttila, 2021*
Skew1	Short-term skewness, i.e., skewness of cryptocurrency *i*'s daily returns in week t-1	-	*Jia et al., 2021*
Skew2	Long-term skewness, i.e., skewness of cryptocurrency *i*'s weekly returns from week t-52 to week t-1	-	*Barberis et al., 2016*
Iskew	Idiosyncratic skewness of cryptocurrency *i*'s weekly returns from week t-52 to t-1	-	*Harvey and Siddique, 2000*
Coskew	Coefficient on the squared market excess return from the regression of cryptocurrency *i*'s weekly excess return on the cryptocurrency market excess return and the squared market excess return from week t-52 to week t-1	-	*Harvey and Siddique, 2000*

Table 2.2 Average cross-sectional summary statistics

Panel A. Mean and standard deviation

	PTV	Beta	Size	Mom	Rev	Illiq	Lt_rev	Vol	Ivol	Max	Min	Volume	StdVolume	Skew1	Skew2	Iskew	Coskew
Mean	-0.2092	0.4723	14.4565	0.0035	0.0021	0.2019	-0.1959	0.1975	0.1597	0.2887	0.2744	9.5643	8.7863	0.0681	0.3939	0.4201	-0.0071
Standard deviation	0.1011	0.4361	2.7824	0.3470	0.2865	1.4476	1.4459	0.1738	0.1483	0.2881	0.2617	3.7945	3.5893	0.6528	0.8671	0.8452	2.3212

Panel B. Pearson's pairwise correlation matrix

	PTV	Beta	Size	Mom	Rev	Illiq	Lt_rev	Vol	Ivol	Max	Min	Volume	StdVolume	Skew1	Skew2	Iskew
Beta	0.0185															
Size	0.6064	-0.0699														
Mom	0.0718	0.0082	0.0603													
Rev	0.0803	0.0061	0.0462	-0.2310												
Illiq	-0.2885	0.0371	-0.3090	-0.0314	-0.0102											
Lt_rev	0.4826	-0.0331	0.3190	-0.0066	-0.0050	-0.1303										
Vol	-0.3567	0.0198	-0.3947	0.0324	0.0992	0.2768	-0.1483									
Ivol	-0.3675	0.0153	-0.4089	0.0468	0.0789	0.2711	-0.1510	0.9520								
Max	-0.2902	0.0129	-0.3346	-0.0217	0.3004	0.2203	-0.1346	0.9213	0.8736							
Min	-0.3457	0.0211	-0.3764	0.0790	-0.1492	0.2602	-0.1327	0.9051	0.8648	0.7235						
Volume	0.5637	-0.0853	0.8657	0.0729	0.0418	-0.3814	0.2432	-0.3437	-0.3580	-0.2843	-0.3320					
StdVolume	0.5484	-0.0842	0.8436	0.0775	0.0623	-0.3596	0.2351	-0.2909	-0.3062	-0.2288	-0.2899	0.9824				
Skew1	0.0075	-0.0083	-0.0036	-0.0292	0.1651	-0.0180	-0.0106	0.0648	0.0636	0.2960	-0.1968	0.0203	0.0387			
Skew2	0.3892	-0.0425	0.0493	0.0273	0.0365	-0.0742	0.2089	-0.0164	-0.0140	0.0054	-0.0321	0.0615	0.0654	0.0388		
Iskew	0.4242	-0.0325	0.1223	0.0382	0.0476	-0.0732	0.1896	-0.0443	-0.0458	-0.0159	-0.0592	0.1274	0.1288	0.0368	0.7551	
Coskew	0.0266	0.0017	0.0036	-0.0023	0.0022	0.0374	-0.0017	-0.0100	-0.0161	-0.0103	-0.0094	0.0150	0.0173	0.0033	0.0827	-0.1047

This table presents the time-series averages of a set of weekly cross-sectional summary statistics. Panel A displays the mean and standard deviation of each variable, and panel B displays the Pearson's pairwise correlation coefficients. *PTV* is the prospect theory value of a cryptocurrency's historical return distribution from week t-52 to t-1. *Beta* is the estimated slope obtained by regressing a cryptocurrency's weekly excess return on the cryptocurrency market excess return from week t-52 to t-1. *Size* is the natural logarithm of a cryptocurrency's market capitalisation at the end of week t-1. *Mom* (momentum) is a cryptocurrency's cumulative return from week t-3 to t-2. *Illiq* (illiquidity) is *Amihud's* (*2002*) measure of illiquidity, which is the mean of a cryptocurrency's absolute daily return divided by its daily volume in week t-1. *Rev* (reversal) is a cryptocurrency's return in week t-1. *Lt_rev* (long-term reversal) is a cryptocurrency's cumulative return from week t-60 to t-13. *Vol* (volatility) is the standard deviation of a cryptocurrency's daily returns in week t-1. *Ivol* is the idiosyncratic volatility of a cryptocurrency's daily returns in week t-1 (*Ang et al. 2006*). *Max* and *Min* are the maximum and the negative of the minimum of a cryptocurrency's daily returns in week t-1 (*Bali et al., 2011*). *Volume* is the natural logarithm of a cryptocurrency's mean daily trading volume in week t-1. *StdVolume* is the natural logarithm of the standard deviation of a cryptocurrency's daily trading volume in week t-1. *Skew1* (short-term skewness) is the skewness of a cryptocurrency's daily returns in week t-1. *Skew2* (long-term skewness) is the skewness of a cryptocurrency's weekly returns from week t-52 to t-1. *Iskew* is the idiosyncratic skewness of a cryptocurrency's weekly returns from week t-52 to t-1 (*Harvey and Siddique, 2000*). *Coskew* is a cryptocurrency's coskewness, which refers to the 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 and Siddique, 2000*). The sample period runs from January 2, 2015 to December 25, 2020.

2.4 Empirical Analysis

2.4.1 Cross-sectional relationship between *PTV* and future returns

2.4.1.1 Portfolio analysis

To examine whether cryptocurrencies with high PT values earn lower average returns than their peers with low PT values (*H1*), we initially conduct a univariate portfolio analysis. The strength of this analysis comes from its non-parametric nature. At the end of each week, we sort cryptocurrencies into decile portfolios based on *PTV*. Decile 1 (10) consists of the cryptocurrencies with the lowest (highest) PT values. We assume that the portfolios are held for one week. Hence, we compute the one-week-ahead equal-weighted and value-weighted mean returns of each *PTV*-sorted decile portfolio.[19] This procedure allows us to generate a time series of weekly returns for each *PTV*-sorted portfolio. Lastly, we use these time series to calculate the mean return in excess of the risk-free rate and the CAPM alpha of each *PTV*-sorted portfolio during the sample period.[20]

Table 2.3 reports the results. We focus on the right-most column, which shows the results for the zero-cost long-short portfolios that long the first decile (lowest *PTV*) and short the tenth decile (highest *PTV*). The mean returns are about 12.9% and 5.9% per week for the equal-weighted and the value-weighted long-short portfolios, respectively. The HAC-robust t-statistics, based on Newey-West standard errors computed using five lags, indicate that they are statistically different from zero at the 1% level.

These figures should be viewed in the light of the typical trading costs in the cryptocurrency market. Based on *Bianchi and Dickerson's* (*2021*) estimates, we adopt a conservative average bid-ask spread of 1% and additional trading fees of 1% as the total transaction costs for the weekly rebalancing of the long-short portfolios. The mean returns net of transaction costs (10.9% and 3.9% per week for the equal-weighted and the value-weighted portfolio, respectively) remain economically significant. The results do not change when we compute the portfolios' CAPM alphas to adjust returns for risk.

These numbers lend initial support to *H1,* according to which cryptocurrencies with higher PT values earn lower average returns than cryptocurrencies with lower PT values. We also note that the mean returns and alphas of the equal-weighted long-short portfolios are greater than those of the value-

[19] As the cross-sectional additivity property does not apply to log returns, we convert log returns to simple returns before calculating the average return of each decile. After constructing *PTV*-sorted portfolio returns, we convert simple returns back to log returns before computing mean excess returns and CAPM alphas.
[20] We construct the weekly risk-free rate based on the one-month US Treasury bill rate from *Kenneth French's website*, and we use the cryptocurrency market index as a proxy for the market portfolio when computing the CAPM alphas.

Table 2.3 Univariate portfolio analysis

	Low	PTV2	PTV3	PTV4	PTV5	PTV6	PTV7	PTV8	PTV9	High	Low-High
Excess return											
EW	0.1334***	0.0881***	0.0619***	0.0474***	0.0401***	0.0283***	0.0160	0.0125	0.0125	0.0049	0.1285***
	(7.09)	(6.12)	(4.53)	(4.05)	(3.35)	(2.61)	(1.47)	(1.05)	(1.12)	(0.65)	(7.47)
VW	0.0682***	0.0444***	0.0306**	0.0310***	0.0192*	0.0156	0.0101	0.0070	0.0179	0.0093	0.0589***
	(4.14)	(2.89)	(2.16)	(2.89)	(1.72)	(1.41)	(0.92)	(0.58)	(1.61)	(1.39)	(3.91)
CAPM alpha											
EW	0.1297***	0.0851***	0.0586***	0.0441***	0.0372***	0.0249**	0.0131	0.0093	0.0098	0.0021	0.1276***
	(6.87)	(5.85)	(4.30)	(3.85)	(3.11)	(2.37)	(1.21)	(0.79)	(0.89)	(0.29)	(7.40)
VW	0.0646***	0.0417***	0.0278*	0.0290***	0.0167	0.0127	0.0070	0.0033	0.0151	0.0061	0.0585***
	(3.87)	(2.74)	(1.96)	(2.71)	(1.50)	(1.19)	(0.63)	(0.28)	(1.39)	(1.00)	(3.85)

This table reports the mean excess returns and CAPM alphas of *PTV*-sorted portfolios, where *PTV* is the prospect theory value of a cryptocurrency's historical return distribution from week t-52 to t-1. The portfolios are formed at the end of each week and held for one week. The rightmost column shows the mean excess returns and CAPM alphas of zero-cost long-short portfolios that long the first decile (lowest *PTV*) and short the tenth decile (highest *PTV*). We report both equal-weighted (EW) and value-weighted (VW) mean excess returns and CAPM alphas, where the market portfolio is proxied by the cryptocurrency market index. The sample period is from January 2, 2015 to December 25, 2020. HAC-robust t-statistics based on Newey-West standard errors (max 5 lags) are shown in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

weighted ones, which suggests that the predictive power of PT is more pronounced among small market-cap cryptocurrencies.[21]

2.4.1.2 Panel regressions with time fixed effects

To control for the factors that have been found to influence the cross-section of asset/cryptocurrency returns, we estimate panel regressions with time fixed effects (FE) by OLS. This allows us to remove the over-time variation in the data and isolate the variation across cryptocurrencies (*Kropko and Kubinec, 2020*). Our preferred regression equation is as follows:

$$\begin{aligned} Return_{i,t} = \beta_0 + \beta_1 PTV_{i,t-1} + \beta_2 Beta_{i,t-1} + \beta_3 Size_{i,t-1} + \beta_4 Mom_{i,t-1} + \\ \beta_5 Rev_{i,t-1} + \beta_6 Illiq_{i,t-1} + \beta_7 Lt\_rev_{i,t-1} + \beta_8 Vol_{i,t-1} + \beta_9 Ivol_{i,t-1} \\ + \beta_{10} Max_{i,t-1} + \beta_{11} Min_{i,t-1} + \text{Time FE} + e_{i,t} \end{aligned} \tag{2.5}$$

where $Return_{i,t}$ represents cryptocurrency i's log return in excess of the risk-free rate in week t, and the regressors are as defined in Table 2.1. To address the dependence in the error term, we estimate two-way clustered standard errors by cryptocurrency and week.[22]

We initially estimate *Eq. (2.5)* without any control variables (column 1 of Table 2.4), and then we gradually include all the controls (columns 2-12). The results show that the coefficient on *PTV* remains negative and statistically significant at conventional levels even after controlling for a set of factors that have predictive power in the cross-section of cryptocurrency returns. These estimates further support *H1*. Specifically, according to our preferred equation (column 7 of Table 2.4), a one cross-sectional standard-deviation increase in the PT value of a cryptocurrency reduces its next week's excess return by 0.71% relative to other cryptocurrencies.[23] For comparison, using data from the US market, *Barberis et al.* (*2016*) estimate that a one-standard-deviation increase in a stock's *PTV* reduces its next *month*'s return by only 0.129%. In other words, the *PTV* effect in the cryptocurrency market is approximately 23 times the size of that in the US stock market.

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[21] The results are also robust if we exclude Bitcoin, which accounts for a large portion of total market capitalisation. In addition, we conduct a bivariate dependent-sort portfolio analysis, which examines the relationship between *PTV* and future returns conditional on a second sort variable (e.g., *Mom*). Our conclusions concerning the equal-weighted long-short portfolios are unaffected, but the evidence is less robust for those that are value-weighted (see Table A4 in the Appendix A).

[22] *Gow et al.* (*2010*) show that, contrary to popular belief, the Newey-West corrected Fama-MacBeth approach produces standard errors that correct only for cross-sectional but not for time-series dependence in the error term. Since an unreported Arellano-Bond autocorrelation test (*Arellano and Bond, 1991*) reveals that the error term in our model is serially correlated, we do not employ the Fama-MacBeth approach. Rather, we choose to estimate panel regressions with time FE and two-way clustering by cryptocurrency and week, which, as shown by *Petersen* (*2009*) and *Gow et al.* (*2010*), produces standard errors that are robust to both cross-sectional and time-series dependence in the error term.

[23] The coefficient on *PTV* is -0.0707 and the average cross-sectional standard deviation of *PTV* is 0.1011. Thus, the magnitude of the effect is -0.71% (= -0.0707×0.1011).

Column 3 (Table 2.4) shows that including the previous week's return (i.e., *Rev*) in the regression substantially reduces the size of the coefficient on *PTV*. This is not surprising, as the strong predictive power of the short-term reversal effect has previously been documented (*Shen et al., 2020*; *Li et al., 2019*).[24]

The skewness-related variables appear in columns 9-12 of Table 2.4. Short-term skewness (i.e., *Skew1*) has been found to predict cryptocurrency returns in the cross-section (*Jia et al., 2021*). However, like *Liu et al.* (*2022*), we find no evidence that *Skew1* helps predict subsequent returns. The estimated coefficient on *Skew2* is negative and statistically significant (column 10 of Table 2.4). *Skew2* measures the skewness of weekly returns from week t-52 to t-1 and can be thought of as an integral part of PT, as it is closely related to its probability weighting component. This result is consistent with the findings of *Barberis et al.* (*2016*). Including this variable in the regression reduces the size of the coefficient on *PTV*. However, the coefficient remains statistically significant at the 5% level, and its size is still economically meaningful. Crucially, this suggests that PT's ability to describe investor behaviour in the cryptocurrency market is not entirely subsumed by a preference for skewness.

Interestingly, while previous work finds support for the predictive power of *Max* (*Grobys and Junttila, 2021*) and *Ivol* (*Zhang and Li, 2020*), we find no evidence of such effects in our dataset, which is possibly due to a more comprehensive set of controls. It is also worth noting that, contrary to previous findings (e.g., *Elendner et al., 2017*; *Liu et al., 2022*; *Liu et al., 2020*; *Shen et al., 2020*), the coefficient on *Size* is estimated to be positive. However, this effect is not statistically robust across the specifications displayed in Table 2.4.[25]

2.4.2 Time-series relationship between *PTV* and future returns

Next, we use panel regressions similar to *Eq. (2.5)* but with cryptocurrency FE to exploit the second dimension of our dataset. By removing the variation across cryptocurrencies and concentrating on the over-time variation in the data (*Kropko and Kubinec, 2020*), we can examine whether, over time, as the PT value of a cryptocurrency rises (falls), its future excess return tends to fall (rise) (*H2*).

Table 2.5 reports the results of this analysis. Here we again gradually add the controls to assess the robustness of the *PTV* effect. The estimates reveal that the coefficient on *PTV* is consistently negative and statistically significant at the 1% level. In other words, there is strong evidence of a negative time-series relationship between a cryptocurrency's PT value and its future excess return. This

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[24] Table A5 in the Appendix A shows the regression output when the *PTV* variable is constructed using returns from week t-53 to t-2 to skip the previous week's return. In the majority of columns, the coefficient on *PTV* remains negative and statistically significant at conventional levels.

[25] In untabulated results, we find that the coefficient on *Size* is negative and statistically significant when *Size* is the only explanatory variable in the regression.

Table 2.4 Panel regressions: Cross-sectional relationship between PTV and subsequent cryptocurrency returns

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
PTV	-0.1195***	-0.1227***	-0.0434**	-0.0382*	-0.0485**	-0.0694***	-0.0707***	-0.0741***	-0.0739***	-0.0471**	-0.0494**	-0.0734***
	(-5.26)	(-5.08)	(-1.98)	(-1.80)	(-2.08)	(-3.10)	(-3.20)	(-3.27)	(-3.26)	(-2.06)	(-2.14)	(-3.22)
Beta		-0.0034	-0.0039	-0.0040	-0.0042	-0.0037	-0.0037	-0.0034	-0.0033	-0.0048	-0.0044	-0.0035
		(-0.74)	(-1.09)	(-1.12)	(-1.19)	(-1.03)	(-1.04)	(-0.96)	(-0.93)	(-1.37)	(-1.25)	(-0.97)
Size		0.0005	0.0020***	0.0020***	0.0020***	0.0015**	0.0015**	0.0008	0.0008	0.0002	0.0005	0.0008
		(0.69)	(2.98)	(3.10)	(2.94)	(2.20)	(2.22)	(1.24)	(1.22)	(0.41)	(0.77)	(1.24)
Mom		-0.0134***	-0.1088***	-0.1086***	-0.1084***	-0.1071***	-0.1069***	-0.1069***	-0.1069***	-0.1061***	-0.1063***	-0.1069***
		(-3.04)	(-19.81)	(-20.17)	(-20.08)	(-19.78)	(-19.76)	(-19.78)	(-19.79)	(-19.75)	(-19.77)	(-19.78)
Rev			-0.3654***	-0.3653***	-0.3647***	-0.3628***	-0.3588***	-0.3586***	-0.3588***	-0.3583***	-0.3583***	-0.3585***
			(-42.75)	(-42.50)	(-42.50)	(-42.12)	(-34.84)	(-34.87)	(-33.29)	(-34.96)	(-34.95)	(-34.89)
Illiq				0.0011***	0.0011***	0.0012***	0.0012***	0.0012***	0.0012***	0.0012***	0.0012***	0.0012***
				(2.63)	(2.60)	(2.80)	(2.78)	(2.86)	(2.87)	(2.86)	(2.88)	(2.87)
Lt_rev					0.0017	0.0022*	0.0022**	0.0023**	0.0024**	0.0029***	0.0025**	0.0023**
					(1.55)	(1.96)	(2.00)	(2.14)	(2.16)	(2.62)	(2.31)	(2.14)
Vol						-0.0067	-0.0742	-0.0744	-0.0741	-0.0717	-0.0728	-0.0743
						(-0.23)	(-1.60)	(-1.60)	(-1.59)	(-1.53)	(-1.56)	(-1.59)
Ivol						-0.0268	-0.0265	-0.0259	-0.0259	-0.0218	-0.0235	-0.0260
						(-0.80)	(-0.78)	(-0.76)	(-0.76)	(-0.64)	(-0.69)	(-0.76)
Max							0.0143	0.0141	0.0150	0.0150	0.0149	0.0140
							(0.79)	(0.78)	(0.72)	(0.83)	(0.82)	(0.78)
Min							0.0324*	0.0325*	0.0315	0.0308	0.0313	0.0326*
							(1.69)	(1.69)	(1.56)	(1.60)	(1.63)	(1.69)
Volume								0.0002	0.0002	0.0001	0.0001	0.0002
								(0.17)	(0.17)	(0.08)	(0.11)	(0.14)
StdVolume								0.0005	0.0005	0.0005	0.0005	0.0006
								(0.38)	(0.38)	(0.32)	(0.39)	(0.40)
Skew1									-0.0004			
									(-0.17)			
Skew2										-0.0092***		
										(-6.73)		
Iskew											-0.0077***	
											(-5.71)	
Coskew												-0.0009
												(-1.16)
Crypto FEs	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
Adj. R-squared	0.1226	0.1310	0.2348	0.2356	0.2355	0.2355	0.2356	0.2357	0.2357	0.2361	0.2360	0.2357
N	110912	106080	106080	105783	105679	105611	105611	105514	105500	105514	105514	105514

This table reports estimates of panel regressions with week FE and a varying set of controls. In all specifications, the dependent variable is the one-week-ahead excess return of the given cryptocurrency. The t-statistics shown in parentheses are based on standard errors clustered by cryptocurrency and week. *PTV* is the prospect theory value of a cryptocurrency's historical return distribution from week t-52 to t-1. *Beta* is the estimated slope obtained by regressing a cryptocurrency's weekly excess return on the cryptocurrency market excess return from week t-52 to t-1. *Size* is the natural logarithm of a cryptocurrency's market capitalisation at the end of week t-1. *Mom* (momentum) is a cryptocurrency's cumulative return from week t-3 to week t-2. *Illiq* (illiquidity) is *Amihud's* (*2002*) measure of illiquidity, which is the mean of a cryptocurrency's absolute daily return divided by its daily volume in week t-1. *Rev* (reversal) is a cryptocurrency's return in week t-1. *Lt_rev* (long-term reversal) is a cryptocurrency's cumulative return from week t-60 to t-13. *Vol* (volatility) is the standard deviation of a cryptocurrency's daily returns in week t-1. *Ivol* is the idiosyncratic volatility of a cryptocurrency's daily returns in week t-1 (*Ang et al., 2006*). *Max* and *Min* are the maximum and the negative of the minimum of a cryptocurrency's daily returns in week t-1(*Bali et al., 2011*). *Volume* is the natural logarithm of a cryptocurrency's mean daily trading volume in week t-1. *StdVolume* is the natural logarithm of the standard deviation of a cryptocurrency's daily trading volume in week t-1. *Skew1* (short-term skewness) is the skewness of a cryptocurrency's daily returns in week t-1. *Skew2* (long-term skewness) is the skewness of a cryptocurrency's weekly returns from week t-52 to t-1. *Iskew* is the idiosyncratic skewness of a cryptocurrency's weekly returns from week t-52 to t-1 (*Harvey and Siddique, 2000*). *Coskew* is a cryptocurrency's coskewness, which refers to the 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 and Siddique,2000*). The sample period runs from January 2, 2015 to December 25, 2020. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table 2.5 Panel regressions: Time-series relationship between PTV and future cryptocurrency returns

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
PTV	-0.4305***	-0.3099***	-0.2045***	-0.1984***	-0.2072***	-0.2060***	-0.2065***	-0.2125***	-0.2120***	-0.1512***	-0.1890***	-0.2112***
	(-8.47)	(-5.10)	(-3.63)	(-3.54)	(-3.53)	(-3.64)	(-3.67)	(-3.75)	(-3.74)	(-2.75)	(-3.03)	(-3.74)
Size		-0.0372***	-0.0237***	-0.0233***	-0.0243***	-0.0244***	-0.0242***	-0.0282***	-0.0284***	-0.0280***	-0.0281***	-0.0281***
		(-6.24)	(-5.12)	(-5.03)	(-5.41)	(-5.40)	(-5.38)	(-6.58)	(-6.62)	(-6.51)	(-6.57)	(-6.54)
Mom		0.0072	-0.0751***	-0.0744***	-0.0737***	-0.0735***	-0.0733***	-0.0732***	-0.0733***	-0.0729***	-0.0729***	-0.0733***
		(0.60)	(-5.42)	(-5.36)	(-5.30)	(-5.35)	(-5.35)	(-5.36)	(-5.37)	(-5.34)	(-5.36)	(-5.37)
Rev			-0.3357***	-0.3353***	-0.3342***	-0.3342***	-0.3245***	-0.3237***	-0.3291***	-0.3240***	-0.3234***	-0.3237***
			(-18.61)	(-18.39)	(-18.22)	(-18.14)	(-16.51)	(-16.51)	(-15.79)	(-16.77)	(-16.68)	(-16.50)
Illiq				0.0013***	0.0013***	0.0013***	0.0013**	0.0014***	0.0014***	0.0014***	0.0014***	0.0014***
				(2.70)	(2.67)	(2.61)	(2.58)	(2.89)	(2.90)	(2.88)	(2.88)	(2.87)
Lt_rev					0.0028	0.0028	0.0028	0.0029	0.0030	0.0031	0.0031	0.0029
					(0.90)	(0.90)	(0.89)	(0.95)	(0.96)	(1.01)	(1.01)	(0.94)
Vol						0.0312	-0.0721	-0.0746	-0.0730	-0.0708	-0.0742	-0.0741
						(0.60)	(-1.06)	(-1.09)	(-1.07)	(-1.04)	(-1.08)	(-1.08)
Ivol						-0.0311	-0.0294	-0.0289	-0.0283	-0.0274	-0.0277	-0.0290
						(-0.50)	(-0.47)	(-0.46)	(-0.45)	(-0.44)	(-0.44)	(-0.46)
Max							0.0125	0.0113	0.0294	0.0115	0.0117	0.0111
							(0.52)	(0.47)	(1.06)	(0.48)	(0.49)	(0.47)
Min							0.0580**	0.0584**	0.0392	0.0560**	0.0576**	0.0585**
							(2.34)	(2.34)	(1.50)	(2.24)	(2.32)	(2.35)
Volume								0.0011	0.0010	0.0007	0.0010	0.0010
								(0.47)	(0.42)	(0.29)	(0.43)	(0.41)
StdVolume								0.0027	0.0028	0.0028	0.0027	0.0028
								(0.82)	(0.85)	(0.86)	(0.83)	(0.85)
Skew1									-0.0077			
									(-1.65)			
Skew2										-0.0121**		
										(-1.98)		
Iskew											-0.0062	
											(-1.62)	
Coskew												-0.0024
												(-1.03)
Crypto FEs	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
Adj. R-squared	0.0011	0.0117	0.1134	0.1136	0.1137	0.1132	0.1134	0.1137	0.1138	0.1141	0.1138	0.1138
N	110902	106074	106074	105776	105671	105603	105603	105506	105492	105506	105506	105506

This table reports estimates of panel regressions with cryptocurrency FE and a varying set of controls. In all specifications, the dependent variable is the one-week-ahead excess return of the given cryptocurrency. The t-statistics shown in parentheses are based on standard errors clustered by cryptocurrency and week. *PTV* is the prospect theory value of a cryptocurrency's historical return distribution from week t-52 to t-1. *Size* is the natural logarithm of a cryptocurrency's market capitalisation at the end of week t-1. *Mom* (momentum) is a cryptocurrency's cumulative return from week t-3 to t-2. *Illiq* (illiquidity) is Amihud's (2002) measure of illiquidity, which is the mean of a cryptocurrency's absolute daily return divided by its daily volume in week t-1. *Rev* (reversal) is a cryptocurrency's return in week t-1. *Lt_rev* (long-term reversal) is a cryptocurrency's cumulative return from week t-60 to t-13. *Vol* (volatility) is the standard deviation of a cryptocurrency's daily returns in week t-1. *Ivol* is the idiosyncratic volatility of a cryptocurrency's daily returns in week t-1 (*Ang et al., 2006*). *Max* and *Min* are the maximum and the negative of the minimum of a cryptocurrency's daily returns in week t-1 (*Bali et al., 2011*). *Volume* is the natural logarithm of a cryptocurrency's mean daily trading volume in week t-1. *StdVolume* is the natural logarithm of the standard deviation of a cryptocurrency's daily trading volume in week t-1. *Skew1* (short-term skewness) is the skewness of a cryptocurrency's daily returns in week t-1. *Skew2* (long-term skewness) is the skewness of a cryptocurrency's weekly returns from week t-52 to t-1. *Iskew* is the idiosyncratic skewness of a cryptocurrency's weekly returns from week t-52 to t-1 (*Harvey and Siddique, 2000*). *Coskew* is a cryptocurrency's coskewness, which refers to the 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 and Siddique*, *2000*). The sample period runs from January 2, 2015 to December 25, 2020. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

result lends support to *H2*.[26] According to our preferred equation (column 7 of Table 2.5), over time, a one time-series standard-deviation increase in the PT value of a cryptocurrency decreases its next week's excess return by about 1.34%.[27]

Based on the estimates in column 10 of Table 2.5, even after controlling for *Skew2*, the *PTV* effect is still statistically and practically significant. This result confirms that investors' preference for skewness cannot fully explain this phenomenon. The implication is that PT must be capturing some important features of individuals' decision making, other than preference for skewness, that affect cryptocurrency pricing.

To gauge whether our results are sensitive to our choice of the dependent variable, we conduct some robustness tests. Following Focke et al. (2020), we repeat the analysis using returns in excess of the market return as the dependent variable. Additionally, following Madsen and Niessner (2019), we repeat the analysis using abnormal excess returns ($= excess\ return_{i,t} - \widehat{Beta_{i,t}} \times market\ excess\ return_t$) as the dependent variable. In both instances, the estimates reveal that our results are robust (see columns 1-2 of Table A8 in the Appendix A).

2.4.3 Two-dimensional relationship between *PTV* and future returns

After focussing on each dimension in isolation, we blend the cross-sectional and the time-series dimensions of our dataset by including in Eq. (2.5) both cryptocurrency and time FE (Kropko and Kubinec, 2020). We begin our analysis by estimating a regression equation where the only regressor is *PTV* (column 1 of Table 2.6), and then we gradually add all the controls (columns 2-12).

Consistent with *H3*, the estimates show that the coefficient on *PTV* is always negative and statistically significant at the 1% level.[28] Our preferred model (column 7 of Table 2.6) suggests that, over time, as the *PTV* of a cryptocurrency rises by one standard deviation relative to the average *PTV* of the active cryptocurrencies, its next week's excess return tends to decrease by about 1.68% relative to the cross-sectional average cryptocurrency excess return.[29]

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[26] Table A6 in the Appendix A shows the regression output when the *PTV* variable is constructed using returns from week t-53 to t-2 to skip the previous week's return. In all but one of the specifications, the coefficient on *PTV* remains negative and statistically significant at the 1% level.

[27] The coefficient on *PTV* is -0.2065, and the average time-series standard deviation of *PTV* is 0.0648. Thus, the magnitude of the effect is -1.34% (= -0.2065×0.0648).

[28] When the *PTV* variable is constructed using returns from week t-53 to t-2 to skip the previous week's return, the coefficient on *PTV* remains negative and statistically significant at the 1% level in all but one of the specifications (see Table A7 in the Appendix A). Also, replacing the dependent variable, i.e., excess returns over the risk-free rate, with returns in excess of the market return or abnormal excess returns does not alter the results (see columns 3-4 of Table A8 in the Appendix A).

[29] The coefficient on *PTV* is -0.2074. To identify a plausible counterfactual, we follow Mummolo and Peterson's (2018) suggestion and compute the standard deviation of the residuals from an auxiliary regression of *PTV* on

Kropko and Kubinec (*2020*) argue that many researchers incorrectly interpret the output of a two-way FE estimator as “a single estimate of X on Y while accounting for unit-level heterogeneity and time shocks.” They suggest that its interpretation is more complex. The description above represents our best effort to communicate the effect of the *PTV* variable in an intuitive way and in line with these authors’ critique.

In the rest of the paper, to minimise the number of tables and figures, we carry out all analyses using the two-way FE model. Consequently, the same interpretation of the coefficient on *PTV* applies in that follows.

2.4.4 Limits to arbitrage

If the relationship between *PTV* and future cryptocurrency returns is driven by investors’ irrational behaviour (as captured by PT), we would expect this relationship to be stronger among cryptocurrencies that are more difficult to arbitrage. Following *Zhang* (*2006*) and *Lam and Wei* (*2011*), we use cryptocurrencies’ market capitalisation (*Size*), age (*Age*), volatility (*Vol*), illiquidity (*Illiq*), and idiosyncratic volatility (*Ivol*) as proxies for the severity of limits to arbitrage.

To test *H4*, according to which the predictive power of PT is stronger among cryptocurrencies that are harder to arbitrage (i.e., those with lower market capitalisation, younger age, higher volatility, higher illiquidity, and higher idiosyncratic volatility), we add to our two-way FE model an interaction between *PTV* and each of these five proxies for difficulty of arbitrage and re-estimate the equation accordingly.

The results, displayed in Table 2.7, are to a large extent consistent with our expectations. The coefficients on the interaction terms *PTV*×*Size* and *PTV*×*Age* are statistically significant at the 5% level, and the coefficients on the interaction terms *PTV*×*Vol* and *PTV*×*Ivol* are significant at the 1% level. The signs of the first two coefficients are positive, while the signs of the latter two are negative, confirming that the predictive power of *PTV* is stronger among cryptocurrencies with lower market capitalisation, younger age, higher volatility, and higher idiosyncratic volatility. As for the fifth proxy,

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cryptocurrency and time FE. This generates a standard deviation of 0.0811. Thus, the magnitude of the *PTV* effect is -1.68% (= -0.2074×0.0811). The rationale is that the two-way FE impose a large reduction in the variation of the explanatory variables, and consequently the overall standard deviation of *PTV* would represent an implausible counterfactual.

Table 2.6 Panel regressions: Two-dimensional relationship between *PTV* and future cryptocurrency returns

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
PTV	-0.5098***	-0.3307***	-0.2094***	-0.2042***	-0.1979***	-0.2054***	-0.2074***	-0.2092***	-0.2085***	-0.1884***	-0.1915***	-0.2087***
	(-12.29)	(-8.42)	(-6.78)	(-6.63)	(-6.06)	(-6.36)	(-6.51)	(-6.52)	(-6.50)	(-5.61)	(-5.60)	(-6.50)
Size		-0.0503***	-0.0249***	-0.0245***	-0.0243***	-0.0244***	-0.0244***	-0.0256***	-0.0257***	-0.0255***	-0.0255***	-0.0256***
		(-11.82)	(-9.00)	(-9.01)	(-8.90)	(-8.98)	(-9.05)	(-9.38)	(-9.44)	(-9.25)	(-9.32)	(-9.36)
Mom		-0.0053	-0.1088***	-0.1086***	-0.1090***	-0.1081***	-0.1079***	-0.1081***	-0.1081***	-0.1079***	-0.1080***	-0.1081***
		(-1.18)	(-19.66)	(-20.10)	(-20.00)	(-19.49)	(-19.51)	(-19.53)	(-19.54)	(-19.54)	(-19.55)	(-19.53)
Rev			-0.3612***	-0.3611***	-0.3611***	-0.3602***	-0.3586***	-0.3585***	-0.3588***	-0.3585***	-0.3585***	-0.3585***
			(-43.28)	(-43.09)	(-42.88)	(-42.51)	(-35.09)	(-35.11)	(-33.41)	(-35.14)	(-35.15)	(-35.12)
Illiq				0.0011**	0.0011**	0.0011**	0.0011**	0.0011**	0.0011**	0.0011**	0.0012**	0.0011**
				(2.09)	(2.09)	(2.17)	(2.17)	(2.27)	(2.27)	(2.27)	(2.27)	(2.26)
Lt_rev					-0.0010	-0.0009	-0.0009	-0.0008	-0.0008	-0.0006	-0.0008	-0.0008
					(-0.71)	(-0.68)	(-0.68)	(-0.62)	(-0.59)	(-0.46)	(-0.60)	(-0.61)
Vol						-0.0036	-0.0860	-0.0866*	-0.0865*	-0.0853	-0.0861	-0.0865*
						(-0.13)	(-1.65)	(-1.66)	(-1.65)	(-1.63)	(-1.65)	(-1.65)
Ivol						-0.0209	-0.0214	-0.0215	-0.0214	-0.0205	-0.0208	-0.0216
						(-0.60)	(-0.60)	(-0.60)	(-0.60)	(-0.57)	(-0.58)	(-0.60)
Max							0.0250	0.0241	0.0251	0.0242	0.0243	0.0241
							(1.21)	(1.16)	(1.06)	(1.17)	(1.17)	(1.16)
Min							0.0322	0.0322	0.0311	0.0314	0.0317	0.0322
							(1.55)	(1.54)	(1.44)	(1.51)	(1.52)	(1.55)
Volume								-0.0009	-0.0008	-0.0010	-0.0009	-0.0009
								(-0.55)	(-0.53)	(-0.63)	(-0.57)	(-0.57)
StdVolume								0.0023	0.0023	0.0023	0.0023	0.0023
								(1.42)	(1.41)	(1.42)	(1.42)	(1.43)
Skew1									-0.0004			
									(-0.18)			
Skew2										-0.0051*		
										(-1.92)		
Iskew											-0.0043*	
											(-1.69)	
Coskew												-0.0008
												(-0.70)
Crypto FEs	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
Adj. R-squared	0.1238	0.1426	0.2410	0.2419	0.2419	0.2415	0.2416	0.2417	0.2418	0.2418	0.2418	0.2417
N	110902	106074	106074	105776	105671	105603	105603	105506	105492	105506	105506	105506

This table reports estimates of panel regressions with cryptocurrency FE, week FE, and a varying set of controls. In all specifications, the dependent variable is the one-week-ahead excess return of the given cryptocurrency. The t-statistics shown in parentheses are based on standard errors clustered by cryptocurrency and week. *PTV* is the prospect theory value of a cryptocurrency's historical return distribution from weekt-52 to t-1. *Size* is the natural logarithm of a cryptocurrency's market capitalisation at the end of week t-1. *Mom* (momentum) is a cryptocurrency's cumulative return from week t-3 to t-2. *Illiq* (illiquidity) is *Amihud's* (*2002*) measure of illiquidity, which is the mean of a cryptocurrency's absolute daily return divided by its daily volume in week t-1. *Rev* (reversal) is a cryptocurrency's return in week t-1. *Lt_rev* (long-term reversal) is a cryptocurrency's cumulative return from week t-60 to t-13. *Vol* (volatility) is the standard deviation of a cryptocurrency's daily returns in week t-1. *Ivol* is the idiosyncratic volatility of a cryptocurrency's daily returns in week t-1 (*Ang et al., 2006*). *Max* and *Min* are the maximum and the negative of the minimum of a cryptocurrency's daily returns in week t-1 (*Bali et al., 2011*). *Volume* is the natural logarithm of a cryptocurrency's mean daily trading volume in week t-1. *StdVolume* is the natural logarithm of the standard deviation of a cryptocurrency's daily trading volume in week t-1. *Skew1* (short-term skewness) is the skewness of a cryptocurrency's daily returns in week t-1. *Skew2* (long-term skewness) is the skewness of a cryptocurrency's weekly returns from week t-52 to t-1. *Iskew* is the idiosyncratic skewness of a cryptocurrency's weekly returns from week t-52 to t-1 (*Harvey and Siddique, 2000*). *Coskew* is a cryptocurrency's coskewness, which refers to the 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 and Siddique, 2000*). The sample period runs from January 2, 2015 to December 25, 2020. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table 2.7 Limits to arbitrage and *PTV* effect

	(1)	(2)	(3)	(4)	(5)
Dependent variable: One-week-ahead cryptocurrency excess return					
PTV	-0.4998***	-0.2546***	-0.1154***	-0.2038***	-0.1298***
	(-3.53)	(-7.53)	(-3.73)	(-6.60)	(-4.19)
PTV×Size	0.0235**				
	(2.39)				
PTV×Age		0.0007**			
		(2.39)			
PTV×Vol			-0.2771***		
			(-4.58)		
PTV×Illiq				-0.0020	
				(-0.76)	
PTV×Ivol					-0.2746***
					(-3.83)
Size	-0.0169***	-0.0253***	-0.0250***	-0.0243***	-0.0248***
	(-5.86)	(-9.89)	(-9.29)	(-9.13)	(-9.22)
Mom	-0.1078***	-0.1074***	-0.1068***	-0.1080***	-0.1068***
	(-19.42)	(-19.46)	(-19.30)	(-19.49)	(-19.27)
Rev	-0.3587***	-0.3580***	-0.3561***	-0.3587***	-0.3568***
	(-35.10)	(-35.08)	(-35.38)	(-35.06)	(-35.25)
Illiq	0.0010*	0.0012**	0.0011**	0.0002	0.0011**
	(1.95)	(2.28)	(2.11)	(0.16)	(2.09)
Lt_rev	-0.0015	-0.0006	-0.0013	-0.0010	-0.0013
	(-1.12)	(-0.45)	(-1.03)	(-0.72)	(-1.01)
Vol	-0.0897*	-0.0862*	-0.2487***	-0.0858	-0.1281**
	(-1.69)	(-1.65)	(-4.21)	(-1.65)	(-2.33)
Ivol	-0.0230	-0.0210	-0.0176	-0.0222	-0.1267***
	(-0.65)	(-0.59)	(-0.49)	(-0.63)	(-2.96)
Max	0.0279	0.0251	0.0464**	0.0252	0.0420*
	(1.33)	(1.21)	(2.11)	(1.22)	(1.94)
Min	0.0325	0.0321	0.0453**	0.0323	0.0426**
	(1.55)	(1.54)	(2.11)	(1.55)	(1.99)
Crypto FEs	Yes	Yes	Yes	Yes	Yes
Week FEs	Yes	Yes	Yes	Yes	Yes
Adj. R-squared	0.2418	0.2417	0.2424	0.2416	0.2421
N	105603	105603	105603	105603	105603

This table presents estimates of panel regressions with two-way FE (cryptocurrency and week). In all specifications, the dependent variable is the one-week-ahead excess return of the given cryptocurrency. *PTV*, which is the prospect theory value of a cryptocurrency's historical return distribution from week t-52 to t-1, is interacted with five variables that proxy for the severity of limits to arbitrage: *Size*, *Age*, *Vol*, *Illiq*, and *Ivol*. *Size* is the natural logarithm of the cryptocurrency's market capitalisation in week t-1, *Age* is the number of weeks for which the cryptocurrency has been listed on Coincodex, *Vol* is the standard deviation of the cryptocurrency's daily returns in week t-1. *Illiq* is *Amihud's* (*2002*) measure of illiquidity, which is the mean of the cryptocurrency's absolute daily return divided by its daily volume in week t-1, and *Ivol* is *Ang et al.'s* (*2006*) measure of idiosyncratic volatility in week t-1. The remaining variables are as defined in Table 2.1. The sample period runs from January 2, 2015 to December 25, 2020. The t-statistics shown in parentheses are based on standard errors clustered by cryptocurrency and week. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

the coefficient on the interaction term *PTV*×*Illiq* is negative as expected but not statistically significantly different from zero.

2.4.5 Disaggregated results by size segment

A crucial question is whether PT's ability to explain cryptocurrency returns is confined to a specific size segment of the market. As Hou et al. (2020) demonstrate, when micro-cap stocks are excluded, the majority of the anomalies discussed in the finance and accounting literature disappear. Since our portfolio analysis reveals that the *PTV* effect is stronger for equal-weighted (cf. value-weighted) long-short portfolios, it is possible that the predictive power of *PTV* is mostly driven by micro-cap cryptocurrencies. If this were the case, the *PTV* effect would be of limited practical interest because high trading costs make anomalies in micro-cap assets hard to exploit.

To investigate this issue, at the end of each week we sort cryptocurrencies into deciles by *Size*. We then re-estimate our preferred two-way FE model separately for each *Size* decile. Figure 2.2 plots the point estimates and confidence intervals for the coefficient on *PTV*. All the point estimates are negative, and with the exception of decile 8, all coefficients are statistically significant at the 1% level. This confirms that the relationship between *PTV* and future returns holds not only for micro-cap cryptocurrencies, whose economic relevance is undeniably very limited, but also for cryptocurrencies in the small- and large-cap segments. This result suggests that the phenomenon explored in this paper has important practical implications for those trading in the cryptocurrency market.[30]

[30] We also re-estimate our preferred two-way FE model separately for each cryptocurrency sector (e.g., DeFi coins, Stablecoins, Privacy coins). The coefficient on *PTV* is negative for 11 out of 12 sectors and is statistically significant for 4 out of 12 sectors (see Table A9 in the Appendix A). Considering that for several of these sectors the number of cryptocurrencies and observations is quite small, these results suggest that the *PTV* effect is not driven by a single cryptocurrency sector but is rather pervasive.

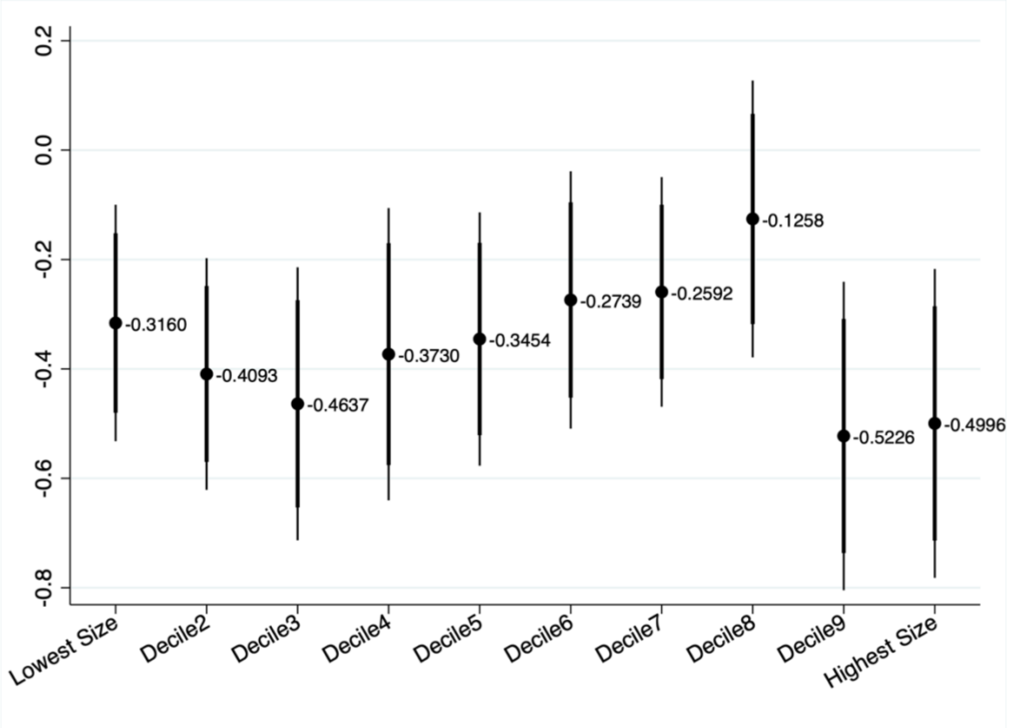

Figure 2.2 *PTV* effect by *Size* decile

This figure plots the point estimates and the 95% and 99% confidence intervals of the coefficient on PTV from panel regressions by Size decile. PTV is the PT value of a cryptocurrency's historical return distribution from week t-52 to t-1. Each week, we sort cryptocurrencies into deciles based on Size. Subsequently, for each decile, we estimate a separate panel regression, where the dependent variable is the one-week-ahead excess return of the given cryptocurrency. Each regression equation includes two-way FE (cryptocurrency and week) and the following controls: *Mom*, *Rev*, *Illiq*, *Lt_rev*, *Vol*, *Ivol*, *Max*, and *Min*. All variables are as defined in Table 2.1. The confidence intervals are based on standard errors clustered by cryptocurrency and week.

2.4.6 Exploration of the individual components of PT

We explore whether all three components of PT other than reference dependence, namely loss aversion (*LA*), probability weighting (*PW*), and the concavity/convexity of the value function (*CC*), play significant roles in explaining investors' behaviour in the cryptocurrency market. To achieve this, we repeat our analyses, but we activate each PT component individually, re-calculate the *PTV* variable accordingly, and re-estimate our preferred two-way FE model.

The results are displayed in Table 2.8. Column 7, where all three components are active, represents the benchmark and is identical to column 7 of Table 2.6. In column 1 (Table 2.8), only the

LA component (measured by λ) is active, while PW and CC are switched off. In other words, we set $\lambda = 2.25$ and set the parameters that govern $PW\,(\gamma, \delta)$ and $CC\,(\alpha, \beta)$ equal to 1 in *Eqs. (2.2)* and *(2.4)*. Similarly, in column 4, both the LA and CC components are active ($\lambda = 2.25$, $\alpha = \beta = 0.88$), while the PW component is switched off ($\gamma = \delta = 1$). The remaining columns have a similar interpretation.

The results reveal that, in columns 1-3 (Table 2.8), the coefficient on PTV is negative and statistically significant at the 1% level. In other words, all three components of PT play significant roles in explaining why a cryptocurrency is appealing or unappealing to investors.

To assess whether any component plays a more dominant part, we follow the informal approach employed by *Barberis et al.* (*2016*) and compare the t-statistics on the PTV coefficients across columns. Furthermore, we compare the values of the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) across columns, with lower AIC/BIC values indicating better model fits. Among the first three columns, the model in which the CC component is active features the lowest AIC/BIC values and the highest t-statistic. The same is true in columns 4-6, in which two components are active at the same time. Although these are not formal statistical tests, the data are consistent with the interpretation that the CC component plays a more substantial role than LA and PW in explaining the behaviour of investors in the cryptocurrency market.

2.4.7 PT vs. EUT

We have investigated whether PT can help describe investor behaviour in the cryptocurrency market. However, the EUT is still the dominant paradigm when it comes to modelling decision-making under risk in the finance literature. In principle, it is possible that the cryptocurrency market is populated only by rational investors who act as predicted by the EUT, or by a mixture of rational investors and irrational investors who act as predicted by PT.

To examine whether we obtain the same results if we assume that investors maximise their expected utility when evaluating cryptocurrencies' historical return distributions (i.e., whether there is a negative relationship between cryptocurrencies' expected utility values and their future returns), we select a specific functional form for the typical investor's utility function. Following *Barberis et al.* (*2016*) and *Zhong and Wang* (*2018*), we assume that investors have a constant relative risk aversion (CRRA) utility function and maximise the following expected utility function:

$$EU = \sum_{i=-m}^{n} \frac{1}{52} \frac{(1 + R_i)^{1-\theta}}{1 - \theta} \tag{2.6}$$

Table 2.8 *PTV* effect based on individual components of PT

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Active PT components:	LA	PW	CC	LA/CC	LA/PW	CC/PW	LA/CC/PW
PTV	-0.3596***	-0.4563***	-1.2471***	-0.3748***	-0.1679***	-0.5780***	-0.2074***
	(-7.50)	(-7.09)	(-11.84)	(-8.01)	(-6.01)	(-7.92)	(-6.51)
Size	-0.0225***	-0.0233***	-0.0176***	-0.0224***	-0.0250***	-0.0224***	-0.0244***
	(-8.56)	(-8.62)	(-6.63)	(-8.44)	(-9.24)	(-8.32)	(-9.05)
Mom	-0.1068***	-0.1061***	-0.1007***	-0.1065***	-0.1083***	-0.1052***	-0.1079***
	(-19.26)	(-19.54)	(-18.92)	(-19.23)	(-19.59)	(-19.40)	(-19.51)
Rev	-0.3562***	-0.3568***	-0.3476***	-0.3556***	-0.3593***	-0.3555***	-0.3586***
	(-35.04)	(-35.04)	(-34.73)	(-34.96)	(-35.16)	(-34.93)	(-35.09)
Illiq	0.0011**	0.0012**	0.0012**	0.0011**	0.0011**	0.0012**	0.0011**
	(2.17)	(2.21)	(2.35)	(2.24)	(2.15)	(2.25)	(2.17)
Lt_rev	0.0007	0.0005	0.0071***	0.0009	-0.0014	0.0015	-0.0009
	(0.55)	(0.32)	(4.79)	(0.69)	(-1.06)	(1.02)	(-0.68)
Vol	-0.0880*	-0.0742	-0.0746	-0.0857	-0.0860	-0.0739	-0.0860
	(-1.68)	(-1.42)	(-1.42)	(-1.64)	(-1.65)	(-1.42)	(-1.65)
Ivol	-0.0234	-0.0137	-0.0117	-0.0222	-0.0210	-0.0135	-0.0214
	(-0.66)	(-0.39)	(-0.33)	(-0.62)	(-0.59)	(-0.38)	(-0.60)
Max	0.0248	0.0229	0.0206	0.0234	0.0252	0.0227	0.0250
	(1.19)	(1.11)	(0.98)	(1.12)	(1.22)	(1.09)	(1.21)
Min	0.0330	0.0270	0.0284	0.0325	0.0321	0.0269	0.0322
	(1.58)	(1.30)	(1.37)	(1.56)	(1.54)	(1.30)	(1.55)
AIC	56606	56635	56418	56615	56706	56606	56691
BIC	56711	56740	56523	56720	56811	56711	56797
Crypto FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Week FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R-squared	0.2422	0.2420	0.2435	0.2421	0.2415	0.2422	0.2416
N	105603	105603	105603	105603	105603	105603	105603

This table reports estimates of panel regressions with two-way FE (cryptocurrency and week). In all specifications, the dependent variable is the one-week-ahead excess return of the given cryptocurrency. All variables are as defined in Table 2.1. What varies across specifications is the type and the number of prospect theory components that are active and feed into the construction of the *PTV* variable. "*LA*" indicates that the loss aversion component is active and is incorporated into the *PTV* variable. "*PW*" indicates that the probability weighting component is active and is incorporated into the *PTV* variable. "*CC*" indicates that the concavity/convexity component is active and is incorporated into the *PTV* variable. Column 7, in which all three components are active, serves as a benchmark. AIC refers to the Akaike Information Criterion, and BIC refers to the Bayesian Information Criterion. The sample period runs from January 2, 2015 to December 25, 2020. The t-statistics shown in parentheses are based on standard errors clustered by cryptocurrency and week. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table 2.9 PTV vs. expected utility value

	θ = 0.5	θ = 2	θ = 3	θ = 4	θ = 5	θ = 6	θ = 7	θ = 8	θ = 9	θ = 10
Panel A. Expected utility value (EU)										
EU	-0.0825***	-0.0015	-0.0000	-0.0000	-0.0000	-0.0000*	-0.0000***	-0.0000	-0.0000*	0.0000
	(-3.54)	(-0.51)	(-0.26)	(-0.62)	(-1.08)	(-1.88)	(-3.62)	(-1.39)	(-1.79)	(0.22)
Crypto FEs	No	No	No	No	No	No	No	No	No	No
Week FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
EU	-0.0739	-0.0044	-0.0000	-0.0000	-0.0000	-0.0000	-0.0000***	-0.0000*	-0.0000***	0.0000
	(-1.61)	(-1.19)	(-0.09)	(-0.17)	(-0.58)	(-1.40)	(-4.75)	(-1.71)	(-3.08)	(0.03)
Crypto FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Week FEs	No	No	No	No	No	No	No	No	No	No
EU	-0.1192***	-0.0012	0.0000	0.0000	-0.0000	-0.0000	-0.0000*	-0.0000	-0.0000	0.0000
	(-3.02)	(-0.37)	(0.84)	(0.38)	(-0.06)	(-0.64)	(-1.83)	(-0.74)	(-1.24)	(0.35)
Crypto FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Week FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Panel B. *PTV* and expected utility value (EU)										
PTV	-0.1339***	-0.0938***	-0.0775***	-0.0721***	-0.0700***	-0.0691***	-0.0689***	-0.0693***	-0.0691***	-0.0729***
	(-5.85)	(-4.73)	(-3.69)	(-3.26)	(-3.14)	(-3.12)	(-3.12)	(-3.11)	(-3.11)	(-3.29)
EU	-0.1543***	0.0048	0.0000	0.0000	-0.0000	-0.0000	-0.0000*	-0.0000	-0.0000	0.0000
	(-6.64)	(1.55)	(1.03)	(0.29)	(-0.22)	(-0.77)	(-1.73)	(-0.58)	(-0.88)	(0.68)
Crypto FEs	No	No	No	No	No	No	No	No	No	No
Week FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
PTV	-0.2430***	-0.2488***	-0.2263***	-0.2163***	-0.2107***	-0.2075***	-0.2061***	-0.2073***	-0.2063***	-0.2103***
	(-4.01)	(-3.86)	(-3.84)	(-3.74)	(-3.68)	(-3.65)	(-3.63)	(-3.63)	(-3.63)	(-3.70)
EU	-0.1708***	0.0112**	0.0000**	0.0000	0.0000	0.0000	-0.0000	0.0000	-0.0000	0.0000
	(-3.20)	(2.48)	(2.35)	(1.32)	(0.73)	(0.29)	(-0.28)	(0.23)	(-0.10)	(0.92)
Crypto FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Week FEs	No	No	No	No	No	No	No	No	No	No
PTV	-0.2572***	-0.2687***	-0.2335***	-0.2192***	-0.2124***	-0.2087***	-0.2070***	-0.2085***	-0.2075***	-0.2122***
	(-7.28)	(-8.22)	(-7.38)	(-6.94)	(-6.75)	(-6.61)	(-6.53)	(-6.60)	(-6.56)	(-6.78)
EU	-0.2074***	0.0134***	0.0000***	0.0000	0.0000	0.0000	-0.0000	0.0000	0.0000	0.0000
	(-4.63)	(3.46)	(2.86)	(1.43)	(0.78)	(0.32)	(-0.22)	(0.32)	(0.02)	(1.01)
Crypto FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Week FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

This table reports estimates of panel regressions with two-way FE (cryptocurrency and week). Only the relevant coefficients are displayed. In all specifications, the dependent variable is the one-week-ahead excess return of the given cryptocurrency, and the controls are *Size*, *Mom*, *Rev*, *Illiq*, *Lt_rev*, *Vol*, *Ivol*, *Max*, and *Min*. In panel A, our key explanatory variable, *PTV*, is replaced by *EU*, which measures the expected utility value of a cryptocurrency's historical return distribution from week t-52 to t-1 under the assumption that the typical investor has a constant relative risk aversion (CRRA) utility function. The parameter θ measures the level of risk aversion and ranges from 0.5 to 10. All other variables are as defined in Table 2.1. In panel B, both *PTV* and *EU* are included in the regressions. The sample period runs from January 2, 2015 to December 25, 2020. The t-statistics shown in parentheses are based on standard errors clustered by cryptocurrency and week. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

where R_i is a cryptocurrency's simple return in week i. In other words, a cryptocurrency's expected utility value at the end of week t-1, EU_{t-1}, depends on its historical return distribution from week t-52 to t-1. The parameter θ measures the level of risk aversion. Following Barberis et al. (2016), we choose values for θ ranging from 0.5 to 10. We then re-estimate our preferred panel regressions with time FE, cryptocurrency FE, and two-way FE, respectively, after replacing the *PTV* variable with the *EU* variable.

The results appear in panel A of Table 2.9. The coefficient on *EU* is usually negative, but its statistical significance is far from robust. Specifically, the coefficient is statistically different from zero at conventional levels in only 9 out of the 30 regressions, and the outcome is highly sensitive to the value of the parameter θ. Gandelman and Hernandez-Murillo (2014) estimate that the value of θ ranges from 0 to 3, and in this region only 2 coefficients (out of 9) are statistically significant at the 10% level. This is only slightly more than would be expected based on pure chance, casting a shadow on the EUT's explanatory power.

In a further analysis, we include both *PTV* and *EU* in the same regression model. The results appear in panel B and show that the predictive power of *PTV* survives the inclusion of *EU*. The coefficient on *PTV* is always negative and statistically different from zero at the 1% level. On the other hand, the sign of the coefficient on *EU* now fluctuates between positive and negative values, and its statistical significance is highly sensitive to the value of θ. This suggests that PT captures some unique features of investors' behaviour and describes how investors evaluate historical return distributions better than the EUT. Consequently, our results are consistent with the interpretation that the number of EUT investors in the cryptocurrency market is small relative to the number of investors who act in line with PT.

2.4.8 Alternative specifications of the *PTV* variable

A natural concern is whether our results are driven by the methodology used to construct the PT value of a cryptocurrency. Our *PTV* variable is based on the parameter values ($\alpha = \beta = 0.88, \lambda = 2.25, \gamma = 0.61, \delta = 0.69$) estimated by Tversky and Kahneman (1992). However, a survey conducted in 53 countries by Rieger et al. (2017) finds significant cross-country variation in PT parameter values. Since some countries are more active than others in the cryptocurrency market, it is possible that our chosen parameter values are not representative of investor behaviour in this market.

To address this issue, using data from DataLight (2019) concerning the number of monthly visits to the 100 most popular cryptocurrency exchanges in the world, we identify the most active countries in the cryptocurrency market for which we can retrieve PT parameter estimates from Rieger et al. (2017)

(see Table A10 in the Appendix A). Next, we re-calculate the *PTV* variable based on each of these country-specific parameter values and re-estimate our preferred two-way FE model accordingly.

Figure 2.3 displays the results (LH panel). These results indicate that, whatever the set of PT parameter estimates we use to construct the *PTV* variable, the coefficient on *PTV* is always negative and statistically significant at the 1% level. We also repeat this analysis using a weighted average of these country-specific PT parameter values, where the weights are the number of monthly visits to the 100 most popular cryptocurrency exchanges as estimated by *DataLight* (*2019*). The results, displayed in the RH panel of Figure 2.3, confirm our previous findings. Both panels of the figure assure us that, if anything, our benchmark estimate of the *PTV* effect, based on *Tversky and Kahneman's* (*1992*) PT parameter values, is a conservative one.

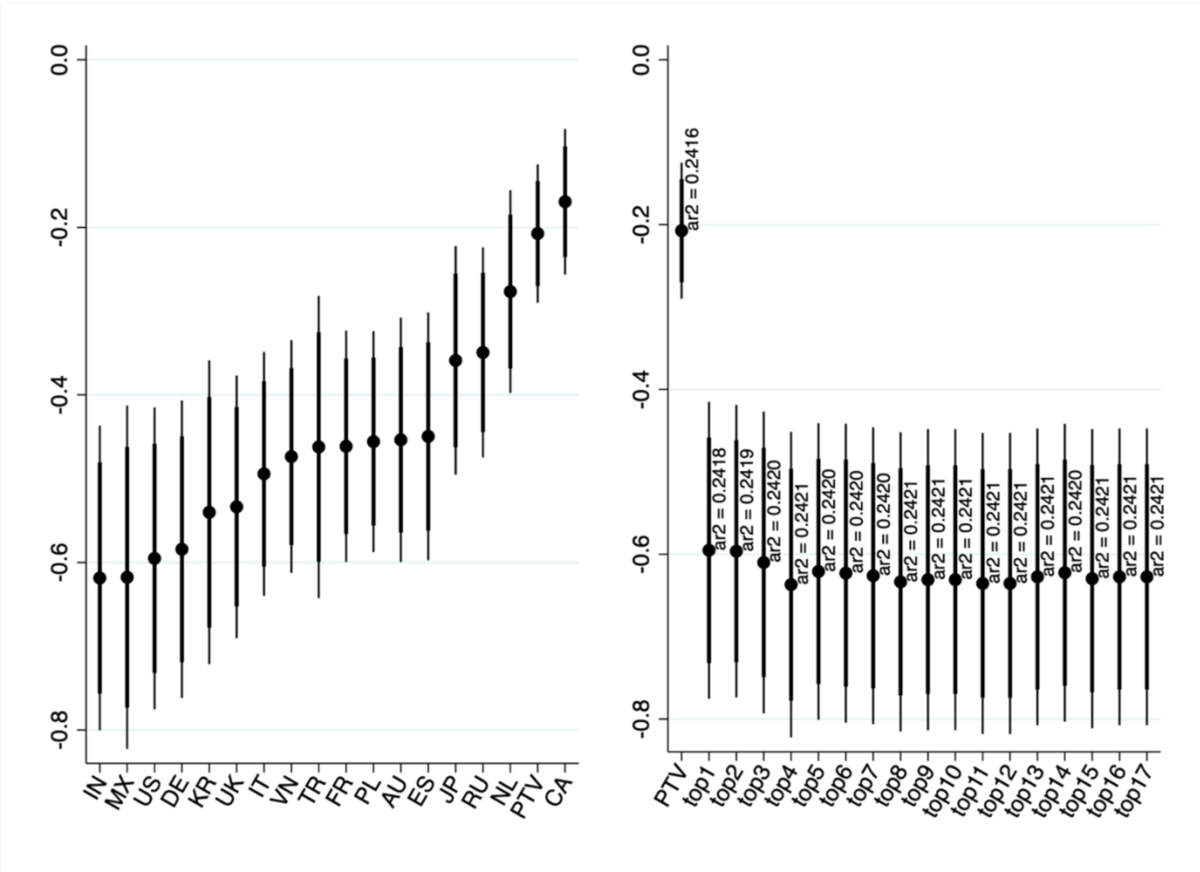

Figure 2.3 *PTV* effect based on country-specific PT parameter estimates

This figure plots the point estimates and the 95% and 99% confidence intervals of the coefficient on *PTV* from a set of panel regressions with two-way FE (cryptocurrency and week). First, based on data from *DataLight* (*2019*), we identify the most active countries in the cryptocurrency market for which we can retrieve country-specific PT parameter estimates (α, β, λ, γ, δ) from *Rieger et al.'s* (*2017*) study. Next, for each set of country-specific parameter estimates, we re-calculate the

PTV variable and regress one-week-ahead cryptocurrency excess returns on *PTV* and the following controls: *Size*, *Mom*, *Rev*, *Illiq*, *Lt_rev*, *Vol*, *Ivol*, *Max*, and *Min*. The left-hand panel displays the resulting point estimates and confidence intervals of the coefficient on *PTV*. The countries in the sample are India (IN), Mexico (MX), United States (US), Germany (DE), South Korea (KR), United Kingdom (UK), Italy (IT), Vietnam (VN), Turkey (TR), France (FR), Poland (PL), Australia (AU), Spain (ES), Japan (JP), Russia (RU), the Netherlands (NL), and Canada (CA). The label "PTV" refers to our benchmark estimate based on *Tversky and Kahneman*'s (*1992*) PT parameter estimates. The point estimates and confidence intervals displayed on the right-hand panel are based on an analogous procedure, but this time we use a weighted average of the country-specific PT parameter estimates to calculate the *PTV* variable. The weights are the number of monthly visits to the 100 most popular cryptocurrency exchanges in the world originating from each of the countries in question, as estimated by *DataLight* (*2019*). For example, the label "top5" indicates that the *PTV* variable is constructed using a weighted average of the PT parameter estimates from the 5 most active countries in the cryptocurrency market. Adjusted R-squared (ar2) values for each regression appear to the right of the corresponding point estimate. The sample period runs from January 2, 2015 to December 25, 2020. The confidence intervals are based on standard errors clustered by cryptocurrency and week.

2.5 Further analyses and robustness tests

To further explore the meaning of our findings and examine their robustness, we conduct several additional tests. The detailed results are presented and discussed in the Appendix A, and we only briefly summarise them here.

We find only marginal evidence that the size of the *PTV* effect is moderated by investor attention, and we find no evidence that it is moderated by investor sentiment or by the amount of uncertainty in the cryptocurrency market. Furthermore, our tests show that the *PTV* effect is fairly stable over time, and it is robust to (1) the length of the historical time window used in the construction of the *PTV* variable, (2) the choice of the reference point against which investors are assumed to gauge gains and losses, and (3) the choice of the dependent variable (e.g., abnormal excess returns in lieu of excess returns).

2.6 Conclusion

Much of the literature on the determinants of cryptocurrency returns typically assumes that market participants act rationally and maximise their expected utility. However, there exists a growing body of research suggesting that investors' behaviour often deviates from that of an expected utility maximiser. Since PT has become the dominant alternative to the EUT, and the cryptocurrency market is mostly populated by financially naïve individual investors (who likely suffer from loss aversion and engage in nonlinear probability weighting, two key components of PT), we set out to investigate whether PT can shed light on the dynamics of cryptocurrency returns.

In line with the theory's predictions, we observe that cryptocurrencies that meet (go against) the preferences of PT investors earn lower (higher) subsequent returns, suggesting that they tend to be overbought (underbought). The effect that we document is economically meaningful and is of importance to both practitioners and academics.

From a practical point of view, our results can help inform investors' speculative strategies in the cryptocurrency market. Although short-selling constraints may raise some concerns, a trading strategy based on the *PTV* effect could still be implemented as a long-only strategy. In other words, a speculative investor could profit from buying the cryptocurrencies that, in the week preceding portfolio formation, exhibit the lowest PT values. We leave it to future research to investigate in greater detail the feasibility of trading strategies based on the *PTV* effect.

Our findings contribute to the cryptocurrency literature and to the behavioural finance literature by shedding light on some of the behavioural forces that shape cryptocurrency pricing. Furthermore, we add to the academic body of knowledge by demonstrating PT's ability to successfully describe decision-making behaviour outside the laboratory and in the presence of large and risky payoffs.

Chapter 3 Can salience theory explain investor behaviour? Real-world evidence from the cryptocurrency market

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). This chapter investigates whether this theory can explain investor behaviour in the cryptocurrency market. Consistent with the theory's predictions, using a sample of 1,738 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.

3.1 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 (*Simon, 1978*; *March, 1982*; *Eysenck, 1982*; *Berger, 1996*). 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 and 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 and 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 (*Kahneman and Tversky, 1973*; *Grether, 1980*). 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 et al.* (*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 et al.* (*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 and 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 and Zaremba, 2022*)? 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 and Zaremba, 2022*)? Secondly, can ST account for investor behaviour in markets other than the stock market?

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 1,738 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 et al., 2021*), who are those most likely to engage in narrow framing (*Liu et al., 2010*) and to extrapolate past returns into the future (*Da et al., 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 et al., 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 3.2 reviews the related literature, and Section 3.3 develops our hypotheses. Section 3.4 describes the data. Section 3.5 illustrates how the ST value of a cryptocurrency is measured. Section 3.6 details the empirical analysis, and Section 3.7 concludes.

3.2 Literature review

3.2.1 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 (*Kahneman and Tversky, 1973*; *Grether, 1980*; *Hamill et al., 1980*), predictions (*Nisbett and Borgida, 1975*; *Bar-Hillel and Fischhoff, 1981*) 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 et al. (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 et al., 2013b*), judicial decisions (*Bordalo et al., 2015*), and asset pricing (*Bordalo et al., 2013a*). *Dertwinkel-Kalt and Köster* (*2020*) empirically test *Bordalo et al.'s* (*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 et al.* (*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 et al.* (*2023*) find that, in the Chinese mutual fund market, funds with greater ST values attract greater net inflows of money.

However, when *Cakici and Zaremba* (*2022*) 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.

3.2.2 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 et al., 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 and 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 and Shapiro, 1956*; *Miller and 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 et al.* (*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 et* *al.* (*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 more than 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.[31]

Lastly, unlike the stock market, the cryptocurrency market is mostly populated by retail investors. A recent JPMorgan survey among 3,400 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 et al., 2020*). Lack of financial sophistication and limited trading experience are often associated with heavier use of heuristics and exacerbation of behavioural biases (*Feng and 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.

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

3.3 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 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 and Li, 2021*; *Zhang et al., 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 et al.* (*2021*) show that the daily reversal effect is more pronounced among small cryptocurrencies, which account for less than 10% of total market cap. 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* (*2022*) 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.

3.4 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 more than 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.[32]

Our data relate to the period from January 1, 2014 to June 30, 2021.[33] We retain only cryptocurrencies for which (1) more than 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 1,738 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 3.1 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 1,604 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 et al., 2021*). Additionally, there is evidence that cryptocurrency returns follow a short-memory process (*Grobys et al., 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.[34] After winsorising these variables at the 1st and 99th percentiles for each

[32] See *Coincodex* (*https://coincodex.com*) for detailed descriptions of the data.
[33] 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.
[34] 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.

Table 3.1 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	23421.97	117787.12	178.65	736.37	4205.32	8.22
2018	168	-0.0605	0.2180	-0.0638	45394.26	248018.97	223.30	1208.42	6461.28	13.05
2019	695	-0.0202	0.3031	-0.0209	9772.46	57779.16	34.74	49.68	244.88	2.23
2020	1328	0.0011	0.3899	-0.0015	7794.30	46280.72	14.10	34.29	167.75	0.92
2021	1604	0.0175	0.4293	-0.0013	40160.84	224344.75	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.

week, we report in Table 3.1 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.

3.5 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.'s* (*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 and Frehen, 2021*).[35]

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.[36] 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.

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[35] 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 2,726 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.

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

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:

$$\sigma(r_{is}, \bar{r}_s) = \frac{|r_{is} - \bar{r}_s|}{|r_{is}| + |\bar{r}_s| + \theta} \tag{3.1}$$

where $\bar{r}_s$ is the log return of the equal-weighted cryptocurrency market index, and θ is a convenience parameter.[37] 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:

$$\tilde{\pi}_{is} = \pi_s \cdot \omega_{is} \tag{3.2}$$

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

$$\omega_{is} = \frac{\delta^{k_{is}}}{\sum_s \delta^{k_{is}} \cdot \pi_s} \quad \delta \in (0,1] \tag{3.3}$$

Eq. (3.3) 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).[38] S represents the set of states, so that $\sum_{s=1}^{S} \pi_s = 1$. The parameter δ 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 δ, 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:[39]

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[37] θ deals with the salience of states in which the cryptocurrency's return is zero. If θ 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.
[38] In case of ties, the returns are further ranked by trading volume.
[39] If there are fewer than half non-missing return observations within the time window, the *STV* variable is assigned a missing value.

$$STV_{i,t-1} = cov[\omega_{is,T}, r_{is,T}] = E^{ST}[r_{is,T}] - \bar{r}_{is,T} \tag{3.4}$$

Eq. (3.4) 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 3.2.

Table 3.3 presents some average cross-sectional summary statistics on cryptocurrency returns, the *STV* variable, and the set of controls.[40] 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* (*2022*) 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* (*2022*) in a sample of international stock markets (0.60).

3.6 Empirical analysis

3.6.1 Cross-sectional relationship between *STV* and future returns

3.6.1.1 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,

[40] Since we also study the time-series relationship between the *STV* variable and future cryptocurrency returns, in Table B1 in the Appendix B we present a number of average time-series summary statistics on the *STV* variable and the set of controls.

Table 3.2 Variable definitions

Variable	Definition	References
Return	Weekly (Friday-to-Friday) log return on a cryptocurrency in week t	*Grobys and Junttila, 2021*
STV	Salience theory value of a cryptocurrency's historical daily return distribution from week t-4 to t-1	*Cosemans and Frehen, 2021*
Beta	Slope obtained by regressing a cryptocurrency daily excess return on the cryptocurrency market excess return from week t-4 to t-1	*Liu et al., 2020*; *Shen et al., 2020*; *Liu et al., 2022*
Size	Natural logarithm of a cryptocurrency's market capitalisation at the end of week t-1	*Elendner et al., 2017*; *Li and 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 and Li, 2021*
Rev	Return on a cryptocurrency in week t-1	*Li and 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 et al., 2021*
Ivol	Idiosyncratic volatility of a cryptocurrency's daily returns from week t-4 to t-1	*Ang et al., 2006*; *Zhang and Li, 2020*
Max	Maximum of a cryptocurrency's daily returns in week t-1	*Bali et al., 2011*; *Grobys and 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 and 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 et al., 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 and 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 and Siddique, 2000*

Table 3.3 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 3.2. The sample period is from January 2, 2015 to June 25, 2021.

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.[41] Lastly, we use the resulting return time series to compute the mean excess return (over the risk-free rate) and CAPM alpha of each decile.[42]

Table 3.4 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 and 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.[43]

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*.[44] 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*.[45] 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.

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[41] 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.
[42] The weekly risk-free rate is derived from the one-month Treasury bill rate from *Kenneth French's website*. When estimating the CAPM alphas, we employ the cryptocurrency market index as a proxy for the market portfolio.
[43] 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).
[44] Indeed, as Table B2 in the Appendix B reveals, the mean values of *Mom*, *Rev*, *Skew1*, *Skew2*, and *Iskew* increase monotonically moving from decile 1 (lowest *STV*) to decile 10 (highest *STV*).
[45] 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.

Table 3.4 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.

The results (see Table B3 in the Appendix B) 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.[46]

3.6.1.2 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 specification is:

$$\begin{aligned} Return_{i,t} = \beta_0 + \beta_1 STV_{i,t-1} + \beta_2 Beta_{i,t-1} + \beta_3 Size_{i,t-1} + \beta_4 Mom_{i,t-1} + \beta_5 Rev_{i,t-1} \\ + \beta_6 Illiq_{i,t-1} + \beta_7 Lt\_rev_{i,t-1} + \beta_8 Vol_{i,t-1} + \beta_9 Ivol_{i,t-1} + \beta_{10} Max_{i,t-1} \\ + \beta_{11} Min_{i,t-1} + \beta_{12} PTV_{i,t-1} + Time\ FE + e_{i,t} \end{aligned} \tag{3.5}$$

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 3.2. The inclusion of time (i.e., week) fixed effects (FE) allows us to isolate the cross-sectional variation in the data (*Kropko and 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 (*Petersen, 2009*; *Gow et al., 2010*).[47]

While *Eq. (3.5)* contains a set of 12 regressors, we start by estimating a simple linear equation with a single explanatory variable, *STV* (column 1 of Table 3.5), 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 3.5), a one cross-sectional standard-deviation increase in the ST value of a cryptocurrency

[46] 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.
[47] 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 and Bond, 1991*), we opt for panel regressions with time FE and cluster-robust standard errors.

reduces its next-week excess return by 0.41% relative to its peers.[48] Considering that the average cross-sectional standard deviation of returns is about 30% per week in our sample (see Panel A of Table 3.3), 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 3.5). 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 Figure 3.1, which is based on the estimates in column 9 of Table 3.5, 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 (*Zhang et al., 2021*; *Zhang and Li, 2021*; *Chen et al., 2022*; *Li et al., 2021*; *Grobys and Junttila, 2021*). In turn, we believe that the ST effect represents a phenomenon that is worthy of further investigation by the academic community.

[48] 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 3.5 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	140914	135333	135333	134957	134722	134430	134430	134429	134298	134273	134294	134298	134298

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 3.2. The sample period is from January 2, 2015 to June 25, 2021. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

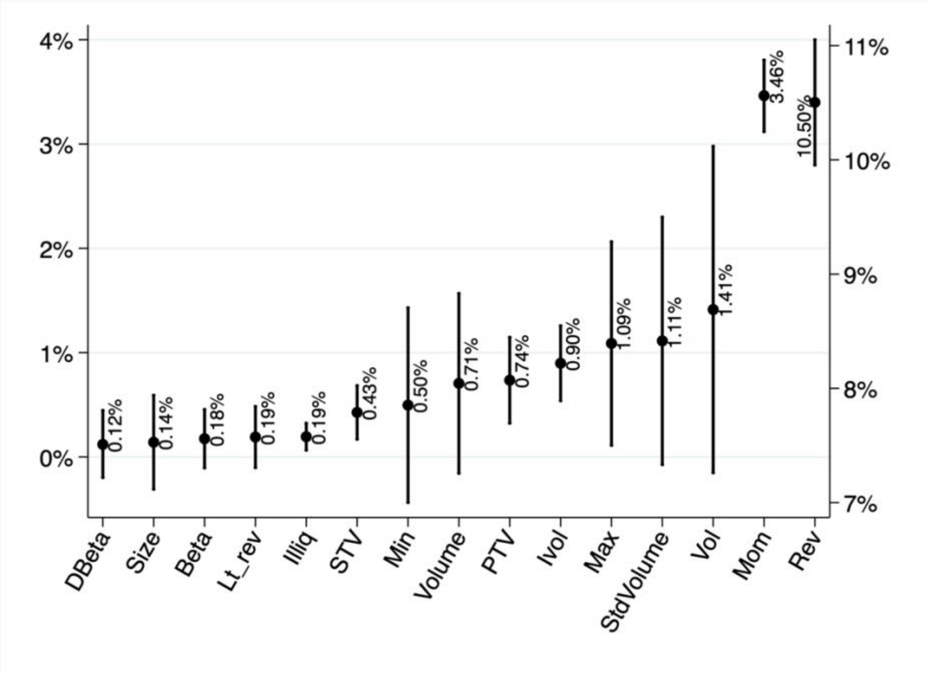

Figure 3.1 Economic significance of the ST effect

This figure is based on the estimates in column 9 of Table 3.5. 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 3.2. 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.

It is also worth noting that, in column 8 (cf. column 7) of Table 3.5, 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.

3.6.2 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 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. (3.5)*) (*Kropko and Kubinec, 2020*). We start by estimating a simple linear regression with cryptocurrency FE and a single explanatory variable, *STV* (column 1 of Table 3.6). Then, we progressively include more covariates (columns 2-13). Table 3.6, 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 3.6), over time, a one time-series standard-deviation increase in a cryptocurrency's ST value reduces its next-week excess return by 0.69%.[49] 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 (= $\text{excess return}_{i,t} - \widehat{Beta}_{i,t} \times \text{market excess return}_t$). Untabulated results reveal that our findings do not change.[50]

3.6.3 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. (3.5)*) (*Kropko and Kubinec, 2020*). We start by estimating a simple regression equation with a single explanatory variable, *STV* (column 1 of Table 3.7). Then, we progressively include more covariates (columns 2-13).

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[49] 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).

[50] 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.

Table 3.6 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	140901	135321	135321	134945	134710	134416	134416	134415	134312	134287	134308	134312	134312

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 3.2. 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 3.7 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	140901	135321	135321	134945	134710	134416	134416	134415	134312	134287	134308	134312	134312

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 3.2. 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 3.7 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 3.7), 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.[51] In what follows, to conserve space and keep the discussion focussed, we conduct all analyses using panel regressions with cryptocurrency and week FE.

3.6.4 ST effect vs. short-term reversal

Cakici and Zaremba (*2022*) 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 Table 3.5, 3.6, and 3.7, 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 B3 in the Appendix B).

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 B4 in the Appendix B). Therefore, we conclude that, in the cryptocurrency market, the predictive power of ST cannot be fully explained by the short-term reversal effect.

[51] 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).

3.6.5 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 et al.* (*2020*) and *Cakici and Zaremba* (*2022*) 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 B5 in the Appendix B). 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 B6 in the Appendix B). In the first classification, we follow *Cakici and Zaremba* (*2022*). 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 3.8, 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

Table 3.8 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	134415	134076	134415	134076

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 3.2. 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.

Table 3.9 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	131359	131359	131359	131359	131359	131359

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 dataset. *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 3.2. Each regression equation includes the following controls: *Mom*, *Rev*, *Lt_rev*, *Max*, *Min,* and *PTV*, which are defined in Table 3.2. 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.

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 3.8 also help us shed light on the progressive disappearance of the ST effect in the US stock market during the past few decades (*Cakici and Zaremba, 2022*). 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 and 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.

3.6.6 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 (*Zhang, 2006*; *Lam and Wei, 2011*) 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 3.9 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 et al.'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 3.7.[52] 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. Figure 3.2 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 (*Ofek et al., 2004*; *Lamont, 2012*). 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 Figure 3.2 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).

[52] We exclude *Size* because, as discussed in Section 3.6.5, there is evidence of an ST effect only among micro-cap cryptocurrencies.

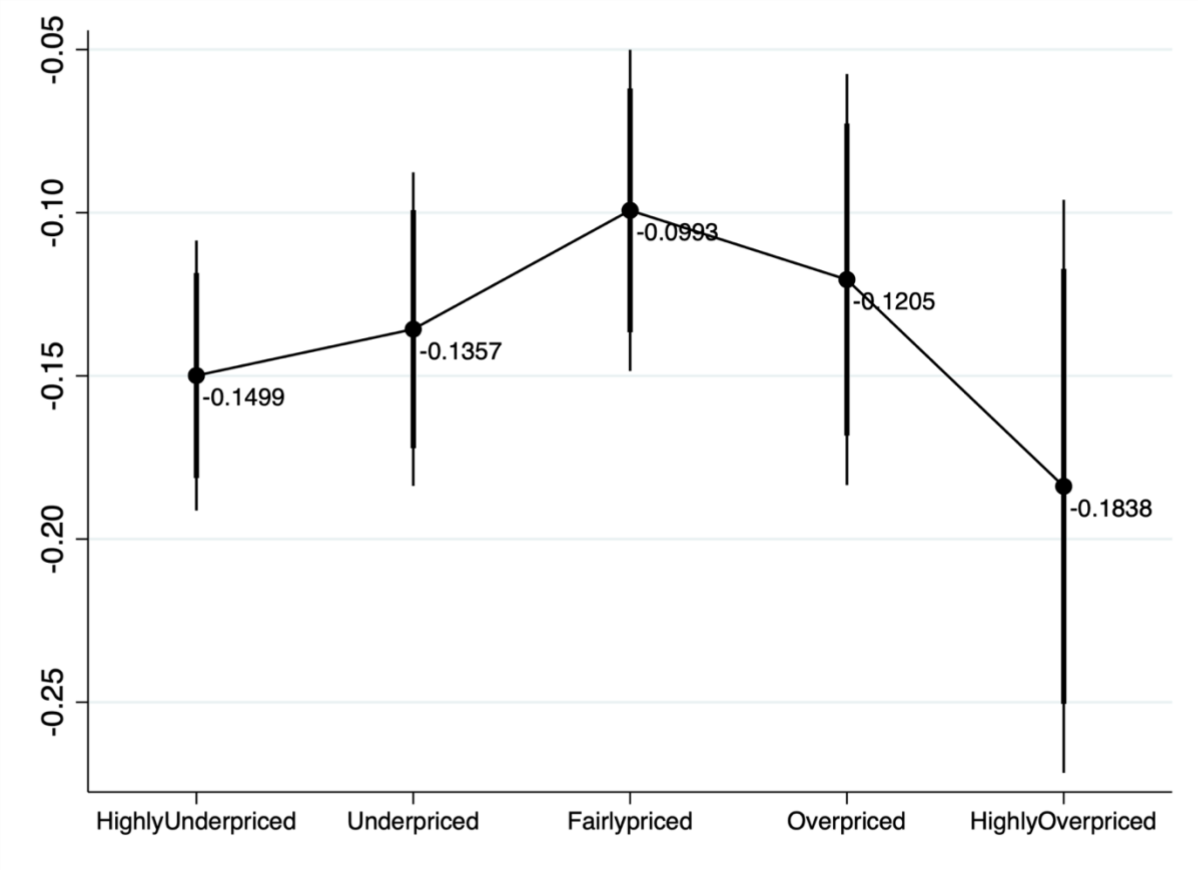


Figure 3.2 Mispricing and ST effect

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.

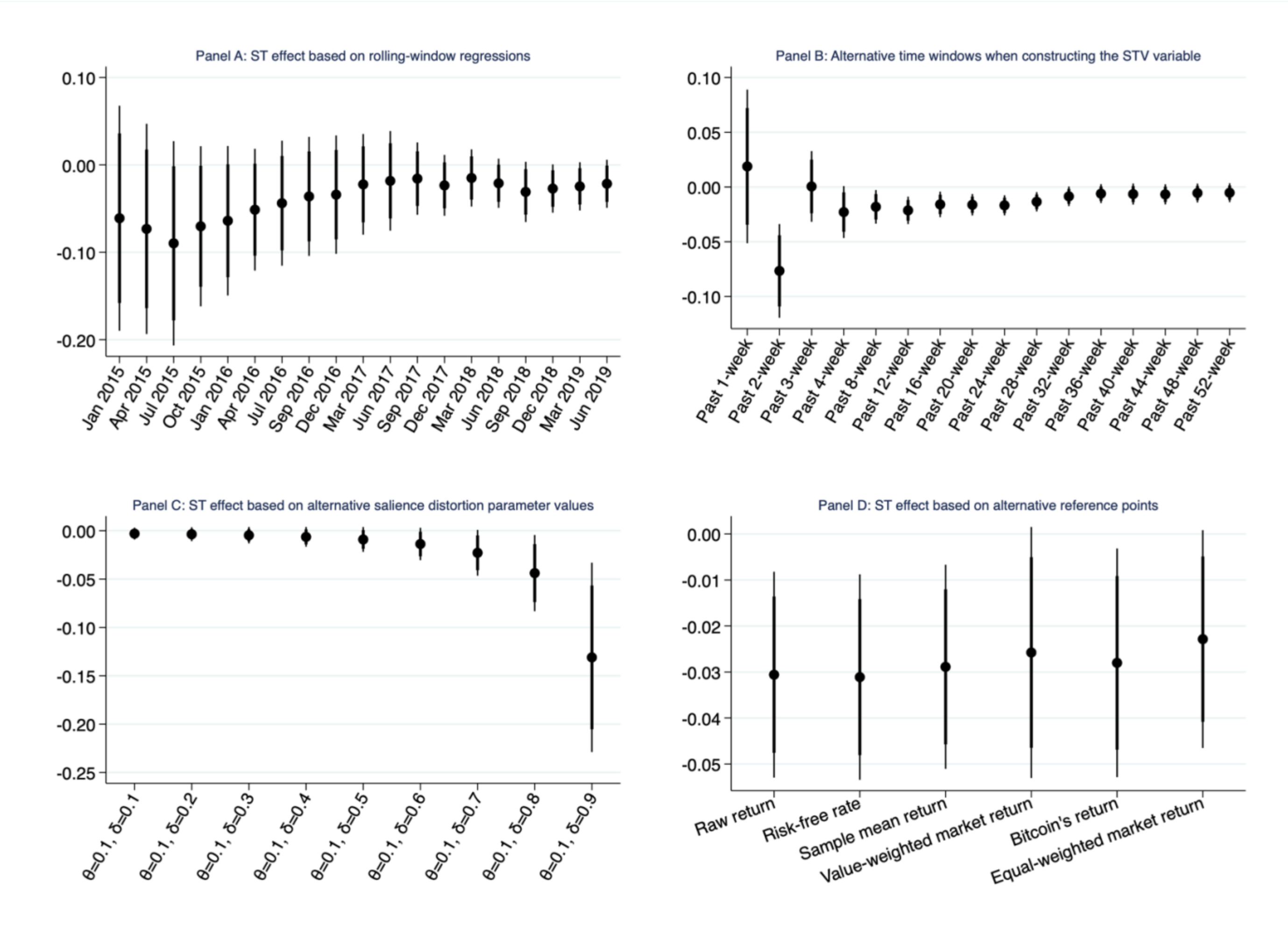
3.6.7 Sensitivity analyses

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.[53] 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 Figure 3.3 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 Figure 3.3 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* (*2022*), suggesting that salient thinkers tend to focus on the recent past when extrapolating historical returns into the future.

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

Figure 3.3 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 3.2. 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 label "Past 8-week" 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 θ constant at 0.1, we let δ 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 label "Raw return" 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.

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. (3.1)* (θ) and investors' degree of salience distortion in *Eq. (3.2)* (δ). First, we re-calculate the *STV* variable using alternative values for θ and δ, and then we re-estimate our preferred panel-regression specification accordingly. Since varying the value of θ (in the region from 0.05 to 0.3) has no material impact on our estimates, in Panel C of Figure 3.3 we only display the output generated by varying the value of δ between 0.1 and 0.9, while keeping θ 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 δ is between 0.5 and 0.9. This result is supported by *Bordalo et al.'s* (*2012*) experimental results, which show that the typical degree of salience distortion (δ) 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 Figure 3.3 shows that the use of alternative reference points does 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 B7 in the Appendix B). 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.

3.7 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 et al., 2005*).

However, only recently has the concept of salience begun to attract the interest of researchers in the fields of economics and finance. *Bordalo et al.* (*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.

Chapter 4 Behavioural theories of investor behaviour: Empirical evidence from the limit order book

This chapter investigates whether investor behaviour in the stock market is consistent with the predictions of well-known behavioural theories (i.e., prospect theory, salience theory, and regret theory). While previous studies employ indirect tests based on the cross-section of stock returns, we observe investor behaviour directly using five years of comprehensive limit order book data from the Taiwan stock exchange. We find that aggregate investor demand for stocks, as proxied by buy-sell order imbalance, is consistent with the predictions of regret theory. However, when the data are broken down by investor type, we find evidence of heterogeneity: The behaviour of domestic individual investors is consistent with regret theory, whereas the behaviour of securities investment trusts is consistent with prospect theory, and that of foreign investors is consistent with both prospect theory and salience theory.

4.1 Introduction

Dissatisfaction with the descriptive power of the expected utility theory (hereafter 'EUT') has resulted in calls for a relaxation of the rationality assumption and a search for answers elsewhere (*Schoemaker, 1982*; *Starmer, 2000*; *Sugden, 2004*). As a result, behavioural theories of choice under risk have emerged, which explicitly incorporate known psychological mechanisms into the modelling of the decision-making process. In this paper, we empirically test three such theories: cumulative prospect theory (hereafter 'PT') (*Tversky and Kahneman, 1992*), salience theory (hereafter 'ST') (*Bordalo et al., 2012*), and regret theory (hereafter 'RT') (*Bell, 1982*; *Loomes and Sugden, 1982*).

There are three key reasons which motivate this choice. First, these theories are perhaps the most celebrated behavioural theories of choice under risk, as they have attracted considerable interest in the literature over the last two decades.[54] Second, empirical applications of these three theories to the analysis of real-world financial market data have gained impetus following the publication of *Barberis et al.'s* (*2016*) study, which investigates PT's ability to explain investor behaviour in stock markets.[55] Lastly, although recent empirical studies have produced results that are generally supportive of the theories in question, they feature several limitations.

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[54] For example, a Google Scholar search from 2000 to the present returns over 4,400 citations for "salience theory", more than 8,800 citations for "regret theory", and over 62,000 citations for "prospect theory".

[55] *Zhong and Wang* (*2018*), *Gu and Yoo* (*2021*), *Chen et al.* (*2022b*), *and Gupta et al.* (*2022*) investigate the descriptive ability of PT in alternative markets. *Cosemans and Frehen* (*2021*), *Cakici and Zaremba* (*2022*), *Chen et al.* (*2022a*), and *Hu et al.* (*2023*) study the descriptive power of ST in the stock and cryptocurrency markets, and *Ballinari and Müller* (*2022*) examine the predictive ability of RT in the stock market.

The first limitation results from the difficulty of observing investor behaviour directly. Consequently, prior studies mostly rely on indirect tests that examine the cross-section of stock returns, rather than investor actions directly. Moreover, by focusing on asset returns, they are unable to distinguish among different investor types, whose behaviour may be heterogeneous (*Shapira and Venezia, 2001*; *Gilad and Kliger, 2008*; *Glaser et al., 2007*). Lastly, prior studies typically investigate each behavioural theory individually instead of adopting a holistic approach and comparing their predictive powers.

The aim of our paper is to address these limitations. We make a number of contributions to the literature: We are the first to test the predictive ability of PT, ST, and RT in the stock market through an examination of investors' order submissions. Specifically, we use a comprehensive and unique dataset that contains all the orders submitted to the Taiwan stock exchange (hereafter 'TWSE') from May 2, 2013 to March 31, 2018. By focusing on investors' actions directly, we provide a more accurate assessment of the extent to which these theories can predict investor demand for a stock, which we measure by buy-sell order imbalance (hereafter 'OIB').[56] Second, since PT, ST, and RT are built upon different behavioural biases and are not necessarily mutually exclusive, we examine them together. This allows us to shed light on their relative merits and predictive abilities. Our results reveal that aggregate investor demand for a stock is consistent (inconsistent) with the predictions of RT (PT and ST). Lastly, we examine whether the predictive abilities of these three theories vary across investor types. Thanks to the granularity of our data, we can classify investors into four categories: individual investors, securities investment trusts, foreign investors, and other non-individual investors (hereafter 'others').[57] As is the case with aggregate investor demand, we find that individual investors' demand is consistent with the predictions of RT. This is not surprising, as individual investors are the dominant group at the TWSE. Conversely, the behaviour of foreign investors is consistent (inconsistent) with the predictions of PT and ST (RT). As for others and securities investment trusts, their behaviour is consistent with PT's predictions, whereas the predictions of both ST and RT fail. In summary, our findings reveal that there exists a meaningful degree of heterogeneity in investor behaviour, and the three theories enjoy varying degrees of success across different investor types. This also leads us to conclude that empirically testing a behavioural theory based only on the cross-section of stock returns or aggregate-level data, as previously done in the literature, may hide important insights.

The rest of the paper is organised as follows. Section 4.2 reviews the three behavioural theories, discusses the existing evidence concerning behavioural heterogeneity across investor types, and develops the hypotheses. Section 4.3 describes the data. Section 4.4 illustrates how we measure OIB

[56] Using OIB to measure investor demand is a common approach in the literature. See, for example, *Barber and Odean* (*2008*), *Bhattacharya et al.* (*2011*), *Della Vedova et al.* (*2022*), and *Chen et al.* (*2021*).
[57] Others include, for example, domestic banks and businesses.

and the PT (ST, RT) value of a stock. Section 4.5 details the empirical analysis, and Section 4.6 concludes.

4.2 Literature review and hypothesis development

4.2.1 Behavioural theories of choice under risk

Behavioural theories of choice under risk aim to describe individuals' decision-making through the incorporation of some commonly observed psychological mechanisms. According to PT, ST, and RT, among the available set of investments, or prospects, an individual will choose the prospect with the highest value. The value of prospect i, $v(i)$, is given by a weighted average of the utilities of its possible outcomes, as follows:

$$v(i) = \sum_{s=1}^{S} \omega_{is}\, u(x_{is}) \tag{4.1}$$

where $u(x_{is})$ represents the utility that the individual derives from prospect i's outcome in state s ($s \in S$), and outcome x is a function of the prospect's payoff and a reference point or counterfactual, depending on the theory in question. The second term, ω_{is}, is the weight that the individual assigns to the utility of prospect i's outcome in state s.

Unlike the EUT, PT, ST, and RT assume that individuals tend to overweight extreme outcomes. However, how this assumption is operationalised varies across the latter three theories. To elaborate, PT (*Tversky and Kahneman, 1992*) incorporates three psychological mechanisms: (1) the reflection effect, meaning that individuals tend to be risk-averse when facing gains but risk-seeking when facing losses, where both gains and losses are measured relative to a reference point; (2) loss aversion, meaning that they dislike losses more than they like gains; and (3) non-linear probability weighting, meaning that they overreact to extreme gains and losses. The first two behavioural biases are modelled by means of a utility function that is kinked at the reference point, concave (convex) in the gain (loss) domain, and steeper in the loss domain. The third bias is modelled via an inverted S-shaped weighting function that applies a transformation to the cumulative distribution of objective probabilities. From this perspective, PT falls into the category of rank-dependent utility models, as it assumes that the weight assigned to an outcome is a function of its rank in the distribution of outcomes, and the weighting function overweights extreme outcomes.

ST, proposed by *Bordalo et al.'s* (*2012*), centres on salience bias, which is a critical attentional mechanism that directs humans' limited cognitive resources towards noticeable/prominent stimuli. Specifically, ST argues that a salient thinker tends to overweight (neglect) salient (non-salient) payoffs when evaluating a prospect. Moreover, when the highest (lowest) payoffs stand out, i.e., the upside (downside) is salient, a salient thinker tends to be risk-seeking (risk-averse). Such behaviour is modelled by means of a weighting function that transforms the objective probability of a payoff based on its salience, where the latter is measured relative to a reference point (e.g., the average payoff across all available prospects in state s).

RT centres on the view that individuals care about what they get as well as what they might have received if they had chosen one of the alternative options (*Bell, 1982*; *Loomes and Sugden, 1982*). This phenomenon arises from feelings of regret, which is the emotional pain that individuals experience after realising that a previously made decision was less than optimal. Therefore, RT assumes that the payoff of a prospect in a state of nature is evaluated relative to a counterfactual. This is achieved through a regret function that computes the regret/rejoicing value of the outcome of a prospect based on its payoff's and its counterfactual's utilities.

In summary, while the three behavioural theories described above model different psychological biases, they all posit that individuals overweight extreme outcomes: the largest gains/losses relative to a reference point in the case of PT, the most salient payoffs in the case of ST, and those that produce the highest levels of regret/rejoicing in the case of RT. Thus, to gain a more comprehensive understanding of their merits, it is meaningful to examine these theories side by side.[58]

4.2.2 Empirical tests of PT, ST, and RT based on financial market data

Barberis et al. (*2016*) are the first to empirically test whether PT can explain how, in the real-world, investors choose among individual stocks. Their analysis focuses on the cross-section of stock returns and provides a blueprint that many subsequent studies have adopted. Specifically, their estimation of the PT value of a stock rests upon three key assumptions: (1) investors assess each stock in isolation (*narrow framing*), (2) they extrapolate past return distributions into the future, and (3) they evaluate these return distributions as described by PT. Using data from the US and 46 international stock markets, *Barberis et al.* (*2016*) find a negative cross-sectional relationship between the PT values of stocks and their future returns. This pattern provides supporting evidence for the predictive power of PT because it is consistent with the notion that, when investors tilt their portfolios toward (away from) stocks that are more (less) attractive according to PT, i.e., stocks with higher (lower) PT values, these stocks become overvalued (undervalued) and earn lower (higher) future returns. Subsequent studies

[58] Note that this section is not intended to provide a comprehensive overview of PT, ST, and RT. We refer the interested reader to the papers that we cited for a more detailed review. The formulas that we use to operationalise these three theories are presented in Section 4.4.2, where we describe how we calculate the PT value, ST value, and RT value of a stock at a point in time.

find analogous results in other markets, such as the bond market (*Zhong and Wang, 2018*) and the cryptocurrency market (*Chen et al., 2022b*).

As *Barberis et al.'s* (*2016*) blueprint has also been followed by researchers testing other behavioural theories, namely ST (*Cosemans and Frehen, 2021*; *Cakici and Zaremba, 2022*; *Chen et al., 2022a*) and RT (*Ballinari and Müller, 2022*), prior studies in this stream of literature share the same limitation: they employ indirect tests based entirely on the cross-section of asset returns. Specifically, they assume that assets that are more (less) attractive to PT, ST, or RT investors tend to attract excess (poor) demand and become overpriced (underpriced), leading to lower (higher) subsequent returns.

We overcome this limitation and shed light on the validity of this chain of causalities as we are able to observe investors' choices directly. Namely, using OIB as a measure of investor demand in the Taiwanese stock market, we can test directly whether investor demand for a stock is consistent with the predictions of these three behavioural theories.[59] If investors act as predicted by PT (ST, RT), then stocks that are more appealing to PT (ST, RT) investors should attract higher net demand and therefore experience higher OIB. We therefore test the following hypothesis:

H1: *Stocks that are more appealing to PT (ST, RT) investors attract higher OIB.*

4.2.3 Behavioural heterogeneity among investors

From a theoretical perspective, researchers often assume that individual investors are more irrational than institutional investors because they are less experienced, trained, and informed. However, recent empirical studies present a more nuanced picture. The literature appears to agree that these two investor types operate under different sets of rules and are affected to different extents by different behavioural biases. For instance, individual investors appear to be more susceptible to a number of factors, including the disposition effect (*Shapira and Venezia, 2001*), name-based heuristics (*Itzkowitz and Itzkowitz, 2017*) and anchoring bias (*Kaustia et al., 2008*). On the other hand, the sentiment-induced mispricing appears to be driven by institutional rather than individual investors (*Devault et al., 2019*), and professional traders are more prone than the layman to other behavioural biases such as priming

[59] A handful of studies in this area (*Gu and Yoo, 2021*; *Hu et al., 2023*; *Gupta et al., 2022*) proxy for investor demand using mutual fund flows. While this is a direct measure of choice, aggregate data, such as fund flows, are subject to information loss and do not allow the researcher to shed light on potential behavioural heterogeneity among investor types (see Section 4.2.3). Secondly, these studies typically do not test multiple behavioural theories jointly. Lastly, studying choice in the mutual fund market is complicated by confounding factors, such as trust in money managers (*Gennaioli et al., 2015*) and the existence of insurance pools within mutual fund families (*Bhattacharya et al., 2013*), which makes it more challenging to isolate the behavioural channels of interest. Thus, our findings complement theirs.

effects (*Gilad and Kliger, 2008*), overconfidence (*Glaser et al., 2007*) and the false consensus effect (*Roth and Voskort, 2014*).

Additionally, although institutional investors may have common features that separate them from individual investors, different types of institutional investors are found to exhibit distinct behavioural biases and trading patterns. These differences may arise from various factors, such as different levels of information advantage (*Chiang et al., 2012*), levels of sophistication (*Grinblatt and Keloharju, 2000*) and cultural differences (*Chui et al., 2010*; *Gupta et al., 2022*). For example, *Grinblatt and Keloharju* (*2000*) find that, on the Finnish stock exchange, foreign investors tend to be momentum investors, while less sophisticated domestic institutional investors tend to be contrarians. Similarly, *Richards* (*2005*) observes that, in six Asian equity markets, foreign investors display positive feedback trading tendencies, whereas domestic individual investors tend to act as contrarians. Meanwhile, there is evidence that foreign investors in both the Japanese and Korean stock markets tend to invest in stocks with different characteristics (e.g., market capitalisation) than those favoured by domestic institutional investors (*Ko et al., 2007*).

All these findings emphasise that investors are heterogeneous in a number of ways, from their degrees of rationality to their trading strategies. Such heterogeneity has also been well documented in the Taiwanese asset markets (e.g., *Barber et al., 2007*; *Chou and Wang, 2011*; *Chang et al., 2015*; *Kuo et al., 2015*). In light of this evidence, while previous studies testing behavioural theories of choice under risk focus on the dynamics of asset returns and are neglectful of potential behavioural heterogeneity among investors, we expect the predictive powers of PT, ST, and RT to vary across investor types. Hence, the following hypothesis shall be tested:

H2: The predictive power of PT (ST, RT) varies across investor types.

4.3 Data and sample preparation

We analyse two datasets: the limit order book from the TWSE and, from Refinitiv DataStream, the characteristics of the firms in the sample, the market index (i.e., the Taiwan capitalisation-weighted stock index, hereafter 'TAIEX'), and the risk-free rate (i.e., the one-month deposit rate posted by five major banks in Taiwan).

4.3.1 Limit order book

This dataset contains all intra-day limit orders submitted during the period May 2, 2013 to March 31, 2018, which amounts to an average of 10.8 million orders per trading day, or a total of approximately

13.1 billion orders.[60] Each order encompasses the following information: (1) the date, time, and type of trade (i.e., regular, block, or odd-lot); (2) the stock identifier; (3) the order direction, classified as either buyer- or seller-initiated; (4) the price, the initial volume, and any adjustments to the initial volume;[61] and (5) the type of investor (i.e., individual investor, foreign investor, others, or securities investment trust). In our analysis, we retain only regular trading orders for common stocks (i.e., we exclude other types of securities such as beneficiary certificates, warrants, TDRs, bonds, convertible securities, ETFs, and ETNs).[62]

Our dataset offers three advantages. First, it contains all limit orders submitted to the TWSE. As a result, our analysis covers all investors who trade on the TWSE and overcomes any potential limitations arising from the use of sub-samples of data (*Barber and Odean, 2008*). Second, the exchange itself identifies the order direction. This provides a significant advantage over other datasets (e.g., Trade and Quote) where the order direction needs to be determined by the researcher (*Lee and Ready, 1991*), which introduces a potentially large source of noise. Third, the exchange itself identifies the trader submitting the order, eliminating misclassification resulting from subjective trader classification algorithms (*Boehmer et al., 2021*).

4.3.2 Firm-level characteristics

We collect data for all active and defunct stocks in the Taiwanese market from DataStream, which results in a universe of 3,708 stocks. We then apply the following filters: First, we keep only stocks listed on the TWSE (*Barber et al., 2009*). Second, we keep only stocks whose prices are quoted in Taiwanese dollars (*Griffin et al., 2010*). Third, we keep only common stocks (i.e., 4-digit Reuters Instrument Codes from 1101 to 9958) (*Griffin et al., 2010*; *Karolyi et al., 2012*). There are 1,035 stocks which survive these screening criteria, and for each of them we collect the daily time series (from the earliest available date to March 31, 2022) of the following firm-level characteristics: adjusted closing price, adjusted trading volume, market capitalisation, book-to-market ratio, number of shares outstanding, and the date when its shares began trading on the TWSE.

Next, following previous studies, we apply a second set of screening criteria: First, we drop all observations on a stock before its shares began trading on the TWSE. Second, since DataStream often returns stale prices after a stock is delisted, we drop all observations on a stock after its daily simple

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[60] Market orders were introduced to the TWSE on March 23, 2020. Before that, investors could only submit limit orders.

[61] On the TWSE, investors are allowed the following actions after submitting an order: decreasing the initial volume, cancelling the order, or decreasing the initial volume and then cancelling the modified order.

[62] In addition, we exclude orders submitted on Saturdays, which amounts to a total of nine trading days in the sample period. We do this for two reasons: DataStream returns no firm-level data for these Saturdays, and the participation rate of non-individual investors is notably lower on Saturdays than on regular trading days.

return no longer differs from zero (*Ince and Porter, 2006*). Third, we assign a missing value to daily simple returns that are greater than +100% or less than -95% (*Cakici and Zaremba, 2022*).[63] Fourth, we drop stocks with negative book values (*Barberis et al., 2016*).

Since daily stock returns and OIB are quite noisy, we use data at a weekly frequency in our analysis. Specifically, we transform the daily time series described above into weekly (Wednesday-to-Wednesday) time series.[64]

4.4 Variable construction and descriptive statistics

4.4.1 Order imbalance

To measure stock i's OIB for investor type g in week t, which represents our proxy for net investor demand, we follow *Barber and Odean* (*2008*) and employ the following formula:

$$OIB_{i,t,g} = \frac{Total\ Buy_{i,t,g} - Total\ Sell_{i,t,g}}{Total\ Buy_{i,t,g} + Total\ Sell_{i,t,g}} \tag{4.2}$$

where $Total\ Buy_{i,t,g}$ ($Total\ Sell_{i,t,g}$) denotes stock i's total final buying (selling) volume, i.e., number of shares, originating from investor type g in week t.[65] Specifically, we compute this variable separately for each of four investor types: individual investors (*OIB_I*), foreign investors (*OIB_F*), others (*OIB_J*), and securities investment trusts (*OIB_M*). We also construct an aggregate measure, *OIB*, by adding up orders across all the four investor types. A higher (lower) *OIB* indicates higher (lower) net demand for the stock of the company in question, as it signals increased (decreased) buying pressure.

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[63] This criterion affects only six daily returns, and we assign a missing value to the corresponding price, market capitalisation, and book-to-market ratio. We further assign a missing value to daily returns where the corresponding trading volume is zero or missing. Note that the TWSE imposed a daily price limit of ±7% before June 1, 2015 and ±10% thereafter. Nevertheless, daily price fluctuations may exceed this limit in response to company events such as IPOs, ex-rights, ex-dividends, and capital reductions.

[64] We assign a missing value to weekly simple returns (and the corresponding price, market capitalisation, and book-to-market ratio) when the weekly volume is zero or missing and when the weekly simple return is greater than +100% or less than -95% (*Cakici and Zaremba, 2022*).

[65] We define the final volume as the volume that incorporates any deductions and cancellations. We assign a missing value to $OIB_{i,t,g}$ when stock i is never traded in week t. In unreported analyses, we assign a missing value to $OIB_{i,t,g}$ when stock i is traded on less than three trading days in week t, and our results are virtually the same. In the Appendix C, we use alternative approaches in the construction of *OIB*. Namely, we measure *OIB* (1) over the following 5-day, 9-day, 12-day, and 2-week period, (2) based on the dollar value of orders, (3) based only on orders submitted during regular trading hours (i.e., from 9:00 am to 1:30 pm), and (4) based only on executed orders. Our main findings remain robust.

4.4.2 Behavioural-theory value of a stock

To compute the PT (RT, ST) value of a stock according to *Barberis et al.'s* (*2016*) method, it is necessary to specify the values of two key parameters. The first parameter concerns the length of the historical time window on which investors are assumed to focus when using past returns to predict the distribution of a stock's future returns. In our base specification, we use a 12-week look-back window, which is consistent with the findings of survey studies on extrapolative return expectations (*Da et al., 2021*). A 12-week window is also in line with the default time window that is typically presented to investors when they search for information on the past performance of a stock on the websites of popular securities companies in Taiwan (e.g., SinoPac Securities). In what follows, each of the twelve 1-week periods within this look-back window represents a possible state of nature, s. Consequently, the objective probability of state s (p_s) equals 1/12 in our base specification.

The second parameter concerns the benchmark against which investors are assumed to evaluate a stock's payoff (i.e., its return in a given week). In the spirit of previous studies (*Barberis et al., 2016*; *Ballinari and Müller, 2022*), we use the TAIEX index as the reference point and the counterfactual in our base specification.[66]

4.4.2.1 PT value of a stock

To compute the PT value of stock i at the end of week t-1 ($PTV_{i,t-1}$), we follow *Barberis et al.'s* (*2016*) method. First, for each week between t-12 and t-1, we compute the excess return (R_{is}) of stock i over the return of the TAIEX index, which represents the gain/loss in state s relative to the reference point. Then, we count the number of negative (m) and non-negative (n) excess returns, and we sort them in ascending order, so that they range from the most negative (R_{i-m}) to the most positive (R_{in}). Subsequently, we compute the utility of each excess return using the value function proposed by *Tversky and Kahneman* (*1992*):

$$u(R_{is}) = \begin{cases} R_{is}^{c} & \text{if } R_{is} \geq 0 \\ -\lambda(-R_{is})^{d} & \text{if } R_{is} < 0 \end{cases} \tag{4.3}$$

where $-m \leq s \leq n$. The next step consists in computing the weight (ω_{is}) assigned to $u(R_{is})$, which is accomplished using the transformation function proposed by *Tversky and Kahneman* (*1992*):

[66] The robustness tests in Section C3 of the Appendix C show that using look-back windows of alternative lengths (i.e., from 4 weeks to 52 weeks) or alternative reference points/counterfactuals (i.e., zero, the risk-free rate, a stock's own sample mean return) does not alter our main findings.

$$\omega_{is} = \begin{cases} \omega^{+}\left(\frac{n-s+1}{12}\right) - \omega^{+}\left(\frac{n-s}{12}\right) & \text{for } 0 \leq s \leq n \\ \omega^{-}\left(\frac{m+s+1}{12}\right) - \omega^{-}\left(\frac{m+s}{12}\right) & \text{for } -m \leq s < 0 \end{cases} \tag{4.4}$$

with:

$$\omega^{+}(p) = \frac{p^{\gamma}}{[p^{\gamma} + (1-p)^{\gamma}]^{\frac{1}{\gamma}}}, \omega^{-}(p) = \frac{p^{\rho}}{[p^{\rho} + (1-p)^{\rho}]^{\frac{1}{\rho}}} \tag{4.5}$$

Lastly, we calculate the value of $PTV_{i,t-1}$ by inserting the computed utilities and corresponding weights into *Eq. (4.1)*. Stocks with higher PT values are more attractive to investors who act as predicted by PT, as they display a more desirable return distribution.

Eqs. (4.3) to *(4.5)* contain five parameters, which are c, d, λ, γ, and ρ, where c, d, γ, ρ $\in$ (0, 1) and $\lambda > 1$. The parameter c (d) measures the concavity (convexity) of the value function, which represents the degree of risk aversion (seeking) over gains (losses); the smaller its value, the more risk averse (seeking) the investor. λ measures the degree of loss aversion; the larger its value, the greater the sensitivity of the investor to losses than to gains of the same magnitude. Lastly, γ (ρ) measures the degree of probability distortion over gains (losses); the smaller its value, the more the investor overweights extreme outcomes. In our base specification, we set c = d = 0.88, λ=2.25, γ=0.61, and ρ = 0.69, as estimated by *Tversky and Kahneman* (*1992*).

4.4.2.2 ST value of a stock

To compute the ST value of stock i at the end of week t-1 ($STV_{i,t-1}$), we follow *Cosemans and Frehen's* (*2021*) method. First, for each week between t-12 and t-1, we compute the salience of stock i's return (r_{is}) relative to the return of the TAIEX index ($\bar{r}_s$) as

$$\sigma(r_{is}, \bar{r}_s) = \frac{|r_{is} - \bar{r}_s|}{|r_{is}| + |\bar{r}_s| + \theta} \tag{4.6}$$

Then, we rank the twelve weekly returns in the look-back window in decreasing order of salience and compute their salience weight as

$$w_{is} = \frac{\delta^{k_{is}}}{\sum_s \delta^{k_{is}} p_{is}}, \delta \in (0,1] \tag{4.7}$$

where k_{is} is the rank of r_{is} and ranges from 1 (most salient) to S (least salient). Lastly, we calculate the value of $STV_{i,t-1}$ based on *Bordalo et al.'s* (*2013*) salience-based asset pricing model. Namely, we compute the covariance between salience weights and weekly returns within the look-back window T between week t-12 and t-1:[67]

$$STV_{i,t-1} = cov[w_{is,T}, r_{is,T}] = \sum_{s=1}^{S} p_{is} w_{is} r_{is} - \sum_{s=1}^{S} p_{is} r_{is} = E^{ST}[r_{is,T}] - \bar{r}_{is,T} \tag{4.8}$$

Stocks with higher ST values are more attractive to investors who act as predicted by ST, as they tend to have salient upsides and non-salient downsides. Eqs. (4.6) and (4.7) contain two parameters: θ in Eq. (4.6) is a convenience parameter, whereas δ in Eq. (4.7) measures the degree of salience distortion and ranges from 0 (maximum salience distortion) to 1 (no salience distortion). In our base specification, we set $\theta = 0.1$ and $\delta = 0.7$, as in Bordalo et al. (2012).

4.4.2.3 RT value of a stock

To compute the RT value of stock i at the end of week t-1 ($RTV_{i,t-1}$), we follow Ballinari and Müller's (2022) method. First, for each week between t-12 and t-1, we compute the utility of stock i's return (r_{is}) and the utility of the return of the TAIEX index ($\bar{r}_s$) as

$$u(r_{is}) = (1 + r_{is})^{\alpha}, u(\bar{r}_s) = (1 + \bar{r}_s)^{\alpha} \tag{4.9}$$

Then, we compute the difference between their utilities ($d_{is} = u(r_{is}) - u(\bar{r}_s)$) and measure the amount of regret/rejoicing in state s using the following regret function:

$$\Psi(d_{is}) = \begin{cases} {d_{is}}^{\beta} & \text{if } d_{is} \geq 0 \\ -(-d_{is})^{\beta} & \text{if } d_{is} < 0 \end{cases} \tag{4.10}$$

Lastly, we calculate the value of $RTV_{i,t-1}$ using Eq. (4.1), where $u(x_{is})$ is replaced by $\Psi(d_{is})$, and its weight (ω_{is}) is the objective probability of state s (i.e., 1/12). Stocks with higher RT values are more attractive to investors who act as predicted by RT, as they tend to display a high potential for rejoicing and a low potential for regret.

The parameter α in Eq. (4.9), where $\alpha \in (0, 1)$, measures the concavity of the value function $u(\cdot)$, while β in Eq. (4.10), where $\beta > 1$, measures the convexity (concavity) of the regret function $\Psi(\cdot)$ over positive (negative) values of d. (Note that, in the case of RT, overweighting of extreme outcomes happens through the convexity of the regret function in the positive domain and its concavity in the negative domain.) In our base specification, we set $\alpha = 0.94$ and $\beta = 1.73$, as estimated by Bleichrodt et al. (2010) through a laboratory experiment.

[67] Note that Eq. (4.8) implies that the ST value of a stock "is equal to the difference between salience-weighted and equal-weighted past returns" (Cosemans and Frehen, 2021).

Table 4.1 Variable definitions

Variables	Definition
Beta	The estimated slope from the regression of a stock's weekly excess return on the market excess return from week t- 12 to week t-1.
BM	The natural logarithm of a stock's book-to-market ratio at the end of week t-1
Coskew	The coefficient on the squared market excess return when regressing a stock's weekly excess return on the market excess return and the squared market excess return from week t-12 to week t-1.
CRO	The chronological return ordering value of a stock's historical weekly return distribution from week t-12 to week t-1, as in *Mohrschladt* (*2021*)
HYRet	The cumulative return on a stock from week t-31 to week t-6
Illiq	The average ratio of a stock's absolute return to its trading volume from day t-20 to day t-1.
Iskew	The idiosyncratic skewness of a stock's weekly returns from week t-12 to week t-1.
Ivol	The idiosyncratic volatility of a stock's daily returns from day t-20 to day t-1.
LOIB	A stock's buy-sell order imbalance in week t-1
Max	The maximum of a stock's daily returns from day t-20 to day t-1.
Min	The negative of the minimum of a stock's daily returns from day t-20 to day t-1.
MRet	The cumulative return on a stock from week t-5 to week t-2
OIB	A stock's buy-sell order imbalance in week t, as defined in *Eq. (4.2)*. We also compute this variable separately for each of four investor types: individual investors (*OIB_I*), foreign investors (*OIB_F*), others (*OIB_J*), and securities investment trusts (*OIB_M*)
PTV	The prospect theory value of a stock's historical weekly return distribution from week t-12 to week t-1, as in *Barberis et al.* (*2016*)
RTV	The regret theory value of a stock's historical weekly return distribution from week t-12 to week t-1, as in *Ballinari and Müller* (*2022*)
Size	The natural logarithm of a stock's market capitalisation at the end of week t-1
Skew	The skewness of a stock's weekly returns from week t-12 to week t-1.
STV	The salience theory value of a stock's historical weekly return distribution from week t-12 to week t-1, as in *Cosemans and Frehen* (*2021*)
Turnover	The ratio of a stock's trading volume to its number of shares outstanding at the end of week t-1
Vol	The standard deviation of a stock's daily returns from day t-20 to day t-1
WRet	The return on a stock in week t-1
52WHMAX	A dummy variable that takes the value of one if the closing price of a stock at the end of week t-1 is within 1% of its 52-week high (i.e., the highest price between week t-52 and week t-1), and zero otherwise, as in *Della Vedova et al.* (*2022*)

Table 4.2 Average cross-sectional summary statistics

Panel A. Mean and standard deviation

	OIB	OIB_I	OIB_F	OIB_J	OIB_M	PTV	STV	RTV	WRet	MRet	HYRet	Turnover	Vol	Size	BM	CRO	WHMAX52
Mean	-0.0194	-0.0613	0.1447	0.1749	-0.1322	-0.0268	0.0058	0.0004	0.0012	0.0051	0.0409	0.0048	0.0172	8.8478	-0.2546	0.0049	0.0915
Standard deviation	0.1181	0.1677	0.4409	0.5536	0.8529	0.0230	0.0244	0.0023	0.0365	0.0752	0.2183	0.0083	0.0093	1.4072	0.5636	0.2792	0.2701

Panel B. Person's pairwise correlation matrix

	OIB	OIB_I	OIB_F	OIB_J	OIB_M	PTV	STV	RTV	WRet	MRet	HYRet	Turnover	Vol	Size	BM	CRO
OIB_I	0.7282															
OIB_F	0.0754	-0.1728														
OIB_J	0.0497	-0.1809	-0.0759													
OIB_M	-0.0594	-0.2092	0.0712	0.0196												
PTV	-0.1033	-0.1657	0.0895	-0.0134	0.1275											
STV	-0.0429	-0.0595	0.0936	-0.0354	0.1141	0.6837										
RTV	-0.0254	-0.0482	0.0972	-0.0372	0.1185	0.7139	0.8800									
WRet	-0.1180	-0.1502	0.0481	-0.0158	0.1754	0.2620	0.1905	0.2171								
MRet	-0.0523	-0.0995	0.1071	-0.0362	0.1255	0.4948	0.4160	0.4746	0.0029							
HYRet	0.0024	-0.0254	0.0760	-0.0412	0.0280	0.2513	0.3372	0.3944	0.0124	0.0240						
Turnover	0.0242	0.0146	0.1352	-0.0999	0.1085	0.1488	0.2883	0.3330	0.2813	0.2228	0.2611					
Vol	0.0607	0.0631	0.0956	-0.0882	0.0951	-0.0288	0.3742	0.3962	0.0965	0.2677	0.2423	0.4372				
Size	0.1335	-0.0342	0.0555	-0.1348	0.0259	0.1319	-0.0574	-0.0376	0.0184	0.0346	0.0834	0.0416	-0.1291			
BM	-0.0968	-0.0098	-0.0760	0.0602	-0.0268	-0.0250	-0.0963	-0.1234	-0.0461	-0.0857	-0.2127	-0.1803	-0.2003	-0.2956		
CRO	-0.1020	-0.1383	0.0514	-0.0093	0.1432	0.0253	-0.0233	-0.0135	0.4085	0.4441	-0.2137	0.1363	0.0758	-0.0031	-0.0019	
WHMAX52	-0.0162	-0.0702	0.0932	-0.0519	0.1122	0.3575	0.2449	0.2776	0.3265	0.2827	0.1943	0.2614	0.1245	0.0933	-0.0984	0.2035

This table shows the time-series averages of a set of weekly cross-sectional summary statistics. Panel A displays the mean and standard deviation of each variable, and Panel B displays the Pearson's pairwise correlation coefficients. All variables are as defined in Table 4.1. The sample period is from May 15, 2013 to March 28, 2018.

4.4.3 Control variables and summary statistics

In our regressions, we control for a set of factors that, according to the literature, may influence investors' order submission behaviour (*Boehmer et al., 2021*; *Mohrschladt, 2021*; *Della Vedova et al., 2022*). All these variables are defined in Table 4.1.

We winsorise each variable at the 1st and 99th percentiles for each week. Table 4.2 shows a number of average cross-sectional summary statistics: Panel A displays the mean and standard deviation of each variable, and Panel B presents the Pearson correlation coefficient for each pair of variables. The correlation coefficient between *OIB* (i.e., aggregate OIB) and *OIB_I* (i.e., OIB among individual investors) is about +0.73, which is not surprising given that individual investors dominate the Taiwanese stock market. At the same time, *OIB_I* is negatively correlated with OIB among non-individual investors (*OIB_F*, *OIB_J*, and *OIB_M*), and *OIB_F* (i.e., OIB among foreign investors) is negatively correlated with *OIB_J* (i.e., OIB among others), which indicates that order submission behaviour varies across investor types.

Figure 4.1 provides information about the relative level of participation of each type of investor over time. Panel A reveals that, on average, individual investors account for about 78% of weekly transaction value, followed by foreign investors (13%), others (8%), and securities investment trusts (1%). These shares remain remarkably stable throughout the sample period. In Panels B, C, and D, we repeat the same analysis after sorting stocks into three segments by market capitalisation: Specifically, we define the micro-cap (small-cap, large-cap) segment as consisting of those stocks that account for the bottom 3% (middle 7%, top 90%) of market capitalisation at the end of each week. As one would expect, it emerges that the share held by individual investors decreases from 91% to 60% moving from the micro-cap to the large-cap segment. Conversely, the proportion accounted for by foreign investors (others) increases from 4% (4%) to 26% (13%).

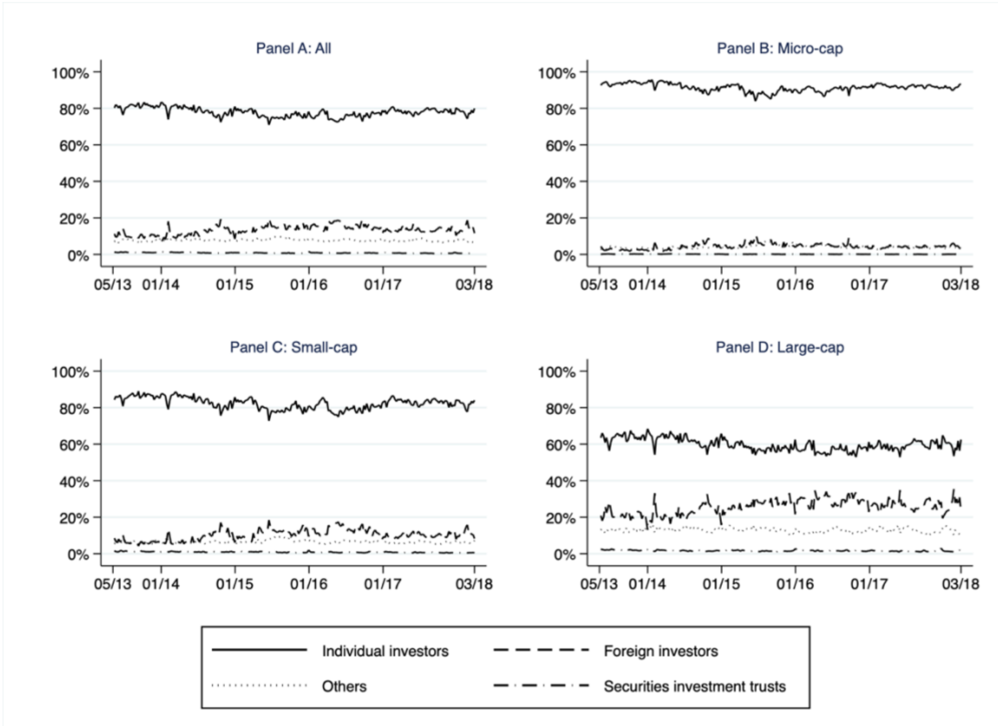


Figure 4.1 Share of weekly transaction value by investor type over time

This figure depicts the temporal evolution of the share of weekly transaction value accounted for by each of four investor types: individual investors, foreign investors, others, and securities investment trusts. In Panel A (B, C, D), total transaction value in a week is computed by adding up the values of all executed orders across all stocks (micro-cap stocks, small-cap stocks, large-cap stocks). We define the micro-cap (small-cap, large-cap) segment as consisting of those stocks that account for the bottom 3% (middle 7%, top 90%) of total market capitalisation at the end of the given week. The sample period is from May 15, 2013 to March 28, 2018.

4.5 Empirical analysis

4.5.1 Behavioural effects and next-month returns

We start our analysis by following previous studies (*Barberis et al., 2016*; *Cosemans and Frehen, 2021*; *Ballinari and Müller, 2022*) and analysing whether the cross-section of stock returns is consistent with the predictions of the behavioural theories under observation. For example, if PT is successful at predicting investor behaviour, the typical investor will find stocks with higher (lower) PT values more (less) attractive. In turn, these stocks will become overbought (oversold) and overpriced (underpriced), earning lower (higher) returns in the future. The same logic applies to ST and RT.

Therefore, we examine whether there is a negative cross-sectional relationship between the behavioural-theory value (e.g., PT value) and next-month returns. Specifically, we employ panel regressions with time fixed effects (FEs) and a set of controls that are common in the literature on the cross-section of stock returns (*Barberis et al., 2016*; *Mohrschladt, 2021*), namely, *Beta*, *Size*, *BM*, *WRet*, *MRet*, *HYRet*, *Illiq*, *Ivol*, *Max*, *Min*, *CRO*, *Skew*, *Iskew*, and *Coskew*. All these variables are defined in Table 4.1. Our regression equation, which we estimate by OLS, is as follows:

$$\begin{aligned} Return_{i,t:t+3} &= \beta_0 + \beta_1 PTV_{i,t-1} + \beta_2 STV_{i,t-1} + \beta_3 RTV_{i,t-1} \\ &+ \beta Controls_{i,t-1} + Week\ FEs + e_{i,t:t+3} \end{aligned} \tag{4.11}$$

where $Return_{i,t:t+3}$ denotes stock i's excess return (over the risk-free rate) from week t to week t+3. $PTV_{i,t-1}$, $STV_{i,t-1}$, and $RTV_{i,t-1}$ measure the PT value, ST value, and RT value of stock i's weekly return distribution from week t-12 to t-1. We include week FEs to isolate the cross-stock variation in the data (*Kropko and Kubinec, 2020*), and we conduct statistical inference based on cluster-robust (stock and week) standard errors.

Table 4.3 reports the results. What varies across columns is the sample period: In column 1, the estimates are based on the full period (July 1991-February 2022) for which we have data on stock returns, whereas in columns 2 and 3 we divide the sample into a pre- (1991-2009) and a post-Great Recession period (2010-2022). In column 4, the estimates are based on the period for which we have access to limit order book data (2013-2018). It emerges that, regardless of the sample period, the coefficient on *RTV* is negative and statistically significant at conventional levels. According to the figures in column 1, a one cross-sectional standard deviation increase in the RT value of a stock reduces its next-month excess return by 0.35% relative to its peers.[68] This pattern provides evidence in support of RT's ability to predict aggregate investor behaviour. For comparison, this effect is about twice the size of that observed by *Ballinari and Müller* (*2022*) in the US stock market.

At the same time, we find no evidence of a negative cross-sectional relationship between either *PTV* or *STV* and future returns. In this respect, our results differ from those observed by *Barberis et al.* (*2016*) and *Cosemans and Frehen* (*2021*) in the US stock market, but they are in line with *Cakici and Zaremba's*

[68] Note that the estimated coefficient on *RTV* is -1.1621, and the average cross-sectional standard deviation of *RTV* between July 1991 and February 2022 is 0.0030. Thus, the size of the effect is -0.35% (= -1.1621×0.0030).

(*2022*) findings concerning ST's predictive power in the Taiwanese stock market. We speculate that these discrepancies may be the result of a combination of factors: "cultural differences in life experiences and education" and corresponding differences in "behavioural inclinations" (*Kim and Nofsinger, 2008*), differences in the composition of the investor population (the US market has long been dominated by institutional investors, while the Taiwanese market is dominated by individual investors), distinct market features, and different trading frictions (*Cakici and Zaremba, 2022*).

4.5.2 Behavioural effects and next-week OIB

While tests based on the cross-section of stock returns provide useful insights, they suffer from two key limitations: (1) They are indirect tests that evaluate the consequences of investors' actions but not the actions themselves, and (2) since stock returns reflect the decisions of the marginal investor, their dynamics may hide meaningful behavioural variations across heterogeneous groups of investors. The granularity of our limit order book dataset allows us to overcome both limitations, as we can observe investors' actions directly, and orders are classified by investor type.

In this section, we examine whether investors' order submissions are consistent with the predictions of the behavioural theories under scrutiny. If this is the case, we expect to observe a positive cross-sectional relationship between PT value (ST value, RT value) and future OIB, as stocks that are more appealing to the typical investor attract higher demand relative to their peers (*H1*). We also investigate the extent to which the predictive ability of these behavioural theories varies across investor types (*H2*).

4.5.2.1 Univariate portfolio analysis

We start with a univariate portfolio analysis, which requires no assumptions about the functional form of the relation between explanatory and response variables. To achieve this, at the end of each week, we first sort stocks into deciles based on one of the three behavioural variables: *PTV*, *STV*, or *RTV*. Decile 1 (10) contains the stocks with the lowest (highest) *PTV*, *STV*, or *RTV*. We then compute the equal-weighted mean *OIB* for each decile portfolio in the following week. After obtaining a time series of mean weekly *OIB* values, we calculate their time-series average for each decile portfolio. The same procedure is repeated for *OIB_I*, *OIB_F*, *OIB_J*, and *OIB_M,* where OIB is computed separately for each investor type.

Table 4.4 reports the results. The estimates in the right-most column represent the mean differences in OIB between decile 10 and decile 1. If investors act in line with the predictions of PT (ST, RT), these mean differences are expected be positive for *PTV*(*STV*, *RTV*)-sorted portfolios. In other words, portfolios

Table 4.3 Panel regressions: Behavioural-theory values and next-month returns

	(1)	**(2)**	**(3)**	**(4)**
Sample period:	1991-2022	1991-2009	2010-2022	2013-2018
PTV	0.0423	0.0476	0.0468	0.0537
	(1.38)	(1.02)	(1.20)	(1.09)
STV	0.0276	0.0348	-0.0109	-0.0170
	(1.09)	(0.96)	(-0.35)	(-0.40)
RTV	-1.1621***	-1.1959***	-0.9834**	-0.9185*
	(-4.43)	(-3.27)	(-2.54)	(-1.75)
Controls	Yes	Yes	Yes	Yes
Week FEs	Yes	Yes	Yes	Yes
Adj. R-squared	0.2860	0.3331	0.2176	0.1585
N	895,620	366,443	529,177	212,815

This table reports the estimates generated by fitting *Eq. (4.11)*. In all specifications, the dependent variable is the one-month-ahead excess return of a stock. *PTV*, *STV*, and *RTV* are the prospect theory value, salience theory value, and regret theory value of a stock's historical weekly return distribution from week t-12 to week t-1, respectively. Each regression contains the following control variables: *Beta*, *Size*, *BM*, *WRet*, *MRet*, *HYRet*, *Illiq*, *Ivol*, *Max*, *Min*, *CRO*, *Skew*, *Iskew*, and *Coskew*. All variables are as defined in Table 4.1. The sample period varies across specifications: In column 1 (2) it runs from July 24, 1991 to February 23, 2022 (December 30, 2009), in column 3 it runs from January 6, 2010 to February 23, 2022, and in column 4 it runs from May 15, 2013 to March 28, 2018. The t-statistics in parentheses are based on standard errors clustered by stock and week. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table 4.4 Univariate portfolio analysis: Behavioural-theory values and next-week OIB

	Low	Decile 2	Decile 3	Decile 4	Decile 5	Decile 6	Decile 7	Decile 8	Decile 9	High	High-Low
Panel A: All											
PTV	0.0121***	-0.0027	-0.0106***	-0.0174***	-0.0236***	-0.0282***	-0.0308***	-0.0341***	-0.0359***	-0.0249***	-0.0370***
	(4.63)	(-0.96)	(-3.48)	(-5.85)	(-6.19)	(-8.14)	(-9.22)	(-10.79)	(-12.50)	(-9.38)	(-13.35)
STV	0.0054*	-0.0061*	-0.0136***	-0.0211***	-0.0269***	-0.0280***	-0.0323***	-0.0326***	-0.0281***	-0.0130***	-0.0184***
	(1.78)	(-1.87)	(-3.75)	(-6.12)	(-7.72)	(-7.89)	(-10.10)	(-12.11)	(-10.46)	(-5.67)	(-6.63)
RTV	0.0116***	-0.0027	-0.0122***	-0.0200***	-0.0274***	-0.0314***	-0.0343***	-0.0350***	-0.0315***	-0.0131***	-0.0247***
	(4.34)	(-0.90)	(-3.66)	(-4.76)	(-6.94)	(-8.38)	(-9.81)	(-12.43)	(-13.54)	(-5.75)	(-9.14)
Panel B: Individual investors											
PTV	-0.0037	-0.0253***	-0.0372***	-0.0510***	-0.0620***	-0.0722***	-0.0809***	-0.0924***	-0.1016***	-0.0929***	-0.0892***
	(-1.31)	(-7.53)	(-9.88)	(-13.34)	(-13.75)	(-15.33)	(-18.99)	(-21.05)	(-28.88)	(-25.17)	(-19.90)
STV	-0.0178***	-0.0355***	-0.0498***	-0.0621***	-0.0736***	-0.0761***	-0.0851***	-0.0849***	-0.0805***	-0.0538***	-0.0360***
	(-5.01)	(-8.19)	(-10.46)	(-13.53)	(-16.36)	(-16.58)	(-23.91)	(-25.58)	(-30.67)	(-22.89)	(-10.30)
RTV	-0.0055*	-0.0231***	-0.0414***	-0.0579***	-0.0719***	-0.0825***	-0.0921***	-0.0977***	-0.0904***	-0.0567***	-0.0512***
	(-1.80)	(-6.08)	(-9.61)	(-10.86)	(-12.98)	(-15.81)	(-20.31)	(-32.56)	(-32.09)	(-23.49)	(-13.84)
Panel C: Foreign investors											
PTV	0.1127***	0.1073***	0.1073***	0.1206***	0.1132***	0.1205***	0.1296***	0.1532***	0.1972***	0.2704***	0.1576***
	(6.99)	(7.22)	(6.85)	(7.17)	(6.89)	(7.08)	(7.30)	(8.44)	(10.64)	(14.33)	(16.92)
STV	0.1184***	0.1046***	0.0973***	0.0981***	0.1118***	0.1313***	0.1535***	0.1689***	0.2096***	0.2438***	0.1255***
	(7.42)	(6.96)	(6.04)	(5.79)	(6.48)	(7.37)	(8.90)	(9.97)	(11.75)	(12.10)	(13.77)
RTV	0.1089***	0.0911***	0.0938***	0.0985***	0.0966***	0.1245***	0.1563***	0.1909***	0.2202***	0.2561***	0.1473***
	(7.05)	(6.48)	(5.81)	(6.21)	(5.57)	(6.43)	(8.57)	(10.25)	(12.17)	(12.75)	(13.79)
Panel D: Others											
PTV	0.1499***	0.1696***	0.1778***	0.1937***	0.2187***	0.2166***	0.2141***	0.1942***	0.1526***	0.0959***	-0.0539***
	(8.64)	(10.16)	(11.39)	(13.49)	(14.29)	(15.79)	(15.26)	(13.88)	(10.60)	(7.88)	(-4.72)
STV	0.1572***	0.1845***	0.2091***	0.2162***	0.2302***	0.1952***	0.1776***	0.1555***	0.1352***	0.1209***	-0.0363***
	(9.85)	(13.37)	(14.46)	(14.10)	(17.34)	(12.78)	(12.33)	(10.80)	(9.05)	(8.55)	(-4.09)
RTV	0.1606***	0.1800***	0.2036***	0.2306***	0.2231***	0.2041***	0.1887***	0.1540***	0.1232***	0.1133***	-0.0473***
	(9.51)	(11.35)	(14.33)	(15.57)	(17.34)	(14.61)	(12.25)	(9.67)	(8.51)	(8.36)	(-4.90)
Panel E: Securities investment trusts											
PTV	-0.2552***	-0.2713***	-0.2482***	-0.2441***	-0.2113***	-0.1607***	-0.1367***	-0.0739***	0.0007	0.0857***	0.3409***
	(-11.19)	(-9.93)	(-9.82)	(-10.56)	(-8.95)	(-7.02)	(-5.61)	(-3.17)	(0.03)	(4.56)	(13.88)
STV	-0.2255***	-0.2663***	-0.2412***	-0.2172***	-0.1925***	-0.1542***	-0.0981***	-0.0428**	0.0021	0.0496***	0.2751***
	(-8.85)	(-11.89)	(-9.66)	(-8.15)	(-7.37)	(-5.72)	(-3.91)	(-2.23)	(0.13)	(2.99)	(11.06)
RTV	-0.2708***	-0.2935***	-0.2712***	-0.2528***	-0.1825***	-0.1605***	-0.0878***	-0.0267	0.0305*	0.0535***	0.3243***
	(-11.18)	(-10.59)	(-10.71)	(-10.33)	(-7.13)	(-5.81)	(-3.43)	(-1.14)	(1.67)	(3.40)	(12.67)

This table reports the one-week-ahead equal-weighted mean order imbalance (*OIB*) of *PTV*-, *STV*-, and *RTV*-sorted decile portfolios. *OIB* is constructed by aggregating orders across all investors (Panel A) or only across individual investors (Panel B), foreign investors (Panel C), others (Panel D), and securities investment trusts (Panel E). At the end of each week t-1, we sort stocks into deciles by one of the three behavioural variables: *PTV*, *STV*, or *RTV*. *PTV*, *STV*, and *RTV* are the prospect theory value, salience theory value, and regret theory value of a stock's historical weekly return distribution from week t-12 to week t-1, respectively. Subsequently, we compute the equal-weighted mean OIB for each decile portfolio in week t. After obtaining a time series of mean weekly OIB values, we calculate their time-series average for each decile portfolio. The sample period is from May 15, 2013 to March 28, 2018. The t-statistics in parentheses are based on Newey-West standard errors with a lag truncation parameter of 4. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

consisting of high-*PTV(STV*, *RTV*) stocks should attract more net buy orders than portfolios consisting of low-*PTV*(*STV*, *RTV*) stocks.

However, contrary to the theories' predictions, in Panel A, where orders are aggregated across all investors, all High-Low differences are negative and highly statistically significant. Similar patterns appear in Panels B and D, where OIB is measured among individual investors and others, respectively. Only in Panels C and E, where OIB is measured among foreign investors and securities investment trusts, respectively, do we observe positive and statistically significant High-Low differences for *PTV*-sorted, *STV*-sorted, and *RTV*-sorted portfolios. The implications are that the order submission behaviour of foreign investors and securities investment trusts is consistent with the predictions of PT, ST, and RT, but all three theories do poorly when it comes to predicting the behaviour of individual investors and others.

These initial results are fairly disappointing, especially in light of the fact that individual investors dominate the Taiwanese market, and none of the three theories seems successful at modelling their decisions. Nevertheless, we should be mindful of not drawing overly strong conclusions from the estimates in Table 4.4, as univariate portfolio analysis ignores the effects of confounding factors that affect investor demand and are correlated with *PTV*, *STV*, and *RTV*.[69]

4.5.2.2 Panel regressions

To overcome the shortcomings of univariate portfolio analysis, we also estimate panel regressions, as follows:[70]

$$\begin{aligned} OIB_{i,t,g} = \beta_0 + \beta_1 PTV_{i,t-1} + \beta_2 STV_{i,t-1} + \beta_3 RTV_{i,t-1} \\ + \beta Controls_{i,t-1} + Week\ FEs + e_{i,t,g} \end{aligned} \tag{4.12}$$

where $OIB_{i,t,g}$ denotes stock i's OIB in week *t* among investor group g, and the control variables are *LOIB*, *WRet*, *MRet*, *HYRet*, *Turnover*, *Vol*, *Size*, *BM*, *CRO*, and *52WHMAX*, as defined in Table 4.1. As we do in *Eq. (4.11)*, we include week FEs to isolate the cross-stock variation in the data (*Kropko and Kubinec, 2020*), and we estimate double-clustered standard errors by stock and week.

[69] Consistent with this point, the estimates in Panel A of Table C1 in the Appendix C show that the mean values of *STV*, *RTV*, *WRet*, *MRet*, *HYRet*, *Size*, and *52WHMAX* increase monotonically moving from the lowest-*PTV* portfolio to the highest-*PTV* portfolio. Analogously, Panel B (Panel C) of Table C1 shows that the mean values of *RTV*, *WRet*, *Mret*, *HYRet*, and *52WHMAX* (*PTV*, *STV*, *Wret*, *Mret*, *HYRet*, *Size*, and *52WHMAX*) increase monotonically across *STV*-sorted (*RTV*-sorted) portfolios.

[70] Throughout the paper, we use panel regressions with time FEs and cluster-robust standard errors instead of relying on the Newey-West corrected Fama-MacBeth approach because *Gow et al.* (*2010*) show that the former method is superior to the latter in the presence of autocorrelation in the error term.

The OLS estimates are displayed in Table 4.5. In columns 1-2, *OIB* is calculated by aggregating orders across all investors: Both with and without controls, contrary to the predictions of PT and ST, the coefficients on *PTV* and *STV* are negative and statistically significant at the 1% level. Conversely, the coefficient on *RTV* is positive and statistically significant at the 1% level. In other words, at the aggregate level, order submission behaviour is consistent with the predictions of RT: Stocks that are more appealing to investors with RT preferences (i.e., higher RT-value stocks) tend to attract more net buy orders. This finding is in line with the results of the indirect test based on the dynamics of stock returns (Section 4.5.1): The negative cross-sectional relationship between RT value and future returns suggests that higher RT-value stocks are more appealing to the marginal investor, and consequently become overbought and overpriced.

To shed light on whether there exist behavioural differences across investor types, in columns 3-10 we focus on each investor type separately. In columns 3-4, where the dependent variable measures OIB among individual investors, we observe again that the coefficient on *RTV* is positive and statistically significant, and those on *PTV* and *STV* are negative and statistically significant. This is not surprising, as individual investors account for the lion's share of trades at the TWSE.

Interestingly, when it comes to foreign investors (columns 5-6), the coefficients on *PTV* and *STV* are positive and statistically significant at the 1% level, whereas, after including all the controls, the coefficient on *RTV* is negative and statistically significant at the 1% level. The implication is that the submission order behaviour of foreign investors is consistent with the predictions of PT and ST but inconsistent with those of RT.

In columns 7-8, where the dependent variable measures OIB among others, the coefficient on *PTV* is positive and statistically significant at the 1% level. On the other hand, when all controls are added to the equation, the coefficient on *STV* is negative and statistically significant at the 10% level, and the coefficient on *RTV* is negative but statistically indistinguishable from zero. Thus, we conclude that the behaviour of others is in line with the predictions of PT, but it is inconsistent with those of ST and cannot be explained by RT.

Lastly, in columns 9-10, where OIB is measured among securities investment trusts, the coefficient on *PTV* is positive and statistically significant at the 1% level. At the same time, the coefficient on *STV* is statistically indistinguishable from zero, and when all controls are added to the equation, the coefficient on *RTV* is negative and statistically significant at the 1% level. In other words, PT (ST and RT) can (cannot) successfully predict the behaviour of this group of investors.

Table 4.5 Panel regressions: Behavioural-theory values and next-week *OIB*

Investor type:	**(1)** All	**(2)** All	**(3)** Individual investors	**(4)** Individual investors	**(5)** Foreign investors	**(6)** Foreign investors	**(7)** Others	**(8)** Others	**(9)** Securities investment trusts	**(10)** Securities investment trusts
PTV	-0.8382***	-0.3130***	-1.9047***	-0.5670***	0.6581***	0.3494**	0.8017***	0.4349***	2.9620***	2.4861***
	(-13.36)	(-10.99)	(-21.30)	(-13.19)	(2.86)	(2.58)	(2.85)	(3.24)	(7.11)	(7.39)
STV	-0.2495***	-0.0644***	-0.1235	-0.0681**	0.5978***	0.3341***	-0.3629	-0.2101*	0.7048	-0.0149
	(-4.64)	(-2.89)	(-1.63)	(-2.16)	(3.28)	(3.39)	(-1.45)	(-1.84)	(1.61)	(-0.04)
RTV	6.8992***	2.4755***	11.0965***	4.4941***	7.8549***	-5.9037***	-11.8768***	-0.4631	14.2342***	-13.5090***
	(12.08)	(8.50)	(14.47)	(10.87)	(3.08)	(-4.61)	(-4.79)	(-0.33)	(2.80)	(-3.19)
LOIB		0.6406***		0.6001***		0.4381***		0.5469***		0.3695***
		(90.75)		(80.71)		(36.87)		(87.69)		(36.45)
WRet		-0.6332***		-0.5754***		-0.2416***		-0.5129***		0.7565***
		(-40.06)		(-26.68)		(-4.23)		(-9.16)		(4.82)
MRet		0.0297***		0.0156*		0.1725***		-0.0309		0.0256
		(5.49)		(1.78)		(5.47)		(-1.08)		(0.32)
HYRet		-0.0091***		-0.0139***		0.0305***		0.0031		-0.0000
		(-5.65)		(-5.89)		(3.73)		(0.38)		(-0.00)
Turnover		0.2661***		0.2237***		2.1636***		-1.9547***		1.9859***
		(4.98)		(3.14)		(6.14)		(-9.10)		(3.77)
Vol		-0.1634**		-0.3768***		1.3148***		-0.8229***		4.5100***
		(-2.14)		(-3.45)		(4.30)		(-2.97)		(6.18)
Size		0.0040***		-0.0007		0.0087**		-0.0274***		0.0166***
		(8.98)		(-0.60)		(2.40)		(-10.81)		(3.28)
BM		-0.0039***		-0.0032**		-0.0108***		-0.0034		0.0054
		(-4.21)		(-2.14)		(-2.61)		(-0.70)		(0.56)
CRO		-0.0088***		-0.0109***		0.0063		-0.0029		0.1389***
		(-6.90)		(-5.12)		(0.88)		(-0.49)		(6.87)
52WHMAX		0.0169***		0.0230***		0.0282***		-0.0208***		-0.0148
		(14.06)		(11.89)		(6.30)		(-4.14)		(-1.22)
Week FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R-squared	0.0622	0.4665	0.0785	0.4230	0.1117	0.2975	0.0354	0.3448	0.0749	0.2234
N	214417	201633	214417	201633	208464	194516	209547	196135	79028	57741

This table reports the estimates generated by fitting *Eq. (4.12)*. In all specifications, the dependent variable is *OIB*, which measures a stock's OIB in week t; this is constructed by aggregating orders across all investors (columns 1-2) or only across individual investors (columns 3-4), foreign investors (columns 5-6), others (columns 7-8), and securities investment trusts (columns 9-10). *PTV*, *STV*, and *RTV* are the prospect theory value, salience theory value, and regret theory value of a stock's historical weekly return distribution from week t-12 to week t-1, respectively. The remaining variables are as defined in Table 4.1. The sample period is from May 15, 2013 to March 28, 2018. The t-statistics in parentheses are based on standard errors clustered by stock and week. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

The picture that emerges from this set of results is multifaceted. RT does a good job of predicting the order submission behaviour of individual investors. Since, at the TWSE, the marginal investor is likely to be an individual investor, the negative cross-sectional relationship between RT value and next-month stock returns (Table 4.3) can be interpreted as a logical consequence of individual investors having RT preferences. At the same time, we find that the behaviour of non-individual investors (i.e., foreign investors, others, and securities investment trusts) is generally inconsistent with the predictions of RT.[71] Intriguingly, the opposite pattern arises with respect to PT, which does a good job of predicting the order submission behaviour of non-individual investors but fails to describe the behaviour of individual investors. As for ST, it can successfully model the behaviour of foreign investors, but it does quite poorly when applied to the remaining investor types. These results lead us to conclude that there exist meaningful behavioural differences across investor types, and consequently one should be wary of investigations that paint investor behaviour with a broad brush.

Overall, our findings provide partial support for *H1*. At the aggregate level, we observe a positive cross-sectional relationship between PT value and future OIB, but a negative cross-sectional relationship between ST (RT) value and future OIB. At the same time, the evidence that the predictive ability of these three theories varies across investor types supports *H2*.

Before discussing the economic significance of the relationships described above, it is useful to examine the estimated effects of the other explanatory variables in *Eq. (4.12)*. Across all investor types, past OIB (*LOIB*) positively predicts current OIB, which is in line with prior findings (*Lee et al., 2004*; *Boehmer et al., 2021*). Interestingly, individual investors seem to follow a contrarian strategy in the short term (*WRet*), chase the trend in the medium term (*MRet*), and act contrarian again in the long term (*HYRet*). On the other hand, foreign investors follow a contrarian strategy in the short term and chase the trend in the medium and long term, and securities investment trusts chase the trend in the short term. With the exception of others, the majority of investor types display a preference for stocks with higher turnover. Foreign investors and securities investment trusts seem to find volatility appealing, while individual investors and others are averse to it. *CRO* measures the recency effect proposed by *Mohrschladt* (*2021*), according to which, all else remaining the same, investors find a stock more attractive when its highest (lowest) historical returns occurred in the more recent (distant) past. While *Mohrschladt* (*2021*) finds evidence of a recency effect in the cross-section of US stock returns, here we observe that only securities investment trusts are attracted to stocks with high *CRO* values. Contrary to the recency effect, individual investors tend to stay away from high-*CRO* stocks, while foreign investors

[71] Note that the "others" group does not contain any individual investors. While the "foreign investors" group might contain a few individual investors, for the most part it is likely to consist of institutional investors (*Barber et al., 2007*; *Hsieh, 2013*).

and others seem to be unaffected. We also control for the 52-week-high effect documented by Della Vedova et al. (2022), according to which, when the price of a stock approaches its 52-week high, households tend to increase their net selling, and institutional investors, who act as their counterparties, tend to increase their net buying. Unlike Della Vedova et al.'s (2022) findings, which are based on data from the Finnish stock market, we observe that individual investors and foreign investors tend to increase their net buying when the price of a stock approaches its 52-week high, and others tend to increase their net selling.[72] Taken together, the effects of the control variables in *Eq. (4.12)* confirm the existence of a meaningful amount of behavioural heterogeneity across investor types.

4.5.2.3 Economic significance

To examine the practical significance of the predictive abilities of PT, ST, and RT, we compare the sizes of the effects of *PTV*, *STV*, and *RTV* with those of other factors that, according to the literature, influence OIB. To achieve this, we standardise both the dependent and explanatory variables in *Eq. (4.12)*. In Figure 4.2, we display the point estimate and 95% confidence interval of the partial effect on a stock's next-week OIB of a change in one of the explanatory variables, all else constant. Each panel focuses on a separate investor type, and to facilitate comparisons, all estimates are displayed with a positive sign.

In the case of individual investors (Panel A), a one cross-sectional standard deviation (SD) increase in the RT value of a stock increases its next-week *OIB* by 6.16% cross-sectional SDs. This effect is larger than the effect of each of the other control variables, with the exclusion of *LOIB* and *WRet*. As for foreign investors (Panel B), a one cross-sectional SD increase in the PT value (ST value) of a stock increases its next-week *OIB* by 1.82% (1.85%) cross-sectional SDs. With the exception of *LOIB*, these effects are of the same order of magnitude as that of each of the other control variables. In the case of others (Panel C), a one cross-sectional SD increase in the PT value of a stock increases its next-week *OIB* by 1.81% cross-sectional SDs. Though the effects of *LOIB* and *Size* are considerably bigger, the impact of *PTV* is of the same order of magnitude as that of each of the remaining control variables. Lastly, when it comes to securities investment trusts (Panel D), a one cross-sectional SD increase in the PT value of a stock increases its next-week *OIB* by 6.70% cross-sectional SDs. With the exclusion of *LOIB*, this effect is larger than (or, at least, on par with) that of each of the other control variables.

[72] In untabulated results, we find that the coefficient on *52WHMAX* is negative (positive) and statistically significant for individual investors and others (foreign investors and securities investment trusts) when *52WHMAX* is the only explanatory variable in the regression. However, when we add *LOIB*, *WRet*, *MRet*, and *HYRet*, which are not included in Della Vedova et al.'s (2022) model, the sign of coefficient on *52WHMAX* switches from negative to positive for individual investors.

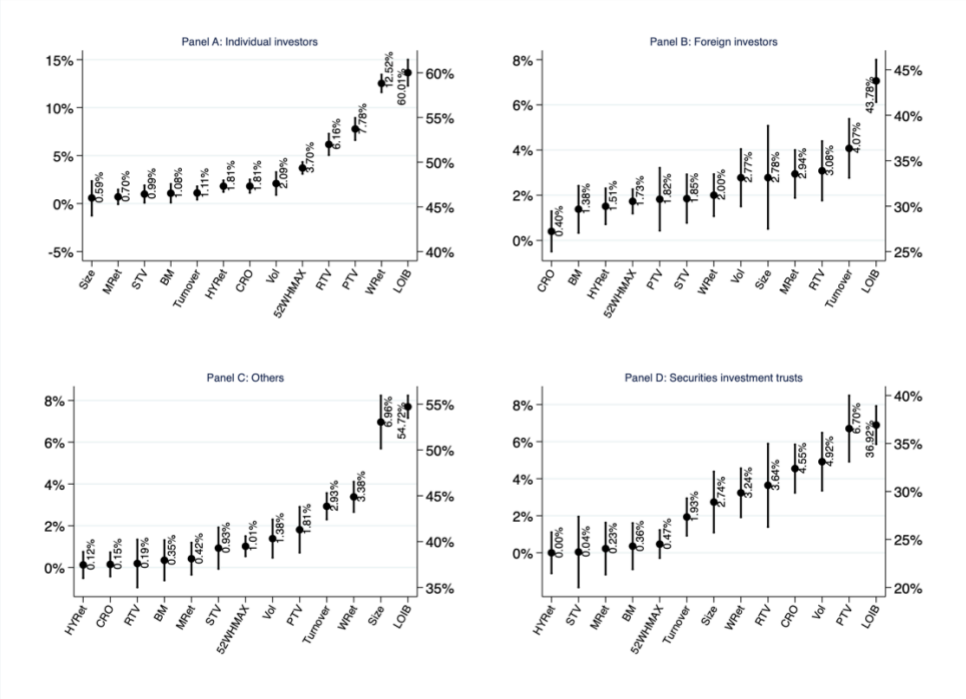


Figure 4.2 Economic significance of the effects of *PTV*, *STV*, and *RTV* on next-week OIB

This figure compares the sizes of the effects of *PTV*, *STV*, and *RTV* with those of other factors that, according to the literature, affect a stock's OIB. In each panel, each point estimate and 95% confidence interval represent the effect on a stock's next-week OIB of a change in one of the explanatory variables in *Eq. (4.12)*, holding all else constant. For ease of comparison, both the dependent and the explanatory variables are standardised, and the figure displays all point estimates with a positive sign. For example, the point estimate of the coefficient on *PTV* in Panel A indicates that a one cross-sectional standard deviation change in a stock's *PTV* leads to a change of 0.0778 cross-sectional standard deviations in its next-week OIB. In Panel A (B, C, D), the estimates are based on the model specification in column 4 (6, 8, 10) of Table 4.5, where *OIB* is constructed by aggregating orders across individual investors (foreign investors, others, securities investment trusts). All variables are as defined in Table 4.1. To improve readability, the effect of *LOIB* (i.e., one-week lagged OIB) is measured on the right y-axis, whereas the effects of the other variables are measured on the left y-axis. The sample period is from May 15, 2013 to March 28, 2018. The confidence intervals are computed on the basis of standard errors clustered by stock and week.

Overall, these estimates lead us to conclude that the predictive powers of the three behavioural theories are economically meaningful. RT (PT) contributes to explaining the order submission behaviour of individual investors (foreign investors, securities investment trusts, and other non-individual investors) at least as much as other prominent factors that have been identified in the literature. In the specific case of foreign investors, ST's contribution can be interpreted as economically relevant as well.

4.5.2.4 Robustness tests

We conduct a battery of tests to verify the robustness of our findings. Specifically, we investigate potential near-multicollinearity issues, employ alternative methodologies in the construction of *OIB*, *PTV*, *STV*, and *RTV*, and repeat our analyses on various sub-samples of data. All these tests are discussed in the Appendix C, and Tables C2 and C3 therein provide a summary of the results. Our conclusion is that our main findings are robust.

4.6 Discussion and conclusion

In this study, we test the predictive power of three distinct behavioural theories (i.e., PT, ST, and RT) by studying the cross-section of returns and investors' order submissions in the Taiwanese stock market. We find that the cross-section of stock returns and aggregate investor demand are consistent (inconsistent) with the predictions of RT (PT and ST). However, when we break down the data by investor type (i.e., individual investors, foreign investors, others, and securities investment trusts), we find that the three theories enjoy varying degrees of success at explaining demand across investor types, which provides evidence of significant behavioural heterogeneity.

First, our results suggest that RT successfully predicts the order submission behaviour of individual investors but not that of institutional investors (i.e., foreign investors, securities investment trusts, and other non-individual investors). This finding indicates that feelings of regret play a decisive role among the former group and is consistent with other regret-related effects that are more evident among individual investors, such as the repurchase effect (*Strahilevitz et al., 2011*) and the disposition effect (*Odean, 1998*). Social contagion is one of the possible factors that may explain the stronger influence of regret among individual investors: observing the returns obtained by others, such as neighbours and friends, fuels the effects of regret (*Shiller, 2015*; *Frydman and Camerer, 2016*), and comparing oneself to others is a trait that is particularly prevalent among individual investors (*Ivković and Weisbenner, 2007*; *Mitton et al., 2018*). Prior research also shows that there exist cross-cultural differences in how individuals experience regret (*Breugelmans et al., 2014*), which may explain why we find that foreign investors' demand is inconsistent with RT's predictions.

Second, our results show that PT is successful at predicting the behaviour of institutional investors. The analysis that we report in Section C3 of the Appendix C further suggests that loss aversion and nonlinear probability weighting are the driving forces behind its explanatory power. Yet, PT fails to explain individual investors' demand. These results indicate that institutional investors in

Taiwan are more likely to exhibit loss aversion and overweight extreme outcomes than retail investors. Admittedly, the literature on this point is mixed. Some authors argue that these two behavioural biases are more prevalent among agents with less (real and perceived) experience (e.g., *Mrkva et al., 2020*; *Baars and Goedde-Menke, 2022*). At the same time, institutional investors, who are generally more experienced, have also been found to exhibit loss aversion (*Haigh and List, 2005*; *Larson et al., 2016*). In fact, institutional investors may be more loss averse than individual investors because their past performance is subject to evaluation by their clients and the public (*O'Connell and Teo, 2009*). Similarly, institutional investors have also been found to exhibit nonlinear probability weighting (e.g., *Abdellaoui et al., 2013*; *Baele et al., 2019*), and in the US stock market, which is dominated by institutional investors, *Barberis et al.* (*2016*) find that nonlinear probability weighting is a driving force behind PT's explanatory power.

Third, we find that ST is successful only at predicting the behaviour of foreign investors. This finding is consistent with *Brennan and Cao* (*1997*), who suggest that foreign investors tend to pay more attention to stocks that exhibit salient returns. This may be because foreign investors are busy monitoring their own domestic markets (or a multitude of foreign markets), and only when Taiwanese firms exhibit salient returns do they divert their attention towards their shares of stock. This effect may also be compounded by the behaviour of the media operating in the foreign investors' own countries, as foreign media are likely to intensify their coverage of Taiwanese firms that experience salient returns.

Our findings contribute to the growing literature on the ability of behavioural theories to explain real-world investor behaviour and provide avenues for future research in financial economics. First, we identify some remarkable differences in investing behaviour across investor types; this leads us to conclude that studies that employ aggregate-level data can only paint a partial picture of how choice under risk occurs in the real world. For example, it would be misleading to conclude that a theory fails to explain investor behaviour when an analysis is conducted only on aggregate-level data, e.g., the cross-section of stock returns. Looking deeper into the composition of the investor population and drawing inter-market comparisons seem promising ways of advancing our understanding in this area.

Second, the question of why, in the Taiwanese market, individual investors tend to be regret averse while institutional investors appear to be loss averse and engage in nonlinear probability weighting requires further in-depth investigation. While we have considered some psychological mechanisms and institutional factors that may contribute to explaining these findings, additional research is necessary. Specifically, cross-cultural differences in behavioural inclinations may play an important role. And they might also help explain why we find that the behaviour of individual investors in Taiwan goes against the predictions of PT and ST, while the behaviour of institutional investors defies the predictions of RT. We believe this area is ripe for investigation.

Chapter 5 Conclusion

This Chapter is organised as follows: Section 5.1 provides a summary of the main findings, contributions, and implications for each of the three studies. Section 5.2 discusses the limitations of the present thesis and provides directions for future research, and Section 5.3 provides concluding remarks.

5.1 Summary of findings, contributions, and implications

5.1.1 Study one

This study explores whether PT can explain returns in the emergent cryptocurrency market. Prior studies on cryptocurrency returns have typically assumed that investors are rational. Instead, given that this market is dominated by unsophisticated individual investors who are more likely to be susceptible to behavioural biases, we examine the explanatory power of PT in this context. Furthermore, the ability of PT to explain the dynamics of asset returns has already been established in several traditional markets, which reinforces the motivation for our analysis.

We make a number of contributions to the literature. Firstly, we augment the cryptocurrency literature by shedding light on some psychological factors that affect investor behaviour in this market (as captured by PT). Specifically, we document a negative relationship between the PT value of a cryptocurrency and its next-week return in the cross-section, which is consistent with the theory's predictions and with prior studies on conventional markets. A key strength of our analysis is that we examine a wide cross-section of cryptocurrencies, rather than focusing solely on the most popular ones, thus ensuring the generalisability of our findings to the whole market. Secondly, we establish that the PT value of a cryptocurrency is also predictive of time-series variation in its expected return, an aspect overlooked by previous research. Lastly, we provide evidence in support of the moderating role of arbitrage constraints and investor attention. This indicates that the PT effect is likely to be behavioural in nature, rather than driven by economic fundamentals. Additionally, our evidence demonstrates that the effect appears in all size segments of the market and is driven by all three components of PT, although the concavity/convexity component seems to play a more pivotal role.

Overall, our findings make valuable contributions both to the field of behavioural finance and to our understanding of the cryptocurrency market by providing insights into the behavioural factors that influence cryptocurrency pricing. Additionally, we add to our understanding of decision-making behaviour by demonstrating that PT can accurately model choice behaviour under risk in real-world settings.

Our findings also have important implications for practitioners. The PT effect that we document in the cryptocurrency market is economically meaningful (especially when compared to that documented in traditional markets). As a result, investors might be able to devise speculative strategies based on this effect. For example, they could contemplate overweighting cryptocurrencies with low PT values (in comparison to their peers), as these cryptocurrencies tend to generate higher excess returns. If short-selling is viable (and as we discussed in Chapter 2, this is not always the case), they could also obtain positive excess returns by setting up zero-cost portfolios that simultaneously go short cryptocurrencies with high PT values and go long cryptocurrencies with low PT values.

5.1.2 Study two

The second study extends the exploration of ST's ability to explain investor behaviour (and asset returns) to the cryptocurrency market. Such an exploration is imperative because empirical tests of ST based on real-world financial market data are exceedingly scarce and have primarily concentrated on the equity market. More importantly, prior studies have produced some conflicting findings.

We make a number of contributions to the literature. Firstly, consistent with *Bordalo et al.'s* (*2013a*) salience-based asset pricing model, we find empirical support for ST. Specifically, in the cross-section, cryptocurrencies with high ST values generate lower next-week returns than cryptocurrencies with low ST values, suggesting that the former are overpriced relative to the latter. This finding is in line with that documented in the equity market, signifying that our study takes an important step toward generalising the predictive power of this theory across financial markets and investor types. Secondly, we show that, in the time-series dimension, there is a negative relationship between the ST value of a cryptocurrency and its next-week returns. This dimension is overlooked in previous research, but it is critical since it provides information about changes in expected returns (as opposed to average returns in the cross-sectional dimension) and can be valuable for implementing trading strategies. Thirdly, we give new impetus to the debate on the ST effect, since prior studies have produced conflicting findings. We establish that, in the cryptocurrency market, the ST effect is not subsumed by the short-term reversal effect. However, the effect is only present in the micro-cap segment. In other words, we only find a statistically significant ST effect for cryptocurrencies that account for the bottom 3% of total market capitalisation. Lastly, our results support the notion that this anomaly is behaviourally driven, as the effect is stronger when arbitrage constraints are more severe.

Overall, our findings make substantial contributions to the behavioural finance literature by evaluating a newly developed theory of choice under risk using data from the cryptocurrency market. Our findings lend support to the theory and enhance our understanding of investor behaviour in this nascent market, offering valuable new insights for researchers.

Our findings also have important implications for the formulation and execution of investment strategies based on the salience anomaly in the cryptocurrency market, and/or other financial markets. We demonstrate that the salience effect in the cryptocurrency market, while economically meaningful, is only observable among micro-cap cryptocurrencies, which are frequently associated with substantial transaction costs. As a result, it is important to note that implementing investment strategies based on this anomaly may be challenging for practitioners.

5.1.3 Study three

The last study examines whether investor behaviour in the Taiwanese stock market is consistent with the predictions of a set of well-known behavioural theories (i.e., PT, ST, and RT). This study is essential because, although the literature has initiated empirical tests of behavioural theories utilising real-world financial market data, existing studies have numerous limitations. Namely, they typically employ indirect tests, ignore possible heterogeneities among investors, and ignore whether the behavioural theories under scrutiny can be reconciled with one another. Instead of merely employing indirect tests based on the dynamics of stock returns, which is the common approach in the existing literature, we also employ direct tests based on the dynamics of order submissions. Furthermore, we examine whether there are behavioural heterogeneities among investor types and whether the predictive powers of PT, ST, and RT can be reconciled with one another.

We address these research gaps and make a number of contributions to the literature. Firstly, we directly observe net investor demand for stocks using the limit order book, which allows us to examine whether the dynamics of investor demand align with the predictions of well-known behavioural theories. Compared to previous studies that rely on indirect tests based on stock return patterns, our approach is more direct and provides more compelling evidence. We discover that, at the aggregate level, the dynamics of stock returns (i.e., an indirect measure) and net investor demand (i.e., a direct measure, which is proxied by buy-sell order imbalance) are consistent with the predictions of RT. It is also worth mentioning that these behavioural effects are economically significant. Secondly, we break down our data by investor type (i.e., individual investors, foreign investors, securities investment trusts, and other non-individual investors) and shed light on behavioural heterogeneities among investors. We find that individual investors' demand is consistent with the predictions of RT, which is akin to the aggregate level result. Instead, foreign investors' demand is consistent with both PT's and ST's predictions, while the order submission behaviours of others and securities investment trusts are consistent with the predictions of PT. Thus, our findings highlight the importance of analysing investor behaviour by investor type. Lastly, instead of focusing on a single theory, we simultaneously test these three non-mutually exclusive theories, which enables us to shed light on the compatibility and interplay between these theories. Overall, our findings make significant contributions to the behavioural finance literature by evaluating the explanatory ability of these three behavioural theories through an innovative and more effective approach.

Our findings also have important implications for future research. First, we show that meaningful behavioural heterogeneities might be overlooked in aggregate (market-level) analyses. Thus, it is crucial to pay attention to multiple investor types or to the composition of the investor population if research must rely on aggregate data. Second, our direct tests can be extended to other international stock markets or to alternative markets. Finally, while previous research on investors' order submission behaviour often ignores the existence of behavioural biases, our findings suggest that these biases play a meaningful role. Thus, future research should pay more attention to behavioural biases when studying investors' order submissions.

5.2 Limitations and suggestions for future studies

Chapters 2 and 3 adopt *Barberis et al.'s* (*2016*) framework and respectively test the predictive abilities of PT and ST by analysing cryptocurrency return patterns. Consequently, the research designs of these two chapters (i.e., data and methodology) are similar. For these two chapters, the first limitation is that our data (and findings) reflect aggregate investor behaviour. Specifically, our data are aggregated from over 200 exchanges worldwide, and the observed return patterns reflect the behaviour of the marginal investor. Future research could focus on specific exchanges, as investors within an exchange are more likely to exhibit homogenous behaviour. By doing so, it may also shed light on the impact of demographic and cultural factors on investor trading behaviour, given that these factors differ across exchanges and regions of the world. In Chapter 2, we make an attempt to address this issue by using country-specific prospect-theory parameter estimates. However, breaking down the data by cryptocurrency exchange is likely to provide a better understanding of the issue at hand.

The second limitation is that we employ an indirect test based on the cross-sectional relationship between the PT (ST) value of cryptocurrencies and their future returns. Although our (indirect) findings support the predictions of PT (ST), we are unable to directly observe investors' demand for cryptocurrencies and consequently cannot provide direct evidence in support of PT (ST). Hence, in future studies, provided the necessary data are available, it would be fruitful for researchers to examine the order submission behaviour of cryptocurrency investors. This way, they could directly test whether the dynamics of investor demand are in line with the predictions of PT, ST, or other behavioural theories.

We also note that, since the PT effect that we document is economically meaningful and pervasive across size segments (whereas the ST effect is confined to the micro-cap segment), future studies on the cryptocurrency market could investigate the feasibility of developing trading strategies based on this anomaly. For instance, researchers could evaluate the profitability of PT-based strategies in the spot and/or futures cryptocurrency markets.

Some limitations arise from the use of limit order data from the Taiwan stock exchange in Chapter 4. Firstly, we argued that one of its strengths is that the exchange identifies the direction and investor type for each order. This reduces the noise resulting from researchers' subjective judgments. Nonetheless, one of the investor types identified by the exchange is "others", which represents all non-individual investors excluding foreign investors and securities investment trusts. This category includes investors such as banks and companies. Regrettably, the exchange does not provide sufficient information concerning the construction of this investor category, and consequently its usefulness is limited. The literature commonly compares the behaviour of foreign and domestic institutional investors (*Grinblatt and Keloharju, 2000*; *Richards, 2005*; *Phansatan et al., 2012*), and we find that the behaviours of securities investment trusts and others are similar. Future research based on order submissions from other exchanges might be able to address this issue more convincingly by employing alternative classifications of investors.

Secondly, one may also worry about the generalisability of our findings. At the very least, we believe that our findings can be generalised to other stock markets in East Asia, as they share similar cultural traits such as collectivism and a long-term orientation (*Chui et al., 2010*; *Docherty and Hurst, 2018*), as well as market characteristics such as the composition of the investor population, the trading behaviour of investor groups, and the regulations and laws governing public companies (*Richards, 2005*; *Ball et al., 2003*). Additionally, our dataset includes data of the order submission behaviour of foreign investors, who are the second biggest group by transaction value and are from the rest of the world. Thus, we believe our results may also be generalised to other international stock markets. Nevertheless, future research could use our approach and test these behavioural theories in other international stock markets or other financial markets to shed more light on the extent to which our findings are generalisable.

Lastly, we use buy-sell order imbalance to measure net investor demand for a stock, which is a widely adopted measure in the related literature (e.g., *Barber and Odean, 2008*; *Bhattacharya et al., 2011*; *Della Vedova et al., 2022*; *Chen et al., 2021*). To mitigate noise from market microstructure and algorithmic trading practices, we adopt several approaches, such as aggregating orders at a weekly frequency, retaining only regular trading orders (i.e., excluding block and odd-lot trades), and using the trading volume (number of shares) after adjustments. However, to further mitigate such noise, future studies could consider taking an investor-level approach, depending on data availability. To be more specific, future research could complement our findings by attempting to observe (or reconstruct) investors' portfolios and test whether they are tilted towards (away from) stocks that are more (less) attractive to PT (ST, RT) investors.

Furthermore, one of the aims of Chapter 4 is to examine whether there exist behavioural heterogeneities across investor types, and we do find evidence in support of behavioural heterogeneities: The behaviour of individual investors is consistent (inconsistent) with the predictions of RT (PT and ST), whereas that of institutional investor is consistent (inconsistent) with PT (RT). We provide possible explanations for these findings based on how different types of investors may engage in distinct psychological mechanisms, as incorporated in these theories, to evaluate the past return distributions of stocks. For instance, institutional investors are prone to loss aversion and exhibit overreaction to extreme returns, which aligns with the "PT investors" paradigm. However, it would be interesting to conduct an in-depth investigation into such phenomena, as well as into why individual investors (institutional investors) exhibit contrarian behaviour that is the opposite of what PT and ST (RT) predict. Future research could focus on exploring psychological, sociological, and institutional factors to deepen our understanding of these findings.

Finally, throughout the thesis, we follow *Barberis et al.'s* (*2016*) three assumptions when measuring the PT (ST, RT) value of an asset: (1) investors exhibit narrow framing, (2) they extrapolate the past return distribution into the future, and (3) they evaluate the return distribution as described by a behavioural theory. These assumptions are fair and are widely accepted in the literature examining the effect of mental accounting on investor trading behaviour and asset prices (*Barberis and Huang, 2001*; *Da et al., 2021*). Also, when estimating the PT (ST, RT) value of a cryptocurrency or stock, we test the robustness of our methodology by using alternative reference points and parameter estimates. However, it is possible that investors may hold subjective extrapolative beliefs, meaning that they modify past returns when extrapolating into the future. Thus, future research may explore this channel, i.e., how exactly investors extrapolate past returns when forming expectations about future performance. Additionally, it would be interesting to explore the distribution of other asset characteristics in addition to returns. For example, investors may interpret past trading volume according to the predictions of a behavioural theory. This is because the historical data and distribution of trading volume are typically accessible and can be readily obtained from websites that provide relevant trading information (e.g., Yahoo Finance), and trading volume also offers useful information on stock-specific features, such as volatility, liquidity, investor attention, etc. (*Han et al., 2022*).

5.3 Concluding remarks

The limitations of EUT in describing real-world decision-making have motivated the development of behavioural theories of choice under risk that consider common psychological mechanisms (*Schoemaker, 1982*; *Starmer, 2000*; *Sugden, 2004*). While most of the support for these theories stems from laboratory studies, the aim of the present thesis is to explore their predictive power using data from real-world financial markets.

Barberis et al. (*2016*) reignite interest in testing PT by using indirect tests based on stock returns patterns. Their approach has been extended to test PT in various traditional financial markets (*Zhong and Wang, 2018*; *Gu and Yoo, 2021*; *Gupta et al., 2022*), as well as other theories such as ST (*Cosemans and Frehen, 2021*; *Hu et al., 2023*; *Cakici and Zaremba, 2022*) and RT (*Ballinari and Müller, 2022*). However, these studies are targeted primarily at traditional financial markets (particularly stock markets) and focus on asset return patterns. They rely on indirect tests (instead of observing investor demand directly) and focus on aggregate investor behaviour. We achieve our research aims by investigating cryptocurrency return patterns (Chapters 2 and 3) and by observing order submissions at both the aggregate level and across investor types on the Taiwan stock exchange (Chapter 4).

Overall, consistent with previous studies on traditional markets, we document that PT and ST contribute to explaining the dynamics of returns in the cryptocurrency market in the cross-sectional and time-series dimensions, suggesting that the behaviour of cryptocurrency investors is consistent with the predictions of PT and ST. Moreover, we show the effects are more economically meaningful when compared with those in traditional markets. For example, in the cross-section, the size of the PT (ST) effect is approximately 23 (13) times the size of that in the US stock market. Additionally, by using buy-sell order imbalance as a proxy for net investor demand, we provide more direct evidence on the ability of these behavioural theories (i.e., PT, ST, and RT) to explain investors' actions. Furthermore, we reveal the presence of behavioural heterogeneities across investor types.

Collectively, the present thesis contributes to the behavioural finance literature by demonstrating the ability of behavioural theories to successfully describe real-world decision-making (and investor behaviour) under risk. Our evidence comes from outside the laboratory and is based on decisions involving large and risky payoffs. Our findings also shed light on behavioural heterogeneities across investor types and on the extent to which these theories can be reconciled with one another. Additionally, this thesis contributes to the growing literature on the cryptocurrency market by providing insights on some behavioural forces that shape cryptocurrency pricing. Our findings enhance our understanding of the functioning of this nascent market and offer new insights into this area of study. Furthermore, the present thesis makes methodological contributions to the behavioural finance and asset pricing literature by introducing novel models that allow for the direct test of behavioural theories and the isolation of the cross-sectional and time-series dimensions.

The findings in this thesis also have meaningful implications for a variety of stakeholders, including investors, financial institutions, governments and policy makers, and academics. For retail and institutional investors, some of the behavioural effects described in the thesis (e.g., PT effect) are economically significant in the cryptocurrency market. Thus, it may be possible to implement profitable trading strategies based on them. At the same time, the high level of irrational behaviour observed in this market serves as a reminder to investors of the potential for irrational investment decisions. This can also enhance the risk management processes for financial institutions by incorporating behavioural biases into their models and implementing educational programmes to mitigate the impact of such irrational decisions on their portfolios. Also, the findings highlight the need for close monitoring by governments and policy makers in the cryptocurrency market. Given the economic significance of this market and the prevalence of irrational trading behaviour, it is imperative that regulations be implemented to mitigate financial stability risks. Furthermore, for academics, this thesis provides novel theoretical and empirical insights that could inform future research in the field. To be specific, we underscore the importance of considering behavioural biases when studying asset returns and order submissions, and we provide an approach for testing behavioural theories directly using order submission data.

Lastly, as discussed in Section 5.2, we acknowledge some limitations of the present thesis and propose several directions for future research, which we hope will further enrich our understanding of investor behaviour.

Appendix A Supplement to Chapter 2

In this Appendix, we provide further details about the construction of the *PTV* variable and additional summary statistics. We also discuss some additional analyses and robustness tests. Supplementary tables and figures are displayed at the end of the Appendix.

A.1 Benchmark length of the historical time window used in the construction of *PTV*

To select the benchmark length of the historical time window used in the construction of the prospect theory (PT) value of a cryptocurrency, we conducted a Google search on December 19, 2020, using the keywords "cryptocurrency historical return". Subsequently, we manually inspected the first 100 results returned by the search engine, 32 of which provide historical cryptocurrency data. These results are summarised in Table A1. The first column shows the website from which the information is extracted. The second column specifies the cryptocurrency whose historical performance is presented by default when the website is accessed. The third column reports the length of the historical time window for which data about price/return are presented by default by the website. "Multi" indicates that the website in question displays multiple tables/charts based on multiple window lengths. The fourth column shows whether price or return is the quantity presented by default. The fifth column reports whether the website displays a table, a chart, or both by default. The last column shows whether the website offers information about cryptocurrencies other than the one presented by default.

A.2 Average time-series summary statistics

Table A2 presents the cross-sectional averages of a set of time-series summary statistics for the key explanatory variable (*PTV*) and the set of control variables. Panel A displays the mean and standard deviation of each variable, and panel B displays the Pearson's pairwise correlation coefficients.

A.3 Characteristics of the *PTV*-sorted portfolios and bivariate dependent-sort portfolio analysis

A key limitation of the univariate portfolio analysis discussed in Section 2.4.1.1 of the main body of the paper is that is does not allow one to control for the confounding effects of other factors that may influence cryptocurrency returns.

Table A3 summarises the main characteristics of the *PTV*-sorted decile portfolios. It is clear that some characteristics (*Size*, *Mom*, *Rev*, *Lt_rev*, *Volume*, *StdVolume*, *Skew2*, *Iskew*) tend to increase monotonically moving from the first to the last decile. Consequently, we want to examine whether the results of our univariate portfolio analysis are driven by factors other than *PTV*. To achieve this, we employ bivariate dependent-sort portfolio analysis.

First, at the end of each week we sort cryptocurrencies into quintiles based on a factor other than *PTV* (e.g., *Beta*). Subsequently, within each quintile, we further sort cryptocurrencies into quintiles based on *PTV*. We assume that the portfolios are held for one week. Lastly, we compute the one-week-ahead return of a given *PTV*-quintile by averaging across the five factor-sorted quintiles. By repeating this procedure for each week, we can generate a time series of returns for each *PTV*-sorted quintile during the sample period.

Table A4 displays the results and reveals that the mean excess returns and CAPM alphas of the equal-weighted long-short portfolios (i.e., Low-High) are all positive and statistically different from zero at the 1% level. The mean excess returns and CAPM alphas of the value-weighted long-short portfolios are all positive, but only 10 (out of 15) are statistically significant at the 5% level. While these results, overall, provide additional support for the predictive power of PT (*H1*), they also highlight the importance of controlling for a number of potential confounding factors, which we do with our panel regressions in Section 2.4.1.2 of the main paper.

A.4 Skipping one week in the construction of *PTV*

Column 3 of Table 2.4 in the main body of the paper shows that including the previous week's return (i.e., *Rev*) in our panel regressions substantially reduces the size of the coefficient on *PTV* (cf. column 2). To investigate the extent to which the *PTV* effect is driven by the previous week's return, we first re-calculate the *PTV* variable using returns from week t-53 to t-2 to skip the previous week's return (i.e., t-1). Subsequently, we re-estimate the panel regressions.

The output is displayed in Tables A5, A6, and A7. In the majority of columns, the coefficient on *PTV* remains negative and statistically significant at conventional levels. Specifically, in the case of our preferred regression specification (column 7), the coefficient on *PTV* is always negative and statistically different from zero at the 1% level. This suggests that, while the previous week's return plays a substantial role, it cannot fully explain the *PTV* effect.

A.5 Alternative dependent variables

In Section 2.4.2 of the main body of the paper we document a negative time-series relationship between a cryptocurrency's PT value and its future excess return. To gauge whether our results are sensitive to our choice of the dependent variable, we conduct some robustness tests.

Following *Focke et al.* (*2020*), we repeat the analysis using returns in excess of the market return as the dependent variable. Additionally, following *Madsen and Niessner* (*2019*), we repeat the analysis using abnormal excess returns ($= excess\ return_{i,t} - \widehat{Beta}_{i,t} \times market\ excess\ return_t$) as the dependent variable. The output is displayed in columns 1-2 of Table A8. In both instances, the estimates reveal that our results are robust.

We do the same for the preferred two-way FE model, and the results are displayed in columns 3-4 of Table A8. Our conclusions remain unchanged.

A.6 Disaggregated results by cryptocurrency sector

In Table A9, we report the results obtained by estimating our preferred two-way FE model separately for each cryptocurrency sector (e.g., DeFi coins, Stablecoins), with the exclusion of the sector "Yield Farming", which contains only 3 cryptocurrencies. The 12-sector classification is from *Coincodex* (note that *Coincodex* assigns some cryptocurrencies to multiple sectors). In column 12, the sample consists of all the cryptocurrencies that do not belong to any specific sector.

Since some sectors contain less than 50 cryptocurrencies, which may affect the validity of the cluster-robust standard errors, we follow *Roodman et al.* (*2019*), and in the last row we also display p-values of the coefficients on *PTV* based on the wild cluster bootstrap-t procedure, where the standard errors are clustered by cryptocurrency and week and bootstrapped on the cryptocurrency dimension (null imposed; 999 replications).

The results show that the estimated coefficient on *PTV* is negative for 11 out of 12 sectors and is statistically different from zero for 4 out of 12 sectors. Considering that, for several of these sectors, the number of cryptocurrencies and observations is very small, these results suggest that the *PTV* effect is not driven by a single cryptocurrency sector but is rather pervasive.

A.7 Country-specific PT parameter estimates

In Table A10, we display data from *DataLight* (*2019*) about the most active countries in the cryptocurrency market. The list is limited to those countries for which country-specific PT parameter estimates are available based on *Rieger et al.'s* (*2017*) survey. Columns 3-7 show the PT parameter estimates (α, β, λ, γ, δ) for the given country from *Rieger et al.* (*2017*). The rightmost column shows the number of monthly visits to the 100 most popular cryptocurrency exchanges in the world originating from the country in question (*DataLight, 2019*).

A.8 Alternative PT reference points

We also test the robustness of our results to our choice of the reference point against which investors measure their gains/losses. Reference dependence is one of the crucial features of PT, and the results presented so far have assumed that investors evaluate a cryptocurrency's historical return relative to the return of the cryptocurrency market index.

Since this choice is somewhat arbitrary, we re-calculate the *PTV* variable using alternative reference points (i.e., zero, the risk-free rate, and the time-series mean of the cryptocurrency's own returns) and re-estimate our preferred two-way FE model accordingly. Table A11 reports the results and shows that the sign, size, and statistical significance of the coefficient on *PTV* are not affected by the chosen reference point, confirming the validity of our findings.

A.9 Alternative lengths of the historical time window underlying the *PTV* variable

We also test the robustness of the results in relation to the length of the time window used to construct the *PTV* variable. The results reported so far have assumed that investors form a mental representation of each cryptocurrency based on its historical return distribution over the previous 52 weeks. To assess the sensitivity of the results to this assumption, we re-calculate the *PTV* variable using alternative window lengths, from 4 weeks to 104 weeks.[73] Subsequently, we re-estimate our preferred two-way FE model. Figure A1 shows the estimated confidence interval for the coefficient on *PTV* for each of these window lengths and reveals that our findings are robust. The coefficient on *PTV* is always negative and statistically significant at the 1% level, and if anything, our benchmark estimate is a conservative one.

A.10 Stability of the *PTV* effect: Rolling-window regressions

Since the cryptocurrency market is a young and rapidly evolving market, it is possible that the relationship between *PTV* and future returns is driven by an abnormal sub-sample of data. To explore

[73] Given an n-week window, we assign a missing value to $PTV_{i,t-1}$ if, between week *t-n* and week *t-1*, the number of non-missing returns for cryptocurrency *i* is less than 20% of *n*.

this issue, we re-estimate our preferred two-way FE model using rolling-window regressions with a fixed window that is 104 weeks (2 years) in length and increments forward 13 weeks (3 months) for each iteration.

Figure A2 shows that the point estimate of the coefficient on *PTV* is always negative and fluctuates within a relatively narrow range. Furthermore, with the exception of the first window, where the number of active cryptocurrencies is small, the coefficient on *PTV* is always statistically significant at the 5% level. This leads us to conclude that the *PTV* effect is fairly stable over time. In particular, the *PTV* effect is stable over "bubble" (e.g., the year 2017) and "non-bubble" periods.

A.11 Amount of uncertainty in the cryptocurrency market, investor attention, and investor sentiment

Even though the size of the *PTV* effect appears to be fairly stable, Figure A2 reveals some modest over-time fluctuations. Therefore, we want to shed light on whether the magnitude of the *PTV* effect is moderated by some observable factors.

We conjecture that, when the amount of uncertainty in the cryptocurrency market is high, the least sophisticated investors may prefer to sit back and watch the market from the sidelines. Analogously, when the market is attracting a lot of investor attention, we would expect a greater number of sophisticated investors (e.g., institutional investors) to enter the market, leading to a reduction in the ratio of unsophisticated-to-sophisticated trading activity. Since unsophisticated investors are more likely to suffer from loss aversion and engage in nonlinear probability weighting (two of the key components of PT), we expect the size of the *PTV* effect to be smaller (in absolute value) when the amount of uncertainty in the market is high and/or when investor attention is high. Conversely, when investor sentiment is high, we would expect a stronger *PTV* effect because sentiment tends to influence the pricing of "securities whose valuations are highly subjective" (*Baker and Wurgler, 2006*), a category that most likely includes cryptocurrencies.

As proxies for the amount of uncertainty in the market, we use *Lucey et al.'s* (*2022*) cryptocurrency uncertainty indices, which are based on news coverage. Specifically, the cryptocurrency policy uncertainty index measures the amount of regulatory policy uncertainty surrounding cryptocurrencies, and the cryptocurrency price uncertainty index measures the amount of uncertainty surrounding cryptocurrency prices. We construct a dummy variable, *HighCryptoPolicyUncertainty* (*HighCryptoPriceUncertainty*) that takes the value of 1 when the value of the cryptocurrency policy (price) uncertainty index in week t-1 is above its sample median, and 0 otherwise. We then re-estimate our preferred two-way FE model with the inclusion of an interaction between *PTV* and *HighCryptoPolicyUncertainty* (*HighCryptoPriceUncertainty*).

The results are reported in columns 1-2 of Table A12. As expected, the coefficient on the interaction term *PTV*×*HighCryptoPolicyUncertainty* is positive, suggesting that PT has less predictive power when there is more regulatory policy uncertainty in the market. Conversely, the coefficient on the interaction term *PTV*×*HighCryptoPriceUncertainty* is negative, suggesting that PT has more predictive power when there is more price uncertainty in the market. However, both coefficients are not statistically different from zero at conventional levels. Put another way, we do not find enough evidence to reject the null hypothesis that the size of the *PTV* effect is not moderated by the amount of uncertainty in the market.

As proxies for the amount of investor attention, we employ the number of Wikipedia pageviews for "cryptocurrency" and "Bitcoin", which are available from the website (*https://pageviews.wmcloud.org*). [74] We construct a dummy variable, *HighCryptoWikiSearch* (*HighBitcoinWikiSearch*) that takes the value of 1 when the average number of pageviews for "cryptocurrency" ("Bitcoin") in week t-1 is above its sample median, and 0 otherwise. We then re-estimate our preferred two-way FE model with the inclusion of an interaction between *PTV* and *HighCryptoWikiSearch* (*HighBitcoinWikiSearch*).

The results are reported in columns 3-4 of Table A12. As expected, the coefficient on the interaction term *PTV*×*HighBitcoinWikiSearch* is positive, and it is statistically significant at the 10% level. Conversely, the coefficient on the interaction term *PTV*×*HighCryptoWikiSearch* is negative but statistically insignificant. This leads us to conclude that there is only marginal evidence that the size of the *PTV* effect is moderated by investor attention.

Lastly, as a proxy for investor sentiment, we use the *sentix Bitcoin Sentiment Index*, which is constructed based on survey data and measures the extent to which investors are bullish about the future price of Bitcoin. We construct a dummy variable, *HighSentiment*, that takes the value of 1 when the value of the sentiment index is above its sample median, and 0 otherwise. We then re-estimate our preferred two-way FE model with the inclusion of an interaction between *PTV* and *HighSentiment*.

The results are reported in column 5 of Table A12. As expected, the coefficient on the interaction term *PTV*×*HighSentiment* is negative, suggesting that PT has more predictive power during high-sentiment regimes. However, the coefficient is not statistically different from zero at conventional levels (t-statistic = -1.52). As such, there is not enough evidence to reject the null hypothesis that the size of the *PTV* effect is not moderated by investor sentiment.

[74] Data about Wikipedia pageviews (*sentix Bitcoin Sentiment Index*) are available from July 1, 2015 (September 8, 2017). Thus, the sample period for this part of the analysis starts from July 17, 2015 (September 15, 2017).

Table A1 How information about the historical performance of cryptocurrencies is typically presented to internet users

Website	Default cryptocurrency	Default historical time window (in days)	Default quantity: price or return?	Default output: table or chart?	Other cryptocurrencies available?
BullionByPost	BTC	0.02 (30 Mins)	Price	Chart	No
Coindesk	BTC	1	Price	Chart	Yes
Crypto.com	BTC	1	Price	Chart	Yes
MarketWatch	BTC	1	Price	Chart	Yes
Coinbase	BTC	1	Price	Chart	Yes
BitcoinPrice.com	BTC	1	Price	Chart	Yes
COINTELEGRAPH	BTC	7	Price	Chart	Yes
Coinhouse	LTC	7	Price	Chart	Yes
Coinmarketcap	BTC	30	Price	Table	Yes
Coincodex	BTC	30	Price	Table	Yes
EUREK HEDGE	Market Index	30	Return	Table	No
Investing.com	BTC	30	Price	Both	Yes
Nasdaq	ETC	30	Price	Table	Yes
BarclayHedge	Market Index	30	Return	Table	No
99BITCOINS	BTC	180	Price	Chart	No
GOLDPRICE	BTC	180	Price	Chart	Yes
UpMyInterest	BTC	365	Return	Table	No
Cryptocurrencychart.com	25 cryptocurrencies	365	Return	Chart	Yes
DQYDJ	BTC	365	Return	Table	Yes
Yahoo ! Finance	BTC	365	Price	Table	Yes
YCHARTS	BTC	365	Price	Chart	Yes
BUSINESS INSIDER	BTC	365	Price	Chart	Yes
TradingView	BTC	365	Price	Chart	Yes
CoinTracking	BTC	365	Return	Table	Yes
CRESCEBT CRYPTO	Market Index & BTC	1460	Price	Chart	No
Bitwise	Market Index & BTC	1460	Return	Chart	No
Statista	BTC	2555	Price	Chart	Yes
COINMETRICS	BTC	3650	Price	Chart	Yes
Buy Bitcoin Worldwide	BTC	3650	Price	Chart	No
barchart	BTC	Multi	Both	Table	Yes
CCi30	Market Index	Multi	Both	Both	No
Coin.dance	BTC	Multi	Return	Table	Yes

This table presents statistics concerning the type of information that internet users are shown by default when searching for data about the historical performance of cryptocurrencies. To construct these statistics, we conducted a Google search on December 19, 2020, using the keywords "cryptocurrency historical return". Subsequently, we manually inspected the first 100 results returned by the search engine, 32 of which provide historical cryptocurrency data.

Table A2 Average time-series summary statistics

Panel A. Mean and standard deviation

	PTV	Beta	Size	Mom	Rev	Illiq	Lt_rev	Vol	Ivol	Max	Min	Volume	StdVolume	Skew1	Skew2	Iskew	Coskew
Mean	-0.3374	0.2476	13.4656	-0.0295	-0.0133	0.8712	-1.2086	0.2685	0.2249	0.3765	0.3843	8.3671	7.4892	0.0024	-0.1199	0.0784	-0.1548
Standard deviation	0.0648	0.2473	0.7076	0.4354	0.3752	2.1458	1.1151	0.1991	0.1654	0.3195	0.3188	1.7708	1.9076	0.684	0.5382	0.4788	1.0459

Panel B. Pearson's pairwise correlation matrix

	PTV	Beta	Size	Mom	Rev	Illiq	Lt_rev	Vol	Ivol	Max	Min	Volume	StdVolume	Skew1	Skew2	Iskew
Beta	0.2215															
Size	0.3012	0.1127														
Mom	0.0312	-0.0278	0.1607													
Rev	0.1281	0.0016	0.2165	-0.2514												
Illiq	-0.0925	-0.0481	-0.2445	-0.0665	-0.0184											
Lt_rev	0.0978	-0.1433	0.0352	-0.0431	-0.0205	0.0067										
Vol	-0.0508	-0.0447	-0.0245	0.0162	0.0339	0.2679	-0.0064									
Ivol	-0.0646	-0.0557	-0.0281	0.0164	0.0377	0.2493	-0.0107	0.9241								
Max	-0.0107	-0.0326	0.0511	-0.0565	0.3121	0.2103	-0.0147	0.8701	0.8159							
Min	-0.0842	-0.0402	-0.0931	0.0775	-0.2531	0.2458	0.001	0.874	0.8057	0.607						
Volume	0.1549	0.0803	0.3993	0.0927	0.0293	-0.4265	-0.0072	0.1012	0.0894	0.1079	0.066					
StdVolume	0.1306	0.0646	0.3464	0.0797	0.0564	-0.2838	-0.0004	0.1771	0.1625	0.1869	0.1256	0.8784				
Skew1	0.0388	0.0078	0.0748	-0.0478	0.2092	-0.0217	-0.0198	0.0185	0.032	0.3151	-0.2817	0.0375	0.0514			
Skew2	0.3421	0.0994	0.1302	0.0329	0.0552	-0.0288	0.0435	-0.019	-0.0243	0.0138	-0.0455	0.0591	0.0558	0.0472		
Iskew	0.2535	-0.0073	0.0994	0.0336	0.076	-0.0261	0.0677	-0.0212	-0.0247	0.0178	-0.0532	0.0396	0.039	0.0461	0.6785	
Coskew	-0.1277	-0.0476	-0.044	-0.0357	-0.0398	0.0259	-0.0399	0.0181	0.0204	0.0032	0.0292	-0.0042	-0.001	-0.0042	-0.0294	-0.0612

This table presents the cross-sectional averages of a set of time-series summary statistics. Panel A displays the mean and standard deviation of each variable, and panel B displays the Pearson's pairwise correlation coefficients. *PTV* is the prospect theory value of a cryptocurrency's historical return distribution from week t-52 to t-1. *Beta* is the estimated slope obtained by regressing a cryptocurrency's weekly excess return on the cryptocurrency market excess return from week t-52 to t-1. *Size* is the natural logarithm of a cryptocurrency's market capitalisation at the end of week t-1. *Mom* (momentum) is a cryptocurrency's cumulative return from week t-3 to t-2. *Illiq* (illiquidity) is *Amihud's* (*2002*) measure of illiquidity, which is the mean of a cryptocurrency's absolute daily return divided by its daily volume in week t-1. *Rev* (reversal) is a cryptocurrency's return in week t-1. *Lt_rev* (long-term reversal) is a cryptocurrency's cumulative return from week t-60 to t-13. *Vol* (volatility) is the standard deviation of a cryptocurrency's daily returns in week t-1. *Ivol* is the idiosyncratic volatility of a cryptocurrency's daily returns in week t-1 (*Ang et al., 2006*). *Max* and *Min* are the maximum and the negative of the minimum of a cryptocurrency's daily returns in week t-1(*Bali et al., 2011*). *Volume* is the natural logarithm of a cryptocurrency's mean daily trading volume in week t-1. *StdVolume* is the natural logarithm of the standard deviation of a cryptocurrency's daily trading volume in week t-1. *Skew1* (short-term skewness) is the skewness of a cryptocurrency's daily returns in week t-1. *Skew2* (long-term skewness) is the skewness of a cryptocurrency's weekly returns from week t-52 to t-1. *Iskew* is the idiosyncratic skewness of a cryptocurrency's weekly returns from week t-52 to t-1 (*Harvey and Siddique, 2000*). *Coskew* is a cryptocurrency's coskewness, which refers to the 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 and Siddique, 2000*). The sample period runs from January 2, 2015 to December 25, 2020.

Table A3 Characteristics of *PTV*-sorted portfolios

Portfolios	Low PTV	PTV2	PTV3	PTV4	PTV5	PTV6	PTV7	PTV8	PTV9	High PTV
PTV	-0.4336	-0.3014	-0.2542	-0.2233	-0.2000	-0.1800	-0.1621	-0.1439	-0.1217	-0.0779
Beta	0.5116	0.4447	0.4487	0.4133	0.4475	0.4620	0.4818	0.5043	0.5037	0.5024
Size	11.5633	12.4939	13.0279	13.4200	13.9723	14.5518	15.2002	15.7438	16.3479	17.8890
Mom	-0.0442	-0.0272	-0.0197	-0.0046	0.0015	0.0091	0.0092	0.0203	0.0246	0.0585
Rev	-0.0435	-0.0340	-0.0114	-0.0129	0.0093	0.0030	0.0140	0.0135	0.0318	0.0403
Illiq	0.8647	0.4454	0.3254	0.2293	0.1198	0.0997	0.0408	0.0365	0.0163	0.0777
Lt_rev	-1.5832	-0.9089	-0.6221	-0.4797	-0.2356	0.0082	0.0763	0.1755	0.5281	1.0751
Vol	0.3390	0.2818	0.2430	0.2149	0.1967	0.1757	0.1566	0.1450	0.1339	0.1228
Ivol	0.2831	0.2342	0.1993	0.1759	0.1600	0.1414	0.1248	0.1145	0.1042	0.0924
Max	0.4729	0.4052	0.3508	0.3132	0.2885	0.2615	0.2315	0.2173	0.2045	0.1871
Min	0.4800	0.3998	0.3426	0.3023	0.2732	0.2418	0.2150	0.1990	0.1786	0.1636
Volume	5.8195	6.9432	7.7032	8.3775	9.0319	9.7595	10.6875	11.3625	12.0639	13.4933
StdVolume	5.3627	6.3599	7.0774	7.6812	8.2468	8.9622	9.8230	10.4620	11.1068	12.4351
Skew1	0.0539	0.0662	0.0434	0.0735	0.0699	0.0906	0.0662	0.0750	0.0816	0.0535
Skew2	-0.2963	0.1238	0.2573	0.3418	0.3955	0.4251	0.4695	0.5433	0.7470	0.9020
Iskew	-0.2522	0.1393	0.2387	0.3110	0.3662	0.4568	0.4919	0.5901	0.7213	1.1429
Coskew	0.2245	-0.1140	-0.0095	-0.1833	-0.2708	-0.3092	-0.0494	0.2359	0.2738	0.1104

At the end of each week, we sort cryptocurrencies into deciles based on PTV. Next, for each decile, we compute the mean values of the characteristics listed in the first column across all cryptocurrencies in the decile. Subsequently, we calculate the time-series averages of these mean characteristic values across all weeks in the sample period.

Table A4 Bivariate dependent-sort portfolio analysis

Excess return	Low	PTV2	PTV3	PTV4	High	Low-High	CAPM alpha	Low	PTV2	PTV3	PTV4	High	Low-High
Beta													
EW	0.1103***	0.0628***	0.0408***	0.0223**	0.0110	0.0992***		0.1064***	0.0599***	0.0375***	0.0193*	0.0081	0.0983***
	(7.17)	(4.85)	(3.48)	(2.15)	(1.24)	(7.92)		(6.94)	(4.62)	(3.23)	(1.89)	(0.93)	(7.87)
VW	0.0546***	0.0308***	0.0306**	0.0173	0.0123*	0.0424***		0.0512***	0.0290**	0.0275**	0.0136	0.0091	0.0421***
	(3.60)	(2.60)	(2.44)	(1.36)	(1.70)	(3.26)		(3.35)	(2.44)	(2.20)	(1.11)	(1.35)	(3.27)
Size													
EW	0.0863***	0.0582***	0.0454***	0.0339***	0.0177*	0.0686***		0.0827***	0.0551***	0.0423***	0.0308***	0.0146	0.0681***
	(5.96)	(4.81)	(4.02)	(3.04)	(1.81)	(6.69)		(5.74)	(4.54)	(3.79)	(2.81)	(1.52)	(6.69)
VW	0.0194*	0.0166	0.0202*	0.0043	0.0096	0.0098		0.0165*	0.0138	0.0170	0.0022	0.0062	0.0104
	(1.95)	(1.35)	(1.75)	(0.47)	(1.51)	(1.33)		(1.68)	(1.11)	(1.51)	(0.24)	(1.09)	(1.43)
Mom													
EW	0.0971***	0.0600***	0.0395***	0.0243**	0.0107	0.0863***		0.0935***	0.0568***	0.0363***	0.0213**	0.0078	0.0857***
	(6.75)	(4.74)	(3.33)	(2.31)	(1.15)	(7.66)		(6.50)	(4.52)	(3.11)	(2.05)	(0.86)	(7.63)
VW	0.0455***	0.0269**	0.0259**	0.0158	0.0120*	0.0335***		0.0427***	0.0249**	0.0230*	0.0128	0.0089	0.0338***
	(3.19)	(2.32)	(2.11)	(1.54)	(1.66)	(2.98)		(2.99)	(2.15)	(1.89)	(1.26)	(1.31)	(3.02)
Rev													
EW	0.1007***	0.0498***	0.0478***	0.0266**	0.0113	0.0894***		0.0973***	0.0465***	0.0444***	0.0234**	0.0086	0.0887***
	(6.63)	(4.33)	(3.90)	(2.34)	(1.35)	(7.37)		(6.40)	(4.08)	(3.68)	(2.09)	(1.04)	(7.33)
VW	0.0394***	0.0300**	0.0262**	0.0157	0.0128*	0.0266***		0.0366***	0.0276**	0.0232**	0.0127	0.0096	0.0270***
	(3.11)	(2.56)	(2.23)	(1.40)	(1.77)	(2.61)		(2.89)	(2.38)	(2.01)	(1.14)	(1.43)	(2.64)
Illiq													
EW	0.0892***	0.0631***	0.0400***	0.0334***	0.0120	0.0772***		0.0858***	0.0601***	0.0366***	0.0301***	0.0090	0.0767***
	(6.31)	(4.69)	(3.75)	(3.03)	(1.32)	(7.53)		(6.09)	(4.46)	(3.51)	(2.77)	(1.02)	(7.53)
VW	0.0173	0.0193	0.0088	0.0133	0.0119*	0.0054		0.0152	0.0161	0.0052	0.0109	0.0086	0.0065
	(1.64)	(1.64)	(0.86)	(1.23)	(1.74)	(0.69)		(1.44)	(1.36)	(0.52)	(1.01)	(1.38)	(0.84)
Lt_rev													
EW	0.1099***	0.0649***	0.0370***	0.0237**	0.0125	0.0974***		0.1063***	0.0616***	0.0338***	0.0205*	0.0097	0.0967***
	(7.05)	(5.34)	(3.38)	(2.15)	(1.30)	(7.40)		(6.79)	(5.11)	(3.13)	(1.90)	(1.02)	(7.36)
VW	0.0567***	0.0268**	0.0163	0.0166	0.0127*	0.0440***		0.0540***	0.0240**	0.0130	0.0139	0.0095	0.0445***
	(3.92)	(2.23)	(1.52)	(1.40)	(1.75)	(3.59)		(3.71)	(2.00)	(1.24)	(1.17)	(1.42)	(3.64)
Vol													
EW	0.0953***	0.0638***	0.0425***	0.0298**	0.0080	0.0874***		0.0916***	0.0606***	0.0393***	0.0266**	0.0053	0.0863***
	(6.50)	(5.18)	(4.08)	(2.46)	(0.93)	(7.63)		(6.26)	(4.98)	(3.83)	(2.22)	(0.62)	(7.56)
VW	0.0299**	0.0236*	0.0223**	0.0114	0.0118	0.0181**		0.0272**	0.0208*	0.0191*	0.0085	0.0086	0.0186**
	(2.50)	(1.94)	(2.20)	(1.16)	(1.64)	(2.04)		(2.27)	(1.73)	(1.90)	(0.88)	(1.28)	(2.11)
Ivol													
EW	0.0950***	0.0637***	0.0426***	0.0268**	0.0103	0.0847***		0.0913***	0.0607***	0.0392***	0.0238**	0.0076	0.0837***
	(6.59)	(5.30)	(3.70)	(2.33)	(1.16)	(7.72)		(6.35)	(5.07)	(3.50)	(2.07)	(0.87)	(7.65)
VW	0.0246**	0.0278***	0.0156	0.0113	0.0129*	0.0117		0.0219*	0.0252**	0.0123	0.0086	0.0097	0.0122
	(2.12)	(2.63)	(1.47)	(0.93)	(1.85)	(1.38)		(1.91)	(2.39)	(1.19)	(0.70)	(1.50)	(1.44)
Max													
EW	0.1103***	0.0582***	0.0402***	0.0265**	0.0035	0.1067***		0.1066***	0.0550***	0.0372***	0.0234*	0.0006	0.1060***
	(7.18)	(5.02)	(3.67)	(2.18)	(0.41)	(8.56)		(6.93)	(4.81)	(3.42)	(1.95)	(0.07)	(8.52)
VW	0.0452***	0.0212*	0.0220**	0.0158	0.0118	0.0334***		0.0424***	0.0189*	0.0188*	0.0130	0.0086	0.0338***
	(3.60)	(1.87)	(2.24)	(1.35)	(1.64)	(3.44)		(3.40)	(1.67)	(1.95)	(1.10)	(1.28)	(3.49)
Min													
EW	0.0874***	0.0594***	0.0457***	0.0329***	0.0143	0.0731***		0.0838***	0.0560***	0.0426***	0.0298***	0.0113	0.0725***

	(6.03)	(5.08)	(3.94)	(3.08)	(1.52)	(6.76)	(5.78)	(4.88)	(3.71)	(2.82)	(1.24)	(6.73)
VW	0.0194*	0.0182*	0.0260**	0.0147	0.0114	0.0081	0.0172	0.0152	0.0232*	0.0119	0.0081	0.0090
	(1.66)	(1.66)	(2.13)	(1.45)	(1.64)	(0.91)	(1.46)	(1.41)	(1.88)	(1.19)	(1.27)	(1.02)
Volume												
EW	0.0874***	0.0584***	0.0490***	0.0325***	0.0132	0.0742***	0.0838***	0.0554***	0.0460***	0.0291***	0.0101	0.0737***
	(5.96)	(4.57)	(4.13)	(3.08)	(1.44)	(6.69)	(5.75)	(4.33)	(3.88)	(2.82)	(1.14)	(6.68)
VW	0.0191*	0.0177	0.0102	0.0107	0.0117*	0.0074	0.0170	0.0145	0.0068	0.0084	0.0084	0.0086
	(1.84)	(1.50)	(1.03)	(0.96)	(1.76)	(0.93)	(1.63)	(1.23)	(0.71)	(0.75)	(1.40)	(1.08)
StdVolume												
EW	0.0890***	0.0593***	0.0436***	0.0326***	0.0144*	0.0745***	0.0853***	0.0563***	0.0405***	0.0293***	0.0114	0.0739***
	(5.99)	(4.41)	(4.14)	(3.01)	(1.66)	(6.34)	(5.78)	(4.17)	(3.84)	(2.78)	(1.35)	(6.32)
VW	0.0206**	0.0189	0.0121	0.0126	0.0118*	0.0089	0.0185*	0.0158	0.0085	0.0103	0.0085	0.0100
	(2.03)	(1.51)	(1.10)	(1.13)	(1.78)	(1.15)	(1.80)	(1.26)	(0.80)	(0.92)	(1.42)	(1.32)
Skew1												
EW	0.1156***	0.0567***	0.0372***	0.0174	0.0138	0.1019***	0.1118***	0.0535***	0.0341***	0.0142	0.0110	0.1008***
	(7.42)	(4.77)	(3.35)	(1.55)	(1.40)	(8.10)	(7.16)	(4.51)	(3.14)	(1.28)	(1.14)	(8.02)
VW	0.0595***	0.0273***	0.0207**	0.0125	0.0119*	0.0476***	0.0559***	0.0253**	0.0179*	0.0097	0.0087	0.0472***
	(3.62)	(2.61)	(2.01)	(1.02)	(1.70)	(3.34)	(3.44)	(2.43)	(1.75)	(0.78)	(1.34)	(3.34)
Skew2												
EW	0.1036***	0.0684***	0.0392***	0.0235**	0.0112	0.0924***	0.0997***	0.0651***	0.0361***	0.0204**	0.0084	0.0912***
	(6.80)	(5.06)	(3.63)	(2.26)	(1.13)	(7.06)	(6.58)	(4.81)	(3.36)	(2.00)	(0.87)	(6.97)
VW	0.0504***	0.0309**	0.0182	0.0122	0.0109	0.0396***	0.0475***	0.0284*	0.0154	0.0096	0.0076	0.0400***
	(3.29)	(2.10)	(1.52)	(1.21)	(1.56)	(2.92)	(3.13)	(1.94)	(1.30)	(0.95)	(1.18)	(2.99)
Iskew												
EW	0.1073***	0.0643***	0.0415***	0.0239**	0.0115	0.0958***	0.1036***	0.0608***	0.0384***	0.0208**	0.0087	0.0950***
	(6.99)	(5.00)	(3.60)	(2.30)	(1.21)	(7.51)	(6.77)	(4.72)	(3.39)	(2.03)	(0.92)	(7.45)
VW	0.0475***	0.0385**	0.0226*	0.0215*	0.0105	0.0370***	0.0441***	0.0361**	0.0201*	0.0188	0.0074	0.0367***
	(3.28)	(2.58)	(1.95)	(1.67)	(1.48)	(3.18)	(3.09)	(2.43)	(1.76)	(1.44)	(1.11)	(3.22)
Coskew												
EW	0.1094***	0.0651***	0.0402***	0.0215*	0.0086	0.1008***	0.1054***	0.0622***	0.0371***	0.0184*	0.0057	0.0997***
	(7.17)	(5.14)	(3.64)	(1.94)	(0.95)	(9.29)	(6.96)	(4.89)	(3.39)	(1.69)	(0.64)	(9.23)
VW	0.0504***	0.0277**	0.0218*	0.0087	0.0132*	0.0372***	0.0478***	0.0253**	0.0189	0.0053	0.0100	0.0378***
	(3.67)	(2.29)	(1.82)	(0.98)	(1.79)	(3.34)	(3.49)	(2.14)	(1.57)	(0.62)	(1.45)	(3.39)

This table reports the mean excess returns and CAPM alphas of double-sorted portfolios. The portfolios are formed at the end of each week and held for one week. We first sort cryptocurrencies into quintiles based on one characteristic (*Beta, Size, Mom, Rev, Illiq, Lt_rev, Vol, Ivol, Max, Min, Volume, StdVolume, Skew1, Skew2, Iskew,* or *Coskew*). Next, within each quintile, we further sort cryptocurrencies into quintiles based on *PTV*. Lastly, the returns of the five *PTV*-sorted portfolios are averaged across the five characteristic-based quintiles. We report both equal-weighted (EW) and value-weighted (VW) mean excess returns and CAPM alphas, where the market portfolio is proxied by the cryptocurrency market index. Since this bivariate analysis requires at least 25 (=5×5) active cryptocurrencies per week, the sample period is from March 27, 2015 to December 25, 2020. HAC-robust t-statistics based on Newey-West standard errors (max 5 lags) are shown in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table A5 Panel regressions: Cross-sectional relationship between *PTV* and subsequent returns (skipping one week in the construction of *PTV*)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
PTV	-0.0098	0.0429*	-0.0361*	-0.0315	-0.0409*	-0.0580***	-0.0590***	-0.0624***	-0.0621***	-0.0362	-0.0371	-0.0617***
	(-0.44)	(1.87)	(-1.73)	(-1.55)	(-1.83)	(-2.67)	(-2.73)	(-2.81)	(-2.79)	(-1.63)	(-1.65)	(-2.76)
Beta		-0.0049	-0.0035	-0.0037	-0.0037	-0.0032	-0.0032	-0.0030	-0.0028	-0.0044	-0.0040	-0.0030
		(-1.08)	(-0.97)	(-1.00)	(-1.02)	(-0.88)	(-0.89)	(-0.81)	(-0.78)	(-1.22)	(-1.11)	(-0.83)
Size		-0.0035***	0.0018***	0.0019***	0.0018***	0.0014*	0.0014*	0.0007	0.0007	0.0001	0.0003	0.0007
		(-5.04)	(2.67)	(2.79)	(2.63)	(1.96)	(1.97)	(1.04)	(1.03)	(0.19)	(0.55)	(1.04)
Mom		-0.0155***	-0.1090***	-0.1088***	-0.1085***	-0.1073***	-0.1071***	-0.1071***	-0.1071***	-0.1062***	-0.1064***	-0.1071***
		(-3.56)	(-19.75)	(-20.12)	(-20.07)	(-19.83)	(-19.79)	(-19.81)	(-19.82)	(-19.76)	(-19.80)	(-19.82)
Rev			-0.3684***	-0.3681***	-0.3680***	-0.3670***	-0.3625***	-0.3624***	-0.3623***	-0.3610***	-0.3611***	-0.3623***
			(-41.96)	(-41.63)	(-41.65)	(-41.47)	(-34.57)	(-34.59)	(-32.99)	(-34.53)	(-34.59)	(-34.60)
Illiq				0.0011**	0.0011**	0.0012***	0.0012***	0.0012***	0.0012***	0.0012***	0.0012***	0.0012***
				(2.49)	(2.47)	(2.66)	(2.64)	(2.71)	(2.71)	(2.69)	(2.71)	(2.71)
Lt_rev					0.0015	0.0019*	0.0019*	0.0021*	0.0021*	0.0027**	0.0024**	0.0021*
					(1.42)	(1.74)	(1.76)	(1.91)	(1.93)	(2.48)	(2.15)	(1.90)
Vol						-0.0053	-0.0686	-0.0685	-0.0684	-0.0675	-0.0685	-0.0685
						(-0.18)	(-1.46)	(-1.45)	(-1.45)	(-1.42)	(-1.45)	(-1.45)
Ivol						-0.0249	-0.0246	-0.0240	-0.0241	-0.0200	-0.0216	-0.0241
						(-0.74)	(-0.72)	(-0.70)	(-0.70)	(-0.58)	(-0.63)	(-0.70)
Max							0.0115	0.0112	0.0111	0.0130	0.0129	0.0112
							(0.63)	(0.61)	(0.53)	(0.71)	(0.70)	(0.61)
Min							0.0321*	0.0322*	0.0323	0.0306	0.0310	0.0323*
							(1.67)	(1.67)	(1.58)	(1.58)	(1.61)	(1.68)
Volume								0.0001	0.0001	-0.0000	-0.0000	0.0000
								(0.04)	(0.06)	(-0.03)	(-0.01)	(0.02)
StdVolume								0.0006	0.0006	0.0005	0.0006	0.0007
								(0.44)	(0.42)	(0.37)	(0.44)	(0.45)
Skew1									0.0000			
									(0.01)			
Skew2										-0.0099***		
										(-7.16)		
Iskew											-0.0086***	
											(-6.17)	
Coskew												-0.0010
												(-1.21)
Crypto FEs	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
Adj. R-squared	0.1212	0.1303	0.2355	0.2363	0.2362	0.2362	0.2362	0.2364	0.2364	0.2369	0.2367	0.2364
N	109397	104649	104649	104357	104264	104197	104197	104101	104088	104101	104101	104101

This table reports estimates of panel regressions with week FE and a varying set of controls. In all specifications, the dependent variable is the one-week-ahead excess return of the given cryptocurrency. The t-statistics shown in parentheses are based on standard errors clustered by cryptocurrency and week. Unlike in the main analysis, here the *PTV* variable is constructed using returns from week t-53 to t-2 to skip the previous week's return. *Beta* is the estimated slope obtained by regressing a cryptocurrency's weekly excess return on the cryptocurrency market excess return from week t-52 to t-1. *Size* is the natural logarithm of a cryptocurrency's market capitalisation at the end of week t-1. *Mom* (momentum) is a cryptocurrency's cumulative return from week t-3 to week t-2. *Illiq* (illiquidity) is *Amihud's* (*2002*) measure of illiquidity, which is the mean of a cryptocurrency's absolute daily return divided by its daily volume in week t-1. *Rev* (reversal) is a cryptocurrency's return in week t-1. *Lt_rev* (long-term reversal) is a cryptocurrency's cumulative return from week t-60 to t-13. *Vol* (volatility) is the standard deviation of a cryptocurrency's daily returns in week t-1. *Ivol* is the idiosyncratic volatility of a cryptocurrency's daily returns in week t-1 (*Ang et al.,2006*). *Max* and *Min* are the maximum and the negative of the minimum of a cryptocurrency's daily returns in week t-1 (*Bali et al., 2011*). *Volume* is the natural logarithm of a cryptocurrency's mean daily trading volume in week t-1. *StdVolume* is the natural logarithm of the standard deviation of a cryptocurrency's daily trading volume in week t-1. *Skew1* (short-term skewness) is the skewness of a cryptocurrency's daily returns in week t-1. *Skew2* (long-term skewness) is the skewness of a cryptocurrency's weekly returns from week t-52 to t-1. *Iskew* is the idiosyncratic skewness of a cryptocurrency's weekly returns from week t-52 to t-1 (*Harvey and Siddique, 2000*). *Coskew* is a cryptocurrency's coskewness, which refers to the 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 and Siddique, 2000*). The sample period runs from January 2, 2015 to December 25, 2020. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table A6 Panel regressions: Time-series relationship between *PTV* and future returns (skipping one week in the construction of *PTV*)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
PTV	-0.1746***	-0.0394	-0.2145***	-0.2096***	-0.2209***	-0.2191***	-0.2199***	-0.2275***	-0.2256***	-0.1704***	-0.2053***	-0.2263***
	(-3.77)	(-0.65)	(-4.05)	(-3.95)	(-3.96)	(-4.05)	(-4.07)	(-4.15)	(-4.12)	(-3.66)	(-3.59)	(-4.15)
Size		-0.0432***	-0.0238***	-0.0234***	-0.0245***	-0.0245***	-0.0244***	-0.0287***	-0.0288***	-0.0283***	-0.0285***	-0.0286***
		(-7.01)	(-5.18)	(-5.07)	(-5.49)	(-5.47)	(-5.44)	(-6.71)	(-6.75)	(-6.58)	(-6.68)	(-6.67)
Mom		0.0072	-0.0746***	-0.0740***	-0.0731***	-0.0729***	-0.0727***	-0.0727***	-0.0727***	-0.0723***	-0.0723***	-0.0727***
		(0.57)	(-5.36)	(-5.30)	(-5.23)	(-5.29)	(-5.29)	(-5.29)	(-5.30)	(-5.27)	(-5.29)	(-5.31)
Rev			-0.3446***	-0.3440***	-0.3432***	-0.3432***	-0.3327***	-0.3320***	-0.3370***	-0.3304***	-0.3310***	-0.3320***
			(-19.57)	(-19.30)	(-19.23)	(-19.18)	(-17.28)	(-17.30)	(-16.50)	(-17.65)	(-17.55)	(-17.28)
Illiq				0.0014***	0.0013***	0.0013***	0.0013**	0.0015***	0.0015***	0.0014***	0.0014***	0.0014***
				(2.70)	(2.65)	(2.60)	(2.56)	(2.89)	(2.90)	(2.86)	(2.87)	(2.87)
Lt_rev					0.0031	0.0031	0.0031	0.0033	0.0033	0.0035	0.0035	0.0033
					(1.00)	(1.00)	(0.99)	(1.05)	(1.06)	(1.11)	(1.11)	(1.04)
Vol						0.0328	-0.0659	-0.0684	-0.0668	-0.0679	-0.0692	-0.0680
						(0.63)	(-0.98)	(-1.01)	(-0.99)	(-1.01)	(-1.03)	(-1.01)
Ivol						-0.0303	-0.0285	-0.0278	-0.0272	-0.0278	-0.0272	-0.0279
						(-0.48)	(-0.45)	(-0.44)	(-0.42)	(-0.44)	(-0.43)	(-0.44)
Max							0.0087	0.0072	0.0241	0.0095	0.0084	0.0071
							(0.36)	(0.30)	(0.87)	(0.40)	(0.35)	(0.30)
Min							0.0585**	0.0590**	0.0410	0.0570**	0.0583**	0.0591**
							(2.37)	(2.37)	(1.57)	(2.28)	(2.35)	(2.38)
Volume								0.0012	0.0011	0.0008	0.0012	0.0011
								(0.51)	(0.47)	(0.34)	(0.48)	(0.46)
StdVolume								0.0029	0.0030	0.0030	0.0029	0.0030
								(0.86)	(0.88)	(0.88)	(0.86)	(0.88)
Skew1									-0.0072			
									(-1.56)			
Skew2										-0.0121**		
										(-2.12)		
Iskew											-0.0063*	
											(-1.89)	
Coskew												-0.0025
												(-1.08)
Crypto FEs	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
Adj. R-squared	-0.0064	0.0078	0.1140	0.1142	0.1143	0.1139	0.1141	0.1144	0.1145	0.1149	0.1145	0.1145
N	109382	104636	104636	104344	104250	104183	104183	104087	104075	104087	104087	104087

This table reports estimates of panel regressions with cryptocurrency FE and a varying set of controls. In all specifications, the dependent variable is the one-week-ahead excess return of the given cryptocurrency. The t-statistics shown in parentheses are based on standard errors clustered by cryptocurrency and week. Unlike in the main analysis, here the *PTV* variable is constructed using returns from week t-53 to t-2 to skip the previous week's return. *Size* is the natural logarithm of a cryptocurrency's market capitalisation at the end of week t-1. *Mom* (momentum) is a cryptocurrency's cumulative return from week t-3 to t-2. *Illiq* (illiquidity) is *Amihud's* (*2002*) measure of illiquidity, which is the mean of a cryptocurrency's absolute daily return divided by its daily volume in week t-1. *Rev* (reversal) is a cryptocurrency's return in week t-1. *Lt_rev* (long-term reversal) is a cryptocurrency's cumulative return from week t-60 to t-13. *Vol* (volatility) is the standard deviation of a cryptocurrency's daily returns in week t-1. *Ivol* is the idiosyncratic volatility of a cryptocurrency's daily returns in week t-1 (*Ang et al., 2006*). *Max* and *Min* are the maximum and the negative of the minimum of a cryptocurrency's daily returns in week t-1(*Bali et al., 2011*). *Volume* is the natural logarithm of a cryptocurrency's mean daily trading volume in week t-1. *StdVolume* is the natural logarithm of the standard deviation of a cryptocurrency's daily trading volume in week t-1. *Skew1* (short-term skewness) is the skewness of a cryptocurrency's daily returns in week t-1. *Skew2* (long-term skewness) is the skewness of a cryptocurrency's weekly returns from week t-52 to t-1. *Iskew* is the idiosyncratic skewness of a cryptocurrency's weekly returns from week t-52 to t-1 (*Harvey and Siddique, 2000*). *Coskew* is a cryptocurrency's coskewness, which refers to the 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 and Siddique, 2000*). The sample period runs from January 2, 2015 to December 25, 2020. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table A7 Panel regressions: Two-dimensional relationship between *PTV* and future returns (skipping one week in the construction of *PTV*)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
PTV	-0.1721***	0.0477	-0.1966***	-0.1921***	-0.1854***	-0.1889***	-0.1895***	-0.1924***	-0.1915***	-0.1678***	-0.1706***	-0.1918***
	(-5.64)	(1.42)	(-6.61)	(-6.51)	(-5.94)	(-6.06)	(-6.06)	(-6.09)	(-6.07)	(-5.15)	(-5.12)	(-6.05)
Size		-0.0623***	-0.0257***	-0.0251***	-0.0250***	-0.0252***	-0.0252***	-0.0266***	-0.0267***	-0.0262***	-0.0263***	-0.0266***
		(-13.22)	(-9.05)	(-9.00)	(-8.90)	(-9.00)	(-9.10)	(-9.43)	(-9.50)	(-9.23)	(-9.33)	(-9.41)
Mom		-0.0070	-0.1087***	-0.1085***	-0.1088***	-0.1080***	-0.1078***	-0.1080***	-0.1081***	-0.1077***	-0.1078***	-0.1080***
		(-1.56)	(-19.50)	(-19.95)	(-19.91)	(-19.46)	(-19.45)	(-19.48)	(-19.48)	(-19.49)	(-19.50)	(-19.48)
Rev			-0.3705***	-0.3701***	-0.3699***	-0.3693***	-0.3670***	-0.3669***	-0.3668***	-0.3660***	-0.3660***	-0.3669***
			(-42.89)	(-42.65)	(-42.60)	(-42.29)	(-35.19)	(-35.19)	(-33.44)	(-35.19)	(-35.28)	(-35.20)
Illiq				0.0011**	0.0011**	0.0012**	0.0012**	0.0012**	0.0012**	0.0012**	0.0012**	0.0012**
				(2.12)	(2.12)	(2.19)	(2.19)	(2.31)	(2.31)	(2.30)	(2.30)	(2.30)
Lt_rev					-0.0010	-0.0010	-0.0011	-0.0009	-0.0009	-0.0006	-0.0009	-0.0009
					(-0.75)	(-0.77)	(-0.79)	(-0.70)	(-0.68)	(-0.47)	(-0.66)	(-0.70)
Vol						-0.0006	-0.0776	-0.0781	-0.0782	-0.0781	-0.0790	-0.0781
						(-0.02)	(-1.51)	(-1.52)	(-1.52)	(-1.51)	(-1.53)	(-1.52)
Ivol						-0.0204	-0.0207	-0.0208	-0.0206	-0.0196	-0.0200	-0.0209
						(-0.57)	(-0.57)	(-0.57)	(-0.57)	(-0.54)	(-0.55)	(-0.58)
Max							0.0212	0.0200	0.0199	0.0210	0.0211	0.0200
							(1.03)	(0.97)	(0.84)	(1.02)	(1.02)	(0.97)
Min							0.0322	0.0322	0.0325	0.0314	0.0317	0.0323
							(1.57)	(1.56)	(1.50)	(1.52)	(1.54)	(1.57)
Volume								-0.0009	-0.0008	-0.0010	-0.0009	-0.0009
								(-0.53)	(-0.50)	(-0.63)	(-0.56)	(-0.56)
StdVolume								0.0025	0.0025	0.0025	0.0025	0.0026
								(1.52)	(1.49)	(1.50)	(1.51)	(1.53)
Skew1									0.0001			
									(0.05)			
Skew2										-0.0067**		
										(-2.57)		
Iskew											-0.0058**	
											(-2.30)	
Coskew												-0.0009
												(-0.76)
Crypto FEs	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
Adj. R-squared	0.1153	0.1398	0.2415	0.2425	0.2425	0.2421	0.2421	0.2423	0.2423	0.2424	0.2423	0.2423
N	109382	104636	104636	104344	104250	104183	104183	104087	104075	104087	104087	104087

This table reports estimates of panel regressions with cryptocurrency FE, week FE, and a varying set of controls. In all specifications, the dependent variable is the one-week-ahead excess return of the given cryptocurrency. The t-statistics shown in parentheses are based on standard errors clustered by cryptocurrency and week. Unlike in the main analysis, here the *PTV* variable is constructed using returns from week t-53 to t-2 to skip the previous week's return. *Size* is the natural logarithm of a cryptocurrency's market capitalisation at the end of week t-1. *Mom* (momentum) is a cryptocurrency's cumulative return from week t-3 to t-2. *Illiq* (illiquidity) is *Amihud's* (*2002*) measure of illiquidity, which is the mean of a cryptocurrency's absolute daily return divided by its daily volume in week t-1. *Rev* (reversal) is a cryptocurrency's return in week t-1. *Lt_rev* (long-term reversal) is a cryptocurrency's cumulative return from week t-60 to t-13. *Vol* (volatility) is the standard deviation of a cryptocurrency's daily returns in week t-1. *Ivol* is the idiosyncratic volatility of a cryptocurrency's daily returns in week t-1 (*Ang et al., 2006*). *Max* and *Min* are the maximum and the negative of the minimum of a cryptocurrency's daily returns in week t-1 (*Bali et al., 2011*). *Volume* is the natural logarithm of a cryptocurrency's mean daily trading volume in week t-1. *StdVolume* is the natural logarithm of the standard deviation of a cryptocurrency's daily trading volume in week t-1. *Skew1* (short-term skewness) is the skewness of a cryptocurrency's daily returns in week t-1. *Skew2* (long-term skewness) is the skewness of a cryptocurrency's weekly returns from week t-52 to t-1. *Iskew* is the idiosyncratic skewness of a cryptocurrency's weekly returns from week t-52 to t-1 (*Harvey and Siddique, 2000*). *Coskew* is a cryptocurrency's coskewness, which refers to the 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 and Siddique, 2000*). The sample period runs from January 2, 2015 to December 25, 2020. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table A8 Alternative choices of the dependent variable

	(1)	(2)	(3)	(4)
Dependent Variable:	Return in excess of the market return	Abnormal excess return	Return in excess of the market return	Abnormal excess return
PTV	-0.3848**	-0.2335***	-0.2074***	-0.2011***
	(-2.32)	(-4.19)	(-6.51)	(-6.47)
Size	-0.0194*	-0.0234***	-0.0244***	-0.0230***
	(-1.67)	(-5.48)	(-9.05)	(-8.53)
Mom	-0.0448	-0.0675***	-0.1079***	-0.1021***
	(-1.00)	(-5.17)	(-19.51)	(-16.86)
Rev	-0.3855***	-0.3191***	-0.3586***	-0.3420***
	(-5.46)	(-12.76)	(-35.09)	(-29.32)
Illiq	0.0005	0.0011**	0.0011**	0.0010**
	(0.68)	(2.42)	(2.17)	(2.12)
Lt_rev	0.0061	0.0054*	-0.0009	-0.0003
	(0.92)	(1.96)	(-0.68)	(-0.18)
Vol	0.0683	-0.0475	-0.0860	-0.0753
	(0.68)	(-0.71)	(-1.65)	(-1.42)
Ivol	-0.2516**	-0.0716	-0.0214	-0.0392
	(-2.26)	(-1.23)	(-0.60)	(-1.08)
Max	0.0358	0.0209	0.0250	0.0285
	(0.88)	(0.90)	(1.21)	(1.43)
Min	0.0415	0.0561**	0.0322	0.0326
	(1.07)	(2.28)	(1.55)	(1.56)
Crypto FEs	Yes	Yes	Yes	Yes
Week FEs	No	No	Yes	Yes
Adj. R-squared	0.1023	0.1164	0.4843	0.2156
N	105603	105603	105603	105603

Columns 1-2 (3-4) of this table report estimates of panel regressions with cryptocurrency FE (week FE and cryptocurrency FE). In columns 1 and 3, the dependent variable is the one-week-ahead return in excess of the market return. In columns 2 and 4, the dependent variable is one-week-ahead abnormal excess return ($= excess\ return_{i,t} - \widehat{Beta_{i,t}} \times market\ excess\ return_t$). PTV is the prospect theory value of a cryptocurrency's historical return distribution from week t-52 to t-1. The remaining control variables are as defined in Table 2.1. The sample period runs from January 2, 2015 to December 25, 2020. The t-statistics shown in parentheses are based on standard errors clustered by cryptocurrency and week. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table A9 Disaggregated results by cryptocurrency sector

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Defi Coins	Binance Smart Chain	Exchange Tokens	Ethereum ERC20	Tron Network	Tokenized Stocks	StableCoins	Proof of Stake	NFT Tokens	Proof of Work	Privacy coins	Unsectored
PTV	-0.2844***	-0.1325	-0.4507	-0.1737***	-1.1050	-0.0401	-1.9086	-0.0454	-0.2552	-0.2438*	0.0494	-0.2303***
	(-3.36)	(-1.34)	(-1.53)	(-4.09)	(-2.16)	(-0.16)	(-2.86)	(-0.35)	(-0.77)	(-1.99)	(0.44)	(-5.95)
Size	-0.0144*	-0.0417	-0.0299***	-0.0245***	0.0877*	-0.0250	-0.0123*	-0.0361***	-0.0002	-0.0127**	-0.0255**	-0.0253***
	(-1.71)	(-1.61)	(-2.91)	(-5.42)	(2.12)	(-1.48)	(-1.97)	(-3.01)	(-0.01)	(-2.27)	(-2.64)	(-7.77)
Mom	-0.0717**	-0.0447	-0.0330	-0.1100***	-0.1136*	-0.1807***	-0.0540	0.0238	-0.0706	0.0169	0.0294	-0.1118***
	(-2.19)	(-1.26)	(-0.95)	(-12.85)	(-2.09)	(-3.37)	(-0.85)	(0.87)	(-1.70)	(0.69)	(1.00)	(-15.59)
Rev	-0.3872***	-0.2587***	-0.1238*	-0.3808***	-0.1631	-0.4806***	-0.1658	-0.1123**	-0.3733***	-0.1458*	-0.1455***	-0.3520***
	(-3.79)	(-4.06)	(-1.95)	(-23.77)	(-1.71)	(-7.15)	(-1.44)	(-2.19)	(-4.88)	(-1.96)	(-2.98)	(-30.08)
Illiq	0.0062***	0.0514	0.0076**	0.0016	0.0056	0.0004	-0.0727**	7813.455*	0.0024	-225.7906	6.8446***	0.0010
	(6.60)	(1.04)	(2.29)	(1.58)	(1.54)	(0.12)	(-2.70)	(1.82)	(0.28)	(-0.75)	(3.89)	(1.50)
Lt_rev	-0.0004	0.0087	0.0195*	-0.0031	0.0039	-0.0305**	0.0379**	0.0039	-0.0041	0.0002	0.0010	0.0004
	(-0.10)	(1.11)	(1.82)	(-1.31)	(0.19)	(-2.25)	(2.31)	(0.48)	(-0.37)	(0.03)	(0.18)	(0.24)
Vol	0.0607	0.9041	-0.9202*	-0.1907**	-0.4627	1.0521*	1.4401	0.2856	-0.4807*	0.7385	0.0360	-0.0125
	(0.23)	(1.06)	(-1.84)	(-2.11)	(-1.21)	(1.81)	(1.05)	(0.67)	(-1.91)	(1.27)	(0.15)	(-0.17)
Ivol	0.0487	-1.0635*	-0.3001	0.0080	-0.8139*	-0.1892	0.8907	0.0672	0.3625	-0.1952	0.3172***	-0.0387
	(0.25)	(-2.01)	(-1.34)	(0.16)	(-1.97)	(-0.39)	(1.58)	(0.27)	(1.19)	(-0.65)	(3.59)	(-0.89)
Max	0.0670	0.0814	0.3031	0.0806***	-0.0062	-0.1584	-0.7271**	-0.1987	-0.0895	-0.3043**	-0.2069	-0.0123
	(0.67)	(0.36)	(1.38)	(2.75)	(-0.03)	(-0.71)	(-2.38)	(-1.20)	(-0.70)	(-2.22)	(-1.67)	(-0.49)
Min	-0.2518***	-0.1204	0.5097**	0.0357	0.6223***	-0.3591**	-0.1040	-0.0353	0.1659	-0.1055	0.0011	0.0231
	(-2.83)	(-0.57)	(2.59)	(0.98)	(3.23)	(-2.34)	(-0.26)	(-0.21)	(0.93)	(-0.80)	(0.01)	(0.84)
Crypto FEs	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
Adj. R-squared	0.3004	0.2891	0.3422	0.2501	0.2260	0.2285	0.3128	0.6228	0.3127	0.5076	0.4396	0.2300
Number of observations	3611	1422	1200	41880	453	688	699	2072	1133	3382	2382	55976
Number of cryptos	51	26	18	629	11	14	14	18	17	18	19	809
Bootstrapped p-values		0.20	0.34		0.41	0.86	0.54	0.76	0.51	0.08	0.68	

This table presents estimates of panel regressions with two-way FE (cryptocurrency and week). The t-statistics shown in parentheses are based on standard errors clustered by cryptocurrency and week. In all specifications, the dependent variable is the one-week-ahead excess return of the given cryptocurrency. *PTV* is the PT value of a cryptocurrency's historical return distribution from week t-52 to t-1. The remaining variables are as defined in Table 2.1. The 12-sector classification is from *Coincodex*. We re-estimate our preferred two-way FE model separately for each sector (columns 1-11), with the exclusion of the sector "Yield Farming," which contains only 3 cryptocurrencies. In column 12, the sample consists of all the cryptocurrencies that do not belong to any specific sector. Since some sectors contain less than 50 cryptocurrencies, which may affect the validity of the cluster-robust standard errors, we follow *Roodman et al.* (*2019*), and in the last row we also display p-values of the coefficients on *PTV* based on the wild cluster bootstrap-t procedure, where the standard errors are clustered by cryptocurrency and week and bootstrapped on the cryptocurrency dimension (null imposed; 999 replications). Note that the total number of cryptocurrencies in this table (1,647 including "Yield Farming") is greater than 1,573 (see footnote 4 in the main body of the paper) because *Coincodex* assigns some cryptocurrencies to multiple sectors. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table A10 Country-specific PT parameter estimates and monthly visits to the 100 most popular cryptocurrency exchanges in the world

Country	Abbreviation	α	β	γ	δ	λ	Monthly visits
USA	US	0.42	0.49	0.44	0.71	1.36	22,260,554
Japan	JP	0.26	0.55	0.71	0.94	1.37	6,142,686
South Korea	KR	0.44	0.68	0.7	0.71	1.28	5,731,772
UK	UK	0.44	0.49	0.47	0.98	1.06	3,898,222
Russia	RU	0.39	0.30	0.41	0.82	1.41	3,183,839
Germany	DE	0.42	0.49	0.44	0.71	1.38	2,528,541
Vietnam	VN	0.56	0.55	0.41	0.94	1.29	2,482,579
Turkey	TR	0.55	1.06	0.55	0.94	1.51	2,414,148
Canada	CA	0.42	0.83	0.44	0.60	1.62	2,027,280
India	IN	0.41	0.49	0.52	0.71	1.38	2,014,631
Australia	AU	0.41	0.45	0.62	1.00	1.08	1,750,188
Italy	IT	0.42	0.55	0.44	0.94	1.43	1,588,534
Poland	PL	0.47	0.55	0.45	0.94	1.59	1,586,770
Mexico	MX	0.31	0.37	0.39	0.68	1.14	1,446,095
Netherlands	NL	0.47	0.90	0.82	0.73	1.47	1,331,690
France	FR	0.41	0.49	0.48	0.98	1.38	1,155,364
Spain	ES	0.44	0.74	0.47	0.88	1.63	990,220

This table shows the list of most active countries in the cryptocurrency market, according to data from *DataLight* (*2019*), for which country-specific PT parameter estimates are available based on *Rieger et al.'s* (*2017*) study. Columns 3-7 show the PT parameter estimates (α, β, λ, γ, δ) for the given country from *Rieger et al.* (*2017*). The rightmost column shows the number of monthly visits to the 100 most popular cryptocurrency exchanges in the world originating from the country in question (*DataLight, 2019*).

Table A11 Alternative PT reference points

	(1)	(2)	(3)
Reference point:	Zero	Risk-free rate	Sample mean of the cryptocurrency's own returns
PTV	-0.2229***	-0.2230***	-0.2228***
	(-6.56)	(-6.56)	(-6.64)
Size	-0.0239***	-0.0239***	-0.0240***
	(-8.87)	(-8.87)	(-8.87)
Mom	-0.1078***	-0.1078***	-0.1078***
	(-19.46)	(-19.46)	(-19.46)
Rev	-0.3585***	-0.3585***	-0.3585***
	(-35.29)	(-35.29)	(-35.32)
Illiq	0.0011**	0.0011**	0.0011**
	(2.15)	(2.15)	(2.19)
Lt_rev	-0.0005	-0.0005	-0.0005
	(-0.36)	(-0.36)	(-0.37)
Vol	-0.0864*	-0.0864*	-0.0861*
	(-1.66)	(-1.66)	(-1.65)
Ivol	-0.0217	-0.0217	-0.0214
	(-0.61)	(-0.61)	(-0.60)
Max	0.0256	0.0256	0.0254
	(1.23)	(1.23)	(1.22)
Min	0.0319	0.0319	0.0317
	(1.53)	(1.53)	(1.52)
Crypto FEs	Yes	Yes	Yes
Week FEs	Yes	Yes	Yes
Adj. R-squared	0.2418	0.2418	0.2418
N	105603	105603	105603

This table reports estimates of panel regressions with two-way FE (cryptocurrency and week). In all specifications, the dependent variable is the one-week-ahead excess return of the given cryptocurrency. In column 1, the *PTV* variable is constructed under the assumption that, instead of evaluating the historical return of a cryptocurrency relative to the return of the cryptocurrency market index, investors use a zero-return as their reference point (i.e., they simply focus on the cryptocurrency's raw return). In column 2, the assumption is that investors' reference point is the risk-free rate of return, and in column 3, the assumption is that investors evaluate the historical return of a cryptocurrency relative to its sample mean return. The sample period runs from January 2, 2015 to December 25, 2020. The t-statistics shown in parentheses are based on standard errors clustered by cryptocurrency and week. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

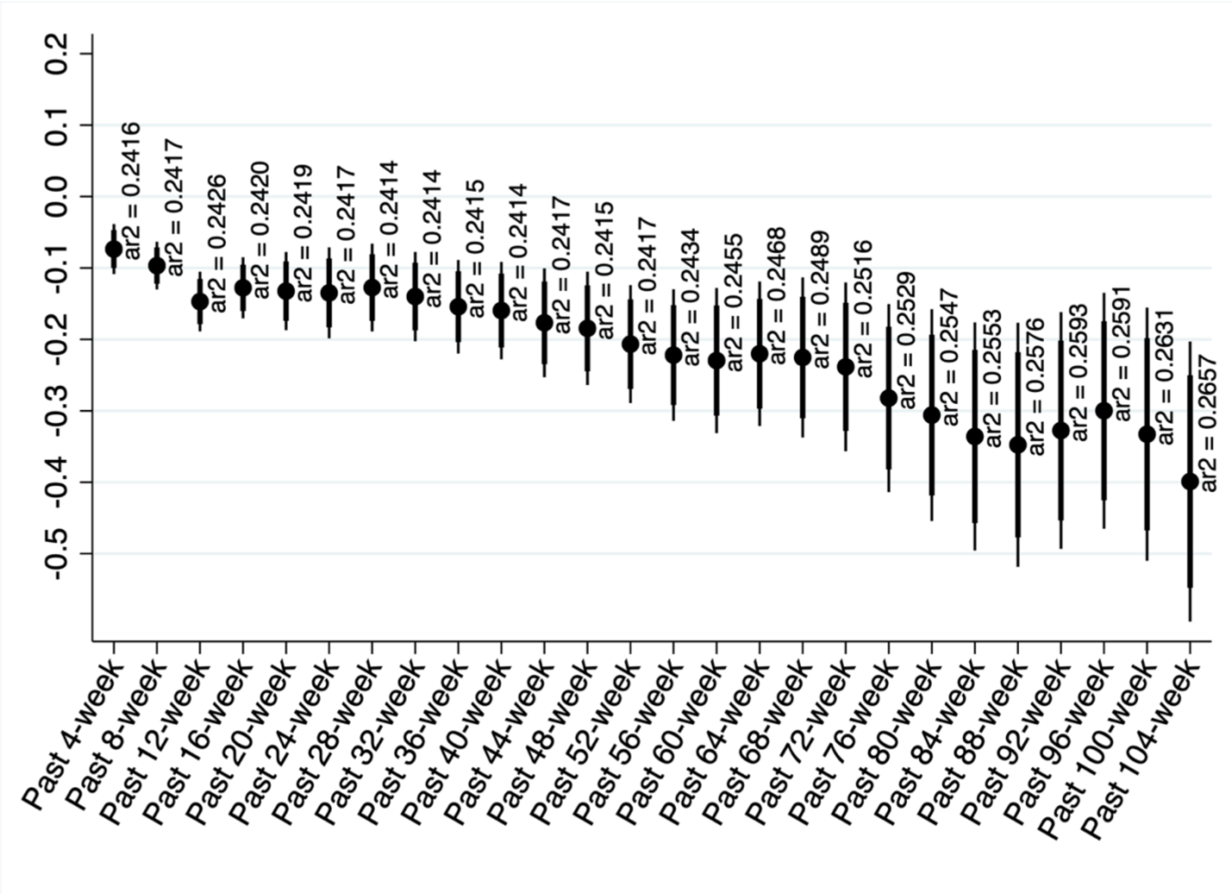
Table A12 PTV effect: Moderating roles of cryptocurrency uncertainty, investor attention, and investor sentiment

	(1)	(2)	(3)	(4)	(5)
PTV	-0.2404***	-0.1964***	-0.1745***	-0.2208***	-0.1700***
	(-3.75)	(-7.01)	(-5.74)	(-6.29)	(-5.18)
PTV×HighCryptoPolicyUncertainty	0.0492				
	(0.74)				
PTV×HighCryptoPriceUncertainty		-0.0159			
		(-0.44)			
PTV×HighCryptoWikiSearch			-0.0559		
			(-1.47)		
PTV×HighBitcoinWikiSearch				0.0629*	
				(1.82)	
PTV×HighSentiment					-0.0528
					(-1.52)
Size	-0.0246***	-0.0244***	-0.0249***	-0.0250***	-0.0277***
	(-8.90)	(-9.10)	(-9.21)	(-9.14)	(-8.60)
Mom	-0.1078***	-0.1080***	-0.1088***	-0.1086***	-0.1126***
	(-19.48)	(-19.49)	(-19.76)	(-19.66)	(-19.93)
Rev	-0.3584***	-0.3587***	-0.3597***	-0.3596***	-0.3683***
	(-35.03)	(-35.07)	(-35.31)	(-35.28)	(-35.89)
Lt_rev	-0.0008	-0.0009	-0.0006	-0.0007	-0.0017
	(-0.63)	(-0.69)	(-0.47)	(-0.52)	(-1.16)
Illiq	0.0011**	0.0011**	0.0011**	0.0011**	0.0011**
	(2.18)	(2.17)	(2.15)	(2.14)	(2.08)
Vol	-0.0857	-0.0862*	-0.0878*	-0.0875*	-0.0763
	(-1.64)	(-1.65)	(-1.68)	(-1.67)	(-1.44)
Ivol	-0.0214	-0.0214	-0.0217	-0.0227	-0.0280
	(-0.60)	(-0.60)	(-0.61)	(-0.64)	(-0.77)
Max	0.0246	0.0251	0.0256	0.0257	0.0285
	(1.19)	(1.21)	(1.23)	(1.24)	(1.32)
Min	0.0323	0.0322	0.0326	0.0326	0.0265
	(1.55)	(1.55)	(1.56)	(1.56)	(1.25)
PTV+PTV×Moderator	-0.1912***	-0.2123***	-0.2305***	-0.1579***	-0.2229***
P-value	0.000	0.000	0.000	0.000	0.000
Crypto FEs	Yes	Yes	Yes	Yes	Yes
Week FEs	Yes	Yes	Yes	Yes	Yes
Adj. R-squared	0.2416	0.2416	0.2425	0.2424	0.2456
N	105603	105603	104913	104913	97002

This table presents estimates of panel regressions with two-way FE (cryptocurrency and week). In all specifications, the dependent variable is the one-week-ahead excess return of the given cryptocurrency. PTV, which is the PT value of a cryptocurrency's historical return distribution from week t-52 to t-1, is interacted with variables that proxy for the amount of uncertainty in the cryptocurrency market, investor attention, and investor sentiment. *HighCryptoPolicyUncertainty* (*HighCryptoPriceUncertainty*) is a dummy variable that takes the value of 1 if Lucey et al.'s (2022) cryptocurrency policy (price) uncertainty index in week t-1 is above its sample median, and 0 otherwise. *HighCryptoWikiSearch* (*HighBitcoinWikiSearc*h) is a dummy variable that takes the value of 1 if the average number of Wikipedia pageviews for "cryptocurrency" ("Bitcoin") in week t-1 is above its sample media, and 0 otherwise. HighSentiment is a dummy variable that takes the value of 1 when the value of the sentix Bitcoin Sentiment Index in week t-1 is greater than its sample median, and 0 otherwise. The remaining variables are as defined in Table 2.1. The sample period runs from January 2, 2015 to December 25, 2020. However, due to data availability, in columns 3-4 (5) the sample period starts on July 17, 2015

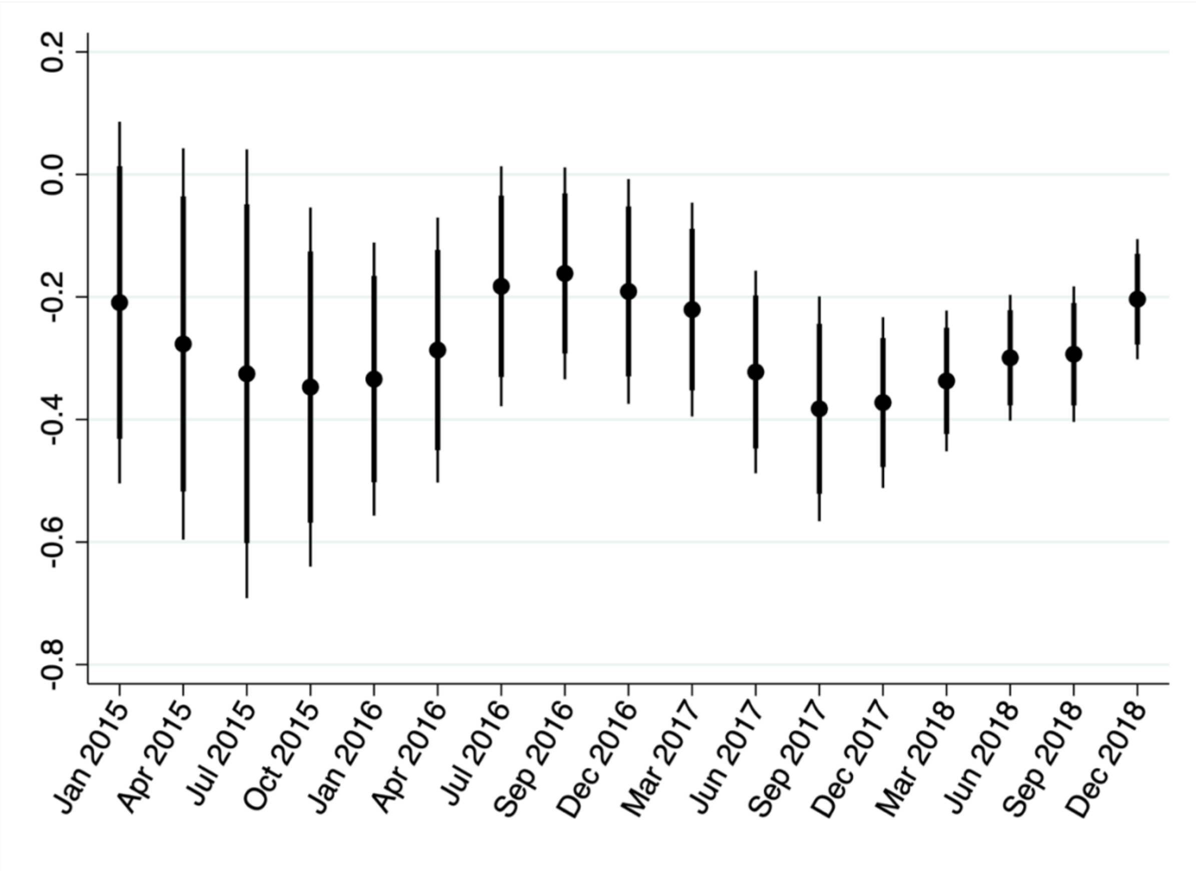
(September 15, 2017). The t-statistics shown in parentheses are based on standard errors clustered by cryptocurrency and week. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Figure A1 Alternative lengths of the historical time window underlying the *PTV* variable



This figure plots the point estimates and the 95% and 99% confidence intervals of the coefficient on *PTV* from the regression of one-week-ahead cryptocurrency excess returns on *PTV* and the following controls: *Size*, *Mom*, *Rev*, *Illiq*, *Lt_rev*, *Vol*, *Ivol*, *Max*, and *Min*. *PTV* is the prospect theory value of a cryptocurrency's historical return distribution. All other variables are as defined in Table 2.1. What varies across specifications is the length of the historical time window on which investors are assumed to focus when forming a mental representation of a cryptocurrency. For example, the label "Past 20-week" on the x-axis indicates that we construct the PT value of a cryptocurrency based on its historical return distribution from week t-20 to t-1. The label "Past 52-week" refers to our benchmark estimate, which is based on a 52-week interval. Adjusted R-squared (ar2) values for each regression appear to the right of the corresponding point estimate. The sample period runs from January 2, 2015 to December 25, 2020. Each regression includes two-way FE (cryptocurrency and week). The confidence intervals are based on standard errors clustered by cryptocurrency and week.

Figure A2 Stability of the PTV effect: Rolling-window panel regressions



This figure plots the point estimates and the 95% and 99% confidence intervals of the coefficient on *PTV* from rolling-window panel regressions. *PTV* is the PT value of a cryptocurrency's historical return distribution from week t-52 to t-1. The fixed window is 104 weeks (2 years) in length and increments forward 13 weeks (3 months) for each iteration. The dependent variable is the one-week-ahead excess return of the given cryptocurrency, and each regression includes two-way FE (cryptocurrency and week) and the following controls: *Size*, *Mom*, *Rev*, *Illiq*, *Lt_rev*, *Vol*, *Ivol*, *Max*, and *Min*. All variables are as defined in Table 2.1. The labels on the x-axis refer to the start of the rolling window. For example, "Jan 2015" indicates that the first regression is based on data from the beginning of January 2015 to the beginning of January 2017. The confidence intervals are based on standard errors clustered by cryptocurrency and week.

Appendix B Supplement to Chapter 3

Table B1 Average time-series summary statistics

FPanel 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	-0.01	0.00	0.48	13.81	-0.02	-0.01	0.81	-0.83	0.28	0.28	0.39	0.39	-0.34	8.58	7.73	0.00	-0.05	0.13	-0.10	0.21
Standard deviation	0.40	0.18	1.31	0.84	0.47	0.40	2.07	1.24	0.20	0.14	0.33	0.33	0.11	1.87	1.97	0.68	0.62	0.54	1.19	0.57

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	-0.07																		
Beta	0.02	0.00																	
Size	-0.21	0.18	0.02																
Mom	-0.01	0.13	-0.02	0.16															
Rev	-0.26	0.15	0.00	0.19	-0.24														
Illiq	0.05	-0.07	0.01	-0.24	-0.06	-0.02													
Lt_rev	-0.04	-0.01	-0.05	0.18	-0.04	-0.03	-0.03												
Vol	0.00	0.03	0.04	0.04	0.05	0.03	0.22	0.02											
Ivol	-0.02	0.06	0.00	0.04	0.04	0.01	0.13	0.04	0.60										
Max	-0.07	0.13	0.03	0.11	-0.02	0.31	0.17	0.01	0.88	0.52									
Min	0.07	-0.07	0.03	-0.03	0.11	-0.26	0.22	0.03	0.88	0.53	0.62								
PTV	-0.10	0.11	-0.01	0.28	-0.01	0.08	-0.08	0.13	0.00	-0.07	0.02	-0.03							
Volume	-0.08	0.12	0.02	0.44	0.11	0.03	-0.44	0.05	0.13	0.04	0.13	0.09	0.17						
StdVolume	-0.07	0.12	0.03	0.40	0.10	0.06	-0.31	0.06	0.20	0.09	0.21	0.15	0.15	0.89					
Skew1	-0.07	0.17	0.00	0.07	-0.04	0.21	-0.03	-0.02	0.02	0.02	0.31	-0.28	0.03	0.04	0.06				
Skew2	-0.09	0.11	0.00	0.23	0.05	0.07	-0.06	0.11	0.01	0.02	0.04	-0.02	0.29	0.10	0.10	0.04			
Iskew	-0.08	0.10	0.01	0.17	0.06	0.09	-0.05	0.07	0.00	-0.01	0.04	-0.04	0.21	0.08	0.08	0.04	0.72		
Coskew	0.00	0.00	-0.02	0.05	-0.05	-0.04	0.01	0.02	0.03	0.04	0.02	0.04	0.08	0.02	0.02	0.00	0.00	-0.03	
DBeta	0.03	-0.01	0.06	-0.05	0.01	-0.02	-0.02	-0.08	-0.05	-0.09	-0.05	-0.04	0.04	-0.01	-0.02	0.00	0.02	0.02	-0.48

This table presents the cross-sectional averages of the time-series summary statistics. 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 3.2. The sample period is from January 2, 2015 to June 25, 2021.

Table B2 Characteristics of STV-sorted portfolios

Portfolios	Low STV	STV2	STV3	STV4	STV5	STV6	STV7	STV8	STV9	High STV
STV	-0.25	-0.09	-0.04	-0.01	0.01	0.03	0.06	0.09	0.15	0.32
Beta	0.76	0.70	0.64	0.64	0.60	0.62	0.65	0.69	0.62	0.63
Size	12.75	13.87	14.93	15.53	15.52	15.35	15.09	14.58	13.93	13.19
Mom	-0.10	-0.06	-0.03	-0.02	-0.01	0.00	0.01	0.04	0.09	0.16
Rev	-0.09	-0.04	-0.02	-0.01	-0.01	0.00	0.01	0.02	0.05	0.13
Illiq	0.74	0.27	0.16	0.10	0.11	0.08	0.13	0.12	0.16	0.39
Lt_rev	-0.44	-0.22	-0.08	-0.02	-0.02	0.02	0.01	-0.07	-0.27	-0.47
Vol	0.35	0.20	0.16	0.13	0.13	0.14	0.15	0.18	0.23	0.37
Ivol	0.36	0.20	0.15	0.13	0.12	0.13	0.15	0.18	0.23	0.38
Max	0.45	0.28	0.22	0.19	0.18	0.20	0.23	0.28	0.36	0.61
Min	0.55	0.30	0.23	0.19	0.18	0.19	0.21	0.25	0.30	0.46
PTV	-0.28	-0.22	-0.20	-0.19	-0.18	-0.19	-0.19	-0.20	-0.22	-0.26
Volume	7.11	8.63	10.08	10.87	10.94	10.78	10.57	9.96	9.16	8.19
StdVolume	6.56	7.85	9.16	9.87	9.94	9.85	9.70	9.20	8.54	7.73
DBeta	0.47	0.47	0.40	0.44	0.41	0.41	0.45	0.44	0.42	0.42
Skew1	-0.17	-0.05	-0.03	0.00	0.04	0.05	0.09	0.16	0.23	0.31
Skew2	0.26	0.39	0.36	0.32	0.36	0.35	0.38	0.40	0.39	0.48
Iskew	0.27	0.42	0.42	0.44	0.42	0.40	0.41	0.44	0.44	0.50
Coskew	-0.09	-0.13	-0.03	0.00	0.10	0.18	0.07	0.01	0.04	-0.24

At the end of each week, we sort cryptocurrencies into deciles by *STV*, which measures the salience theory value of a cryptocurrency's historical daily return distribution from week t-4 to t-1. Next, for each decile, we calculate the mean values of the characteristics listed in the first column across all cryptocurrencies that belong to the decile. Subsequently, we compute the time-series averages of these mean characteristic values across all weeks.

Table B3 Bivariate dependent-sort portfolio analysis

Excess return	Low	STV2	STV3	STV4	High	Low-High	CAPM alpha	Low	STV2	STV3	STV4	High	Low-High
Beta													
EW	0.1034***	0.0469***	0.0418***	0.0436***	0.0315***	0.0718***		0.1028***	0.0463***	0.0414***	0.0430***	0.0309***	0.0719***
	(7.14)	(4.43)	(4.26)	(3.82)	(2.88)	(7.85)		(7.10)	(4.39)	(4.22)	(3.78)	(2.85)	(7.87)
VW	0.0264**	0.0123	0.0221**	0.0122	-0.0069	0.0333***		0.0259**	0.0119	0.0216**	0.0118	-0.0074	0.0333***
	(2.22)	(1.43)	(2.46)	(1.08)	(-0.65)	(3.26)		(2.21)	(1.39)	(2.42)	(1.05)	(-0.70)	(3.25)
Size													
EW	0.0956***	0.0480***	0.0439***	0.0443***	0.0364***	0.0593***		0.0951***	0.0474***	0.0433***	0.0438***	0.0358***	0.0593***
	(6.66)	(4.75)	(4.26)	(4.10)	(3.12)	(6.35)		(6.62)	(4.71)	(4.22)	(4.06)	(3.08)	(6.35)
VW	0.0173	0.0128	0.0236**	0.0129	0.0065	0.0108		0.0170	0.0123	0.0232**	0.0125	0.0061	0.0109
	(1.64)	(1.51)	(2.51)	(1.37)	(0.50)	(1.35)		(1.61)	(1.46)	(2.47)	(1.33)	(0.47)	(1.36)
Mom													
EW	0.0991***	0.0464***	0.0377***	0.0392***	0.0379***	0.0611***		0.0985***	0.0458***	0.0371***	0.0386***	0.0374***	0.0612***
	(7.07)	(4.52)	(3.68)	(3.38)	(3.56)	(6.76)		(7.03)	(4.48)	(3.63)	(3.35)	(3.52)	(6.76)
VW	0.0241**	0.0163**	0.0179**	0.0096	-0.0040	0.0282***		0.0237**	0.0158*	0.0174**	0.0092	-0.0044	0.0281***
	(2.25)	(1.98)	(2.05)	(0.94)	(-0.32)	(2.83)		(2.23)	(1.93)	(2.00)	(0.91)	(-0.35)	(2.82)
Rev													
EW	0.0921***	0.0448***	0.0402***	0.0385***	0.0526***	0.0395***		0.0915***	0.0442***	0.0397***	0.0380***	0.0520***	0.0395***
	(6.26)	(4.46)	(3.90)	(3.55)	(4.56)	(4.10)		(6.21)	(4.43)	(3.85)	(3.51)	(4.54)	(4.10)
VW	0.0160	0.0172*	0.0151*	0.0104	-0.0029	0.0189**		0.0157	0.0169*	0.0146*	0.0099	-0.0033	0.0190**
	(1.51)	(1.71)	(1.81)	(1.16)	(-0.25)	(2.10)		(1.49)	(1.68)	(1.76)	(1.12)	(-0.28)	(2.09)
Illiq													
EW	0.0923***	0.0500***	0.0436***	0.0456***	0.0327***	0.0596***		0.0917***	0.0495***	0.0431***	0.0450***	0.0321***	0.0595***
	(6.55)	(4.85)	(4.36)	(4.10)	(2.86)	(7.01)		(6.51)	(4.81)	(4.31)	(4.06)	(2.83)	(7.00)
VW	0.0155	0.0154*	0.0231**	0.0085	0.0066	0.0088		0.0152	0.0149*	0.0226**	0.0081	0.0062	0.0089
	(1.44)	(1.86)	(2.55)	(0.91)	(0.51)	(1.13)		(1.42)	(1.82)	(2.52)	(0.87)	(0.49)	(1.14)
Lt_rev													
EW	0.1049***	0.0428***	0.0407***	0.0392***	0.0415***	0.0634***		0.1043***	0.0423***	0.0401***	0.0387***	0.0408***	0.0635***
	(7.14)	(4.20)	(4.07)	(3.46)	(3.62)	(6.28)		(7.09)	(4.16)	(4.02)	(3.42)	(3.59)	(6.30)
VW	0.0249**	0.0146	0.0177**	0.0133	0.0006	0.0242**		0.0244**	0.0143	0.0173**	0.0130	0.0001	0.0243**
	(2.16)	(1.61)	(2.21)	(1.30)	(0.05)	(2.49)		(2.13)	(1.58)	(2.17)	(1.26)	(0.01)	(2.49)
Vol													
EW	0.0911***	0.0541***	0.0459***	0.0334***	0.0432***	0.0480***		0.0905***	0.0536***	0.0454***	0.0328***	0.0426***	0.0480***
	(6.43)	(5.29)	(4.26)	(3.19)	(3.69)	(4.78)		(6.39)	(5.25)	(4.21)	(3.14)	(3.66)	(4.77)
VW	0.0211*	0.0137	0.0168*	0.0078	0.0140	0.0071		0.0207*	0.0133	0.0162*	0.0074	0.0137	0.0070
	(1.82)	(1.58)	(1.92)	(0.83)	(1.27)	(0.73)		(1.81)	(1.54)	(1.86)	(0.79)	(1.25)	(0.72)
Ivol													
EW	0.0941***	0.0529***	0.0492***	0.0422***	0.0289***	0.0652***		0.0935***	0.0523***	0.0487***	0.0416***	0.0283***	0.0653***
	(6.71)	(5.14)	(4.46)	(3.74)	(2.68)	(6.18)		(6.68)	(5.08)	(4.41)	(3.70)	(2.65)	(6.18)
VW	0.0175	0.0169*	0.0153*	0.0088	0.0164	0.0011		0.0171	0.0165*	0.0148*	0.0083	0.0161	0.0010

	(1.50)	(1.78)	(1.92)	(1.00)	(1.36)	(0.14)	(1.47)	(1.74)	(1.87)	(0.95)	(1.33)	(0.13)
Max												
EW	0.1022***	0.0478***	0.0358***	0.0346***	0.0472***	0.0550***	0.1016***	0.0473***	0.0353***	0.0341***	0.0466***	0.0551***
	(7.27)	(4.38)	(3.54)	(3.09)	(4.28)	(5.62)	(7.23)	(4.34)	(3.49)	(3.04)	(4.25)	(5.63)
VW	0.0272**	0.0137	0.0122	0.0159	0.0036	0.0236***	0.0268**	0.0133	0.0116	0.0155	0.0034	0.0234***
	(2.21)	(1.35)	(1.47)	(1.65)	(0.34)	(2.74)	(2.19)	(1.32)	(1.42)	(1.62)	(0.31)	(2.71)
Min												
EW	0.0891***	0.0533***	0.0480***	0.0418***	0.0333***	0.0558***	0.0885***	0.0527***	0.0475***	0.0413***	0.0327***	0.0558***
	(6.42)	(5.05)	(4.70)	(3.82)	(2.92)	(5.85)	(6.38)	(5.00)	(4.65)	(3.78)	(2.89)	(5.84)
VW	0.0182*	0.0145*	0.0147*	0.0130	0.0074	0.0108	0.0179*	0.0141*	0.0141*	0.0127	0.0071	0.0108
	(1.68)	(1.75)	(1.73)	(1.40)	(0.58)	(1.10)	(1.66)	(1.71)	(1.68)	(1.37)	(0.56)	(1.10)
PTV												
EW	0.0946***	0.0500***	0.0390***	0.0509***	0.0332***	0.0614***	0.0940***	0.0494***	0.0385***	0.0503***	0.0326***	0.0615***
	(6.80)	(4.83)	(3.93)	(4.47)	(2.91)	(6.82)	(6.76)	(4.79)	(3.89)	(4.43)	(2.88)	(6.82)
VW	0.0224**	0.0127	0.0196**	0.0172	-0.0013	0.0237**	0.0220**	0.0122	0.0192**	0.0167	-0.0016	0.0235**
	(2.04)	(1.64)	(2.24)	(1.44)	(-0.11)	(2.49)	(2.01)	(1.59)	(2.20)	(1.40)	(-0.13)	(2.47)
Volume												
EW	0.0979***	0.0461***	0.0445***	0.0391***	0.0422***	0.0557***	0.0973***	0.0457***	0.0439***	0.0385***	0.0416***	0.0557***
	(6.96)	(4.48)	(4.41)	(3.63)	(3.51)	(6.13)	(6.91)	(4.44)	(4.37)	(3.57)	(3.49)	(6.13)
VW	0.0181*	0.0131	0.0166*	0.0067	0.0109	0.0071	0.0178*	0.0127	0.0162*	0.0063	0.0106	0.0072
	(1.76)	(1.60)	(1.91)	(0.68)	(0.86)	(0.87)	(1.74)	(1.55)	(1.87)	(0.64)	(0.84)	(0.88)
StdVolume												
EW	0.0944***	0.0508***	0.0408***	0.0395***	0.0424***	0.0520***	0.0938***	0.0503***	0.0403***	0.0389***	0.0418***	0.0519***
	(6.53)	(4.96)	(4.10)	(3.67)	(3.49)	(5.31)	(6.49)	(4.92)	(4.06)	(3.62)	(3.47)	(5.31)
VW	0.0157	0.0139*	0.0190**	0.0075	0.0080	0.0077	0.0154	0.0135	0.0186**	0.0070	0.0077	0.0077
	(1.51)	(1.68)	(2.07)	(0.71)	(0.60)	(0.82)	(1.48)	(1.63)	(2.03)	(0.67)	(0.58)	(0.83)
DBeta												
EW	0.1015***	0.0454***	0.0396***	0.0409***	0.0406***	0.0609***	0.1009***	0.0448***	0.0391***	0.0404***	0.0398***	0.0611***
	(7.11)	(4.32)	(3.92)	(3.64)	(3.51)	(6.25)	(7.06)	(4.28)	(3.88)	(3.60)	(3.48)	(6.27)
VW	0.0219**	0.0162*	0.0119	0.0159	-0.0003	0.0221**	0.0214**	0.0157*	0.0115	0.0156	-0.0007	0.0222**
	(2.11)	(1.73)	(1.60)	(1.58)	(-0.02)	(2.26)	(2.08)	(1.68)	(1.55)	(1.55)	(-0.05)	(2.26)
Skew1												
EW	0.1011***	0.0479***	0.0381***	0.0322***	0.0470***	0.0540***	0.1005***	0.0474***	0.0376***	0.0317***	0.0464***	0.0541***
	(7.18)	(4.37)	(3.71)	(3.00)	(4.01)	(5.60)	(7.13)	(4.34)	(3.67)	(2.95)	(3.98)	(5.60)
VW	0.0217**	0.0217**	0.0219**	0.0072	0.0021	0.0197*	0.0213**	0.0212*	0.0215**	0.0067	0.0017	0.0196*
	(2.06)	(2.00)	(2.03)	(0.75)	(0.17)	(1.90)	(2.03)	(1.96)	(1.99)	(0.70)	(0.13)	(1.89)
Skew2												
EW	0.1065***	0.0399***	0.0399***	0.0399***	0.0429***	0.0636***	0.1060***	0.0393***	0.0394***	0.0394***	0.0423***	0.0637***
	(7.61)	(3.68)	(3.85)	(3.75)	(3.60)	(6.86)	(7.56)	(3.64)	(3.82)	(3.71)	(3.57)	(6.87)
VW	0.0222**	0.0089	0.0165**	0.0147	0.0005	0.0217***	0.0218**	0.0084	0.0161**	0.0143	0.0000	0.0218***
	(2.08)	(1.05)	(2.10)	(1.41)	(0.04)	(2.64)	(2.05)	(1.00)	(2.05)	(1.38)	(0.00)	(2.64)
Iskew												
EW	0.1080***	0.0407***	0.0387***	0.0395***	0.0410***	0.0670***	0.1074***	0.0402***	0.0382***	0.0390***	0.0403***	0.0671***
	(7.49)	(4.09)	(3.73)	(3.45)	(3.57)	(7.27)	(7.44)	(4.05)	(3.69)	(3.41)	(3.53)	(7.27)

VW	0.0277**	0.0137	0.0166*	0.0043	0.0028	0.0250**	0.0272**	0.0133	0.0162*	0.0039	0.0024	0.0249**
	(2.27)	(1.50)	(1.93)	(0.43)	(0.21)	(2.45)	(2.26)	(1.46)	(1.88)	(0.39)	(0.18)	(2.44)
Coskew												
EW	0.1044***	0.0430***	0.0348***	0.0456***	0.0412***	0.0632***	0.1038***	0.0424***	0.0343***	0.0451***	0.0405***	0.0633***
	(7.21)	(4.04)	(3.51)	(4.10)	(3.61)	(6.31)	(7.16)	(4.00)	(3.47)	(4.06)	(3.57)	(6.33)
VW	0.0303**	0.0095	0.0131	0.0193*	0.0061	0.0241**	0.0299**	0.0091	0.0127	0.0189*	0.0056	0.0243**
	(2.53)	(1.05)	(1.54)	(1.86)	(0.45)	(2.35)	(2.52)	(1.00)	(1.50)	(1.83)	(0.41)	(2.36)

This table reports the mean excess returns and CAPM alphas of double-sorted portfolios. We form the portfolios at the end of each week and hold them for one week. At the end of each week, we first sort cryptocurrencies into quintiles by one characteristic (*Beta, Size, Mom, Rev, Illiq, Lt_rev, Vol, Ivol, Max, Min, PTV, Volume, StdVolume, DBeta, Skew1, Skew2, Iskew,* or *Coskew*). Next, within each quintile, we further sort cryptocurrencies into quintiles by *STV*. All the variables are defined in Table 3.2. Lastly, the one-week-ahead return on a given *STV*-quintile is calculated by averaging across the five characteristic-based quintiles. This procedure generates a time series of returns for each *STV*-quintile. We report both equal-weighted (EW) and value-weighted (VW) mean excess returns and CAPM alphas, where we use the value-weighted cryptocurrency market index as a proxy for the market portfolio. Since bivariate portfolio analysis requires at least 25 active cryptocurrencies per week, the sample period is from March 27, 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.

Table B4 Panel regressions: Two-dimensional relationship between STV and future cryptocurrency returns (skipping one week in the construction of STV)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
STV	-0.0351***	-0.0024	-0.0366***	-0.0348***	-0.0371***	-0.0378***	-0.0376***	-0.0352***	-0.0360***	-0.0359***	-0.0355***	-0.0358***	-0.0360***
	(-4.65)	(-0.35)	(-4.30)	(-4.08)	(-4.34)	(-4.39)	(-4.39)	(-4.16)	(-4.29)	(-4.31)	(-4.27)	(-4.30)	(-4.29)
Size		-0.0560***	-0.0289***	-0.0283***	-0.0262***	-0.0269***	-0.0270***	-0.0238***	-0.0255***	-0.0256***	-0.0253***	-0.0254***	-0.0255***
		(-15.85)	(-11.76)	(-11.74)	(-10.70)	(-10.94)	(-11.04)	(-10.14)	(-10.12)	(-10.14)	(-10.03)	(-10.10)	(-10.11)
Mom		-0.0050	-0.0985***	-0.0983***	-0.0998***	-0.0988***	-0.0988***	-0.0970***	-0.0973***	-0.0973***	-0.0972***	-0.0973***	-0.0973***
		(-1.44)	(-20.82)	(-21.04)	(-21.18)	(-20.70)	(-20.66)	(-20.32)	(-20.43)	(-20.42)	(-20.40)	(-20.45)	(-20.43)
Rev			-0.3512***	-0.3508***	-0.3522***	-0.3515***	-0.3545***	-0.3520***	-0.3520***	-0.3530***	-0.3520***	-0.3520***	-0.3520***
			(-43.42)	(-43.36)	(-43.45)	(-42.97)	(-36.92)	(-36.62)	(-36.59)	(-34.92)	(-36.60)	(-36.61)	(-36.59)
Illiq				0.0012**	0.0012**	0.0012**	0.0012**	0.0012**	0.0012**	0.0013**	0.0013**	0.0013**	0.0012**
				(2.50)	(2.43)	(2.47)	(2.49)	(2.40)	(2.57)	(2.57)	(2.57)	(2.57)	(2.57)
Lt_rev					-0.0055***	-0.0058***	-0.0057***	-0.0025*	-0.0024*	-0.0024*	-0.0023*	-0.0024*	-0.0024*
					(-4.69)	(-4.83)	(-4.85)	(-1.87)	(-1.78)	(-1.76)	(-1.68)	(-1.78)	(-1.78)
Vol						0.0093	-0.0844*	-0.0887*	-0.0915*	-0.0912*	-0.0916*	-0.0916*	-0.0916*
						(0.78)	(-1.81)	(-1.89)	(-1.95)	(-1.94)	(-1.95)	(-1.95)	(-1.95)
Ivol						-0.0535***	-0.0518***	-0.0633***	-0.0611***	-0.0610***	-0.0590***	-0.0606***	-0.0611***
						(-4.06)	(-3.96)	(-4.86)	(-4.79)	(-4.78)	(-4.67)	(-4.76)	(-4.79)
Max							0.0387**	0.0416**	0.0401**	0.0436**	0.0404**	0.0402**	0.0401**
							(2.28)	(2.45)	(2.36)	(2.32)	(2.38)	(2.37)	(2.36)
Min							0.0253	0.0266	0.0268	0.0232	0.0264	0.0267	0.0268
							(1.39)	(1.45)	(1.46)	(1.15)	(1.44)	(1.45)	(1.46)
PTV								-0.1439***	-0.1452***	-0.1449***	-0.1299***	-0.1399***	-0.1449***
								(-5.48)	(-5.46)	(-5.46)	(-4.72)	(-5.03)	(-5.45)
Volume									-0.0022	-0.0022	-0.0022	-0.0022	-0.0022
									(-1.44)	(-1.44)	(-1.49)	(-1.45)	(-1.46)
StdVolume									0.0042**	0.0043**	0.0043**	0.0042**	0.0043**
									(2.53)	(2.53)	(2.55)	(2.54)	(2.54)
Skew1										-0.0015			
										(-0.59)			
Skew2											-0.0039		
											(-1.40)		
Iskew												-0.0014	
												(-0.54)	
Coskew													-0.0005
													(-0.53)
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	0.1163	0.1370	0.2313	0.2319	0.2323	0.2327	0.2328	0.2334	0.2336	0.2336	0.2336	0.2336	0.2336
N	138934	133698	133698	133320	133092	132852	132852	132851	132749	132727	132744	132749	132749

This table reports 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. Unlike in the main analysis, here *STV* measures the salience theory value of a cryptocurrency's historical daily return distribution from week t-5 to t-2. In other words, we skip the previous week's daily returns when constructing the *STV* variable. The remaining variables are defined in Table 3.2. 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 B5 WLS 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	-0.1901***	-0.1822***	-0.0574**	-0.0563**	-0.0577**	-0.0406	-0.0372	-0.0314	-0.0365	-0.0370	-0.0346	-0.0353	-0.0368
	(-7.27)	(-6.81)	(-2.09)	(-2.05)	(-2.10)	(-1.61)	(-1.55)	(-1.33)	(-1.57)	(-1.59)	(-1.49)	(-1.52)	(-1.58)
Size		-0.0318***	-0.0236***	-0.0236***	-0.0215***	-0.0208***	-0.0208***	-0.0177***	-0.0212***	-0.0213***	-0.0208***	-0.0212***	-0.0214***
		(-8.04)	(-6.95)	(-6.95)	(-6.59)	(-6.43)	(-6.40)	(-5.10)	(-5.78)	(-5.77)	(-5.80)	(-5.85)	(-5.88)
Mom		0.0158	-0.0239	-0.0240	-0.0262*	-0.0270*	-0.0272*	-0.0244	-0.0271*	-0.0270*	-0.0270*	-0.0269*	-0.0272*
		(1.25)	(-1.61)	(-1.62)	(-1.76)	(-1.80)	(-1.82)	(-1.63)	(-1.74)	(-1.74)	(-1.74)	(-1.73)	(-1.76)
Rev			-0.2060***	-0.2057***	-0.2079***	-0.2111***	-0.2078***	-0.2042***	-0.2070***	-0.2106***	-0.2071***	-0.2070***	-0.2071***
			(-11.20)	(-11.12)	(-11.25)	(-10.67)	(-8.62)	(-8.43)	(-8.54)	(-7.85)	(-8.56)	(-8.55)	(-8.55)
Illiq				-0.0028**	-0.0028**	-0.0028**	-0.0028**	-0.0027**	-0.0026*	-0.0026*	-0.0025*	-0.0025*	-0.0025*
				(-2.23)	(-2.16)	(-2.06)	(-2.06)	(-2.08)	(-1.85)	(-1.85)	(-1.83)	(-1.84)	(-1.82)
Lt_rev					-0.0085***	-0.0085***	-0.0085***	-0.0057**	-0.0057**	-0.0057**	-0.0052**	-0.0054**	-0.0056**
					(-3.68)	(-3.67)	(-3.69)	(-2.15)	(-2.14)	(-2.14)	(-1.99)	(-2.01)	(-2.12)
Vol						0.0671	0.2798***	0.2706**	0.2730***	0.2694***	0.2726***	0.2733***	0.2737***
						(1.63)	(2.67)	(2.56)	(2.60)	(2.62)	(2.60)	(2.60)	(2.60)
Ivol						-0.0982***	-0.1010***	-0.1098***	-0.1003***	-0.0999***	-0.0936***	-0.0975***	-0.1004***
						(-3.12)	(-3.26)	(-3.65)	(-3.47)	(-3.49)	(-3.22)	(-3.37)	(-3.47)
Max							-0.0837**	-0.0798**	-0.0865**	-0.0753*	-0.0856**	-0.0860**	-0.0871**
							(-2.12)	(-2.02)	(-2.29)	(-1.70)	(-2.27)	(-2.28)	(-2.31)
Min							-0.0612	-0.0579	-0.0608	-0.0697	-0.0618	-0.0618	-0.0609
							(-1.45)	(-1.37)	(-1.45)	(-1.47)	(-1.48)	(-1.48)	(-1.45)
PTV								-0.2014**	-0.2091**	-0.2087**	-0.1783*	-0.1877**	-0.2047**
								(-2.10)	(-2.18)	(-2.18)	(-1.86)	(-1.98)	(-2.15)
Volume									-0.0022	-0.0023	-0.0022	-0.0023	-0.0022
									(-0.68)	(-0.71)	(-0.67)	(-0.70)	(-0.68)
StdVolume									0.0069**	0.0070**	0.0069**	0.0070**	0.0070**
									(2.43)	(2.44)	(2.42)	(2.47)	(2.47)
Skew1										-0.0023			
										(-0.69)			
Skew2											-0.0057*		
											(-1.90)		
Iskew												-0.0041	
												(-1.46)	
Coskew													-0.0044
													(-1.53)
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	0.3377	0.3447	0.3725	0.3727	0.3735	0.3738	0.3741	0.3750	0.3763	0.3764	0.3765	0.3764	0.3765
N	138551	135321	135321	134945	134710	134416	134416	134415	134312	134287	134308	134312	134312

This table reports the weighted least-squares (WLS) estimates of panel regressions with cryptocurrency FE, week FE, and a varying set of controls. The weights are given by the market capitalisation of a cryptocurrency relative to total market capitalisation at the end of each week. 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 measures 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 3.2. 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 B6 Allocation of cryptocurrencies to size segments

1. Based on aggregate market cap	**Segment**	**Combined market cap**	**Percentage of cryptos**	**2. Based on number of active cryptos**	**Segment**	**Combined market cap**	**Percentage of cryptos**
	Micro	3%	86%		Micro	0.45%	60%
	Small	7%	8%		Small	1.46%	20%
	Large	90%	6%		Large	98.08%	20%

This table displays how, at the end of each week, we allocate cryptocurrencies to three size segments: Micro-cap, small-cap, and large-cap. We employ two alternative classification methods (note that Bitcoin is included in the sample). The first classification method is based on aggregate market capitalisation: The micro-cap (small-cap, large-cap) segment consists of those cryptocurrencies that account for the bottom 3% (next 7%, top 90%) of total market capitalisation. The second classification method 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 segment, the next 20% to the small-cap segment, and the top 20% to the large-cap segment. The combined market capitalisation of each size segment and the percentage of cryptocurrencies falling into each size segment are displayed next to each segment.

Table B7 Disaggregated results by cryptocurrency sector

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Defi Coins	Binance Smart Chain	Exchange Tokens	Ethereum ERC20	Tron Network	Tokenized Stocks	StableCoins
STV	-0.0663	-0.1131	0.1635	-0.0230	-0.3325	-0.0966	-0.1863
	(-1.52)	(-1.66)	(1.27)	(-1.41)	(-2.55)	(-1.17)	(-0.91)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Crypto FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Week FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R-squared	0.3014	0.2584	0.2846	0.2411	0.2749	0.2181	0.1996
Number of observations	5080	2109	1573	53506	671	942	1068
Number of cryptos	60	29	20	665	13	15	18
Bootstrapped p-values		0.14	0.33		0.25	0.19	0.65

	(8)	(9)	(10)	(11)	(12)	(13)
	Gaming	Proof of Stake	NFT Tokens	Proof of Work	Privacy coins	Unsectored
STV	-0.1020	-0.0528	-0.1844**	-0.0228	0.0101	-0.0211**
	(-1.38)	(-0.69)	(-2.28)	(-0.40)	(0.10)	(-2.10)
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	0.2485	0.6068	0.2815	0.4798	0.3652	0.2230
Number of observations	2101	2554	1710	3856	2901	70421
Number of cryptos	28	19	22	19	21	920
Bootstrapped p-values	0.25	0.50	0.03	0.61	0.94	

This table presents estimates generated by panel regressions with cryptocurrency FE and week FE. The t-statistics in parentheses are based on standard errors clustered by cryptocurrency and week. In all specifications, 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 from week t-4 to t-1. The control variables are *Size*, *Mom*, *Rev*, *Illiq*, *Lt_rev*, *Vol*, *Ivol*, *Max*, *Min,* and *PTV*, which are defined in Table 3.2. We sort the cryptocurrencies into 14 sectors according to the information provided by *Coincodex*. We then re-estimate our preferred panel-regression specification separately for each sector (columns 1-12), with the exclusion of the "Yield Farming" and "Meme Coins" sectors, which contain only 3 and 5 cryptocurrencies, respectively. In column 13 ("Unsectored"), the sample consists of all the cryptocurrencies that do not belong to any specific sector. When a sector contains less than 50 cryptocurrencies, the cluster-robust standard errors may be biased. For this reason, we follow *Roodman et al.* (*2019*) and compute the p-values of the coefficients on *STV* using the wild cluster bootstrap-t procedure, where the standard errors are clustered by cryptocurrency and week and bootstrapped on the cryptocurrency dimension (null imposed; 999 replications). The results show that the estimated coefficient on *STV* is negative for 11 out of 13 sectors and is statistically different from zero for 2 out of 13 sectors. Note that *Coincodex* assigns some cryptocurrencies to multiple sectors, and consequently the total number of cryptocurrencies in this table (1,857, including "Yield Farming" and "Meme Coins") is greater than 1,738 (cf. Section 3.4 in the main text). *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Appendix C Supplement to Chapter 4

Sections C.1 to C.4 describe a battery of robustness tests. Supplementary tables and figures are displayed at the end of the Appendix.

C.1 Potential near-multicollinearity issues

Since the PT, ST, and RT value of a stock at a given point in time are computed based on the same historical distribution of returns, a natural concern is whether *PTV*, *STV*, and *RTV* are highly correlated with one another, which might lead to near-multicollinearity issues. Indeed, Panel B of Table 4.2 reveals that the correlation coefficient between *PTV* and *STV* (*PTV* and *RTV*, *STV* and *RTV*) is about 0.68 (0.71, 0.88). To address this concern, for each investor group we first compute the variance inflation factor (VIF) of each explanatory variable in Eq. (4.12): The VIFs of *PTV* (*RTV*, *STV)* range between 7.7 and 8.2 (6.1 and 7.2, 4.9 and 5) across investor groups, and the VIFs of the remaining variables are always less than 7, with the exception of *Vol*, for which we observe a value of 9.77 in the case of securities investment trusts. Since, according to *Lee et al.* (*2018*), "a standard rule of thumb threshold for the detection of [near-]multicollinearity" is 10, we conclude that the observed correlations among variables are unlikely to represent a problem in the present setting.

Nevertheless, since any such threshold is somewhat arbitrary, we also re-estimate Eq. (4.12) with one behavioural variable (i.e., *PTV*, *STV*, or *RTV*) at a time. The results, displayed in Table C2, show that our conclusions remain mostly unchanged. The only noticeable difference is that, according to this alternative specification, ST can correctly predict not only the behaviour of foreign investors but also that of securities investment trusts.

C.2 Alternative approaches in the construction of OIB

In our base specification, the dependent variable in Eq. (4.12), *OIB*, represents a stock's cumulative OIB in the following week and is computed based on the volume of limit orders submitted at any time of the trading day (i.e., from 8:30 am to 2:30 pm). To examine the robustness of our results, we separately try each of the following alternatives: (1) we replace *OIB* in Eq. (12) with the cumulative OIB over the following 5-day, 9-day, 12-day, and 2-week period; (2) we calculate *OIB* based on the dollar value of limit orders; (3) we calculate *OIB* using only orders submitted during regular trading hours (i.e., from 9:00 am to 1:30 pm); and (4) we calculate *OIB* using only executed orders. Tables C4-C7 display the estimates generated by each of these robustness tests, and Panel A of Table C3 provides a summary of the results. More specifically, in Table C3, to save space, for each investor group we report information only about the behavioural variables whose estimated effects in Table 4.5 are consistent with the underlying theory's predictions. Columns 3-6 of Table C3 show that, for each of these behavioural variables, the results are fully robust to any changes in the methodology behind the construction of *OIB*.

C.3 Alternative approaches in the construction of *PTV*, *STV*, and *RTV*

To explore whether our results are driven by the methodology behind the construction of the behavioural variables, we employ a number of tests. In the first, we re-calculate *PTV*, *STV*, and *RTV* using alternative look-back window lengths, from 4 weeks (i.e., from week t-4 to week t-1) to 52 weeks (i.e., from week t-52 to week t-1), but with gaps. For each of these alternatives, we then re-estimate Eq. (4.12). The resulting point estimates and 95% and 90% confidence intervals of the coefficients on *PTV*, *STV*, and *RTV* are displayed in Figure C1. (Note that, for comparison, we include the window length from our base specification, i.e., 12 weeks.) Column 3 of Panel B in Table C3 provides a summary of the results broken down by investor group: RT's predictive ability with respect to the behaviour of individual investors is fully robust, as the coefficient on *RTV* is positive and significant at least at the 5% level across all look-back-window lengths. PT's predictive ability with respect to the behaviour of foreign investors, securities investment trusts, and other non-individual investors is quite robust, as the coefficient on *PTV* is positive and statistically significant at least at the 5% level in no less than 8 instances (out of 19). And ST's predictive power with respect to the behaviour of foreign investors is robust, as the coefficient on *STV* is positive and statistically different from zero at least at the 5% level in 18 cases (out of 19).

In a second test, we re-calculate *PTV*, *STV*, and *RTV* using alternative reference points or counterfactuals (i.e., zero, the risk-free rate, and the time-series mean of the stock's own returns). For each of these alternatives, we then re-estimate Eq. (4.12). The resulting point estimates and 95% and 90% confidence intervals of the coefficients on *PTV*, *STV*, and *RTV* are displayed in Figure C2. (Note that, for comparison, we include the reference point or counterfactual from our base specification, i.e., the return on the TAIEX index.) Column 4 of Panel B in Table C3 provides a summary of the results for each investor group: RT's and ST's predictive abilities are fully robust to the use of alternative counterfactuals or reference points. Analogously, the predictive power of PT remains intact for all but one group (foreign investors).

In a third test, we re-calculate PTV, STV, and RTV using alternative parameter values. In the case of PTV, to explore whether all three components of PT play a role in affecting investor behaviour, we activate each component separately in Eqs. (4.3) and (4.5). Specifically, to isolate the loss aversion ("*LA*") component, we set $c = d = 1,\ \lambda = 2.25, \gamma = 1,\ \rho = 1$. To focus on the probability weighting ("*PW*") component, we set $c = d = 1,\ \lambda = 1,\ \gamma = 0.61,\ \rho = 0.69$. And to isolate the impact of the concavity/convexity of the value function ("*CC*"), we set $c = d = 0.88,\ \lambda = 1,\ \gamma = 1,\ \rho = 1$. We also experiment by activating multiple components at once ("*LA/CC*", "LA/*PW*", and "*CC/PW*") and adopting the Taiwan-specific PT parameter values ("*TW*") estimated by *Rieger et al.* (*2017*). Moving to STV, in Eq. (4.7) we use alternative salience distortion parameter (δ) values ranging between 0.1 and 0.9. As for RTV, we increase or decrease by one SD the values of the parameters α and β (*Bleichrodt et al., 2010*) in Eq. (4.12). For each of these alternatives, we then re-estimate Eq. (4.12) while holding all else the same. The resulting point estimates and 95% and 90% confidence intervals of the coefficients on PTV, STV, and RTV are displayed in Figure C3. (Note that, for comparison, we include the default parameter values.) Column 5 of Panel B in Table C3 provides a summary of the results broken down by investor group: RT's predictive ability with respect to the behaviour of individual investors is fully robust to the use of alternative parameter values. When it comes to PT, *LA* seems to affect all types of non-individual investors, whereas *PW* and *CC* appear to affect only the behaviour of foreign investors and securities investment trusts. Additionally, for the latter two groups, the effect of PTV is robust to using Taiwan-specific PT parameter values. As for ST, its predictive power with respect to the behaviour of foreign investors is robust to using salience distortion parameter values in the range between 0.5 and 0.9, which is consistent with *Bordalo et al.'s* (*2012*) experimental results.

C.4 Sub-sample analyses

To examine the temporal stability of the coefficients on PTV, STV, and RTV, we re-estimate Eq. (4.12) using a rolling-window approach, where a 2-year observation window moves forward by 13 weeks (3 months) for each iteration. The resulting point estimates and 95% and 90% confidence intervals of the coefficients on PTV, STV, and RTV are displayed in Figure C4. Column 3 of Panel C in Table C3 provides a summary of the results broken down by investor group: In the case of individual investors, the coefficient on RTV is always positive, statistically significant, and its size is fairly stable over time, suggesting that RT's predictive ability is fully robust to using alternative sub-sample periods. PT's predictive power with respect to the behaviour of non-individual investors is quite robust as well: Although the coefficient on PTV is not always statistically different from zero at conventional levels, its sign is always positive, as predicted by PT, and its size is remarkably stable over time. Lastly, the predictive power of ST with respect to the behaviour of foreign investors is largely robust, as the coefficient on *STV* is always positive and its size fluctuates within a narrow range, though the coefficient itself is not always statistically significant at conventional levels.

To investigate whether the predictive abilities of PT, ST, and RT vary across market segments, we repeat our analyses after sorting the stocks in the sample into size, price, and turnover segments. Specifically, at the end of each week, following *Boehmer et al.* (*2021*), we first sort stocks into three size segments (i.e., micro, small, and large, as defined in Section 4.4.3) by market capitalisation. Next, we construct a dummy variable, *Small* (*Large*), that takes the value of 1 if a stock falls into the small-cap (large-cap) segment, and 0 otherwise. Lastly, we re-estimate Eq. (4.12) after adding to the model the *Small* and *Large* dummy variables, interactions between *Small* and *PTV*, *STV*, and *RTV,* and interactions between *Large* and *PTV*, *STV*, and *RTV*. We follow an analogous approach when we sort stocks into terciles (low, medium, and high) by market price and when we sort them into terciles (low, medium, and high) by turnover. The resulting point estimates and 95% and 90% confidence intervals of the coefficients on *PTV*, *STV*, and *RTV* are displayed in Figures C5-C7. Columns 4-6 of Panel C in Table C3 provide a summary of the results broken down by investor group: RT correctly predicts the behaviour of individual investors across all market segments. Moving to PT, the picture that emerges is more nuanced. It correctly predicts the behaviour of securities investment trusts across all segments, but its predictive power with respect to the behaviour of foreign investors is confined to large-cap and low-priced stocks. Similarly, when it comes to others, its predictive power is confined to micro/small-cap, low/medium-price, and low/medium-turnover stocks. Lastly, ST correctly predicts the behaviour of foreign investors in the small/large-cap, medium/high-price, and high-turnover segments.

In summary, the results of all these tests lead us to conclude that our main findings are considerably robust to using alternative sub-samples of data.

Table C1 Characteristics of *PTV*-, *STV*-, and *RTV*-sorted portfolios

	PTV	STV	RTV	LOIB	WRet	MRet	HYRet	Turnover	Vol	Size	BM	CRO	WHMAX52
Panel A: *PTV*-sorted													
Low	-0.0719	-0.0219	-0.0021	0.0059	-0.0130	-0.0510	-0.0115	0.0054	0.0230	8.5067	-0.3420	0.0146	0.0014
PTV2	-0.0493	-0.0095	-0.0008	-0.0038	-0.0074	-0.0280	-0.0027	0.0040	0.0184	8.6466	-0.2603	0.0098	0.0031
PTV3	-0.0397	-0.0041	-0.0003	-0.0119	-0.0044	-0.0169	0.0030	0.0036	0.0164	8.6960	-0.2185	0.0059	0.0078
PTV4	-0.0329	0.0002	0.0000	-0.0203	-0.0031	-0.0094	0.0106	0.0035	0.0155	8.7290	-0.2044	-0.0019	0.0136
PTV5	-0.0274	0.0032	0.0002	-0.0247	-0.0013	-0.0040	0.0154	0.0033	0.0146	8.7769	-0.1831	-0.0107	0.0244
PTV6	-0.0225	0.0062	0.0004	-0.0294	-0.0001	0.0023	0.0215	0.0033	0.0141	8.8605	-0.1895	-0.0157	0.0405
PTV7	-0.0178	0.0088	0.0006	-0.0302	0.0020	0.0089	0.0316	0.0034	0.0138	8.9563	-0.2066	-0.0132	0.0679
PTV8	-0.0126	0.0131	0.0009	-0.0340	0.0049	0.0192	0.0504	0.0042	0.0147	9.0493	-0.2287	-0.0090	0.1260
PTV9	-0.0055	0.0203	0.0015	-0.0349	0.0096	0.0368	0.0871	0.0059	0.0169	9.1431	-0.2860	0.0074	0.2165
High	0.0112	0.0412	0.0042	-0.0147	0.0249	0.0936	0.2034	0.0118	0.0243	9.1165	-0.4279	0.0623	0.4131
Panel B: *STV*-sorted													
Low	-0.0639	-0.0311	-0.0020	0.0006	-0.0101	-0.0425	-0.0175	0.0050	0.0204	8.7545	-0.2923	0.0141	0.0051
STV2	-0.0433	-0.0166	-0.0009	-0.0081	-0.0055	-0.0224	-0.0143	0.0032	0.0155	8.8463	-0.2281	0.0149	0.0123
STV3	-0.0344	-0.0098	-0.0005	-0.0157	-0.0032	-0.0133	-0.0080	0.0026	0.0135	8.8954	-0.1980	0.0137	0.0290
STV4	-0.0281	-0.0048	-0.0003	-0.0225	-0.0016	-0.0070	-0.0020	0.0025	0.0122	8.9517	-0.1883	0.0074	0.0500
STV5	-0.0243	-0.0001	-0.0001	-0.0285	-0.0005	-0.0018	0.0011	0.0025	0.0123	8.9465	-0.1772	0.0075	0.0662
STV6	-0.0219	0.0050	0.0001	-0.0296	0.0007	0.0024	0.0109	0.0030	0.0133	8.9520	-0.1964	0.0015	0.0865
STV7	-0.0197	0.0109	0.0003	-0.0338	0.0026	0.0087	0.0325	0.0039	0.0153	8.9344	-0.2253	-0.0005	0.1078
STV8	-0.0173	0.0185	0.0008	-0.0323	0.0048	0.0184	0.0596	0.0052	0.0181	8.8744	-0.2676	-0.0048	0.1366
STV9	-0.0129	0.0291	0.0017	-0.0248	0.0082	0.0348	0.1109	0.0075	0.0216	8.8246	-0.3362	-0.0033	0.1854
High	-0.0026	0.0564	0.0054	-0.0032	0.0166	0.0741	0.2376	0.0128	0.0296	8.5004	-0.4373	-0.0012	0.2366
Panel C: *RTV*-sorted													
Low	-0.0702	-0.0268	-0.0023	0.0051	-0.0127	-0.0522	-0.0287	0.0050	0.0214	8.6115	-0.3126	0.0197	0.0005
RTV2	-0.0473	-0.0136	-0.0010	-0.0039	-0.0075	-0.0288	-0.0240	0.0031	0.0159	8.7253	-0.2131	0.0217	0.0027
RTV3	-0.0370	-0.0080	-0.0006	-0.0145	-0.0043	-0.0184	-0.0195	0.0026	0.0137	8.8162	-0.1740	0.0168	0.0088
RTV4	-0.0295	-0.0039	-0.0003	-0.0216	-0.0025	-0.0106	-0.0108	0.0023	0.0124	8.8826	-0.1584	0.0061	0.0218
RTV5	-0.0240	-0.0002	-0.0001	-0.0294	-0.0008	-0.0033	-0.0019	0.0023	0.0120	8.9799	-0.1532	-0.0007	0.0415
RTV6	-0.0199	0.0039	0.0001	-0.0334	0.0014	0.0042	0.0104	0.0028	0.0127	9.0238	-0.1814	-0.0016	0.0819
RTV7	-0.0171	0.0092	0.0004	-0.0355	0.0035	0.0125	0.0314	0.0037	0.0146	9.0147	-0.2393	-0.0041	0.1190
RTV8	-0.0140	0.0163	0.0008	-0.0344	0.0062	0.0231	0.0695	0.0052	0.0175	9.0045	-0.2902	-0.0073	0.1583
RTV9	-0.0103	0.0271	0.0018	-0.0273	0.0101	0.0405	0.1220	0.0079	0.0217	8.8886	-0.3575	-0.0027	0.2068
High	0.0008	0.0535	0.0057	-0.0031	0.0188	0.0844	0.2623	0.0136	0.0300	8.5323	-0.4673	0.0014	0.2737

At the end of each week t-1, we sort stocks into deciles by *PTV* (Panel A), *STV* (Panel B), and *RTV* (Panel C). *PTV*, *STV*, and *RTV* are the prospect theory value, salience theory value, and regret theory value of a stock's historical weekly return distribution from week t-12 to week t-1, respectively. Then, we compute the equal-weighted mean values of the characteristics listed in the first row for each decile across all stocks that belong to the decile. Lastly, we calculate the time-series averages of these mean characteristic values across all weeks. The sample period is from May 15, 2013 to March 28, 2018.

Table C2 Panels regressions: One behavioural variable at a time and next-week *OIB*

Panel A: Individual investors						
	(1)	(2)	(3)	(4)	(5)	(6)
PTV	-1.2186***	-0.3270***				
	(-24.02)	(-12.10)				
STV			-0.4299***	-0.0647***		
			(-9.33)	(-3.32)		
RTV					-3.4276***	0.4193*
					(-6.64)	(1.78)
Controls	No	Yes	No	Yes	No	Yes
Week FEs	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R-squared	0.0690	0.4221	0.0456	0.4214	0.0440	0.4213
N	214417	201633	214417	201633	214417	201633
Panel B: Foreign investors						
	(1)	(2)	(3)	(4)	(5)	(6)
PTV	1.6425***	0.2269**				
	(13.07)	(2.42)				
STV			1.6657***	0.1398**		
			(14.56)	(2.20)		
RTV					18.1879***	-0.6393
					(12.53)	(-0.77)
Controls	No	Yes	No	Yes	No	Yes
Week FEs	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R-squared	0.1095	0.2973	0.1105	0.2973	0.1108	0.2973
N	208464	194516	208464	194516	208464	194516
Panel C: Others						
	(1)	(2)	(3)	(4)	(5)	(6)
PTV	-0.2954*	0.2465***				
	(-1.93)	(2.91)				
STV			-0.8133***	-0.0163		
			(-7.08)	(-0.24)		
RTV					-9.5214***	0.3215
					(-7.88)	(0.37)
Controls	No	Yes	No	Yes	No	Yes
Week FEs	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R-squared	0.0336	0.3448	0.0346	0.3448	0.0349	0.3448
N	209547	196135	209547	196135	209547	196135
Panel D: Securities investment trusts						
	(1)	(2)	(3)	(4)	(5)	(6)
PTV	4.4543***	1.6812***				
	(15.57)	(6.23)				
STV			3.9578***	0.5880**		
			(14.57)	(2.59)		
RTV					45.3776***	4.5534
					(14.73)	(1.63)
Controls	No	Yes	No	Yes	No	Yes
Week FEs	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R-squared	0.0738	0.2232	0.0711	0.2225	0.0718	0.2224
N	79028	57741	79028	57741	79028	57741

This table reports the estimates generated by fitting variations on Eq. (4.12). In all specifications, the dependent variable is *OIB*, which measures a stock's OIB in week t; this is constructed by aggregating all orders across individual investors (Panel A), foreign investors (Panel B), others (Panel C), and securities investment trusts (Panel D). In each regression, only one behavioural variable among *PTV*, *STV*, and *RTV* is included in the equation at a time: *PTV* enters the equation in columns

1-2, *STV* in columns 3-4, and *RTV* in columns 5-6. Each regression equation includes the following control variables: *LOIB*, *WRet*, *MRet*, *HYRet*, *Turnover*, *Vol*, *Size*, *BM*, *CRO*, and *52WHMAX*. All the variables are as defined in Table 4.1. The sample period is from May 15, 2013 to March 28, 2018. The t-statistics in parentheses are based on standard errors clustered by stock and week. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table C3 Robustness tests

Panel A: Alternative approaches in the construction of *OIB*

(1) Investor type	(2) Variable	(3) Next 5-day, 9-day, 12-day, and 2-week OIB	(4) Order value	(5) Only regular trading hours	(6) Only executed orders
Individual investors	RTV	Robust	Robust	Robust	Robust
Foreign investors	PTV	Robust	Robust	Robust	Robust
	STV	Robust	Robust	Robust	Robust
Others	PTV	Robust	Robust	Robust	Robust
Securities investment trusts	PTV	Robust	Robust	Robust	Robust

Panel B: Alternative approaches in the construction of *PTV*, *STV*, and *RTV*

Investor type	Variable	Look-back window lengths (19)	Reference points or counterfactuals (4)	Parameter values
Individual investors	RTV	All	All	All
Foreign investors	PTV	8	1	7 (out of 8)
	STV	18	All	5 (out of 9)
Others	PTV	15	All	4 (out of 8)
Securities investment trusts	PTV	12	All	All

Panel C: Sub-sample analyses

Investor type	Variable	Rolling-window regressions (12)	Size segments	Price segments	Turnover segments
Individual investors	RTV	All	All	All	All
Foreign investors	PTV	2	Large	Low	None
	STV	6	Small, Large	Medium, High	High
Others	PTV	3	Micro, Small	Low, Medium	Low, Medium
Securities investment trust	PTV	All	All	All	All

This table provides a summary of the results of a battery of robustness tests, and its content is based on the estimates displayed in Tables A4-A7 and Figures C1-C7. To save space, for each investor type (column 1) we report information only about the behavioural variables whose estimated effects in Table 4.5 are consistent with the underlying theory's predictions. Panel A displays the outcomes of estimating Eq. (4.12) after using alternative approaches in the construction of *OIB*. Specifically, in column 3 the dependent variable measures the cumulative OIB over the next 5-day, 9-day, 12-day, and 2-week period. In column 4, it measures OIB based on the dollar value of limit orders. In column 5, it measures OIB based only on orders submitted during regular trading hours (i.e., from 9:00 am to 1:30 pm), and in column 6, it measures OIB based only on executed orders. "Robust" indicates that the sign of the coefficient of interest is the same as in our base specification (Table 4.5), and the coefficient is statistically significant at conventional levels. Panel B displays the outcomes of estimating Eq. (4.12) after using alternative approaches in the construction of *PTV*, *STV*, and *RTV*. Specifically, in column 3 the length of the look-back window varies between 4 weeks and 52 weeks (but with gaps), for a total of 19 window lengths. In column 4, *PTV*, *STV*, and *RTV* are constructed using alternative reference points or counterfactuals (zero, the risk-free rate, and the stock's own sample mean return), and in column 5, they are constructed using alternative parameter values. Panel C displays the outcomes of estimating Eq. (4.12) on various sub-samples of data: In column 3, the results are based on a set of 12 rolling-window regressions. In column 4 (5, 6), the stocks in the sample are sorted into three segments by market capitalisation (price, turnover). The figures displayed in Panels B and C indicate in how many instances (out of the total number of tests that we run, as specified in the column header) the sign of the coefficient of interest is the same as in our base specification (Table 4.5) and the coefficient is statistically significant at least at the 5% level.

Table C4 Panel regressions: Behavioural-theory values and next 5-day, 9-day, 12-day, and 2-week *OIB*

Panel A
Dependent variable: Next 5-day *OIB*

	(1)	(2)	(3)	(4)	(5)
Investor type:	**All**	**Individual investor**	**Foreign investors**	**Others**	**Securities investment trusts**
PTV	-0.4359***	-0.7799***	0.3286**	0.3667**	2.8635***
	(-12.05)	(-14.26)	(2.32)	(2.42)	(6.82)
STV	-0.0610**	-0.0805**	0.4196***	-0.2483*	0.3037
	(-2.24)	(-2.01)	(3.71)	(-1.81)	(0.80)
RTV	3.1204***	5.6487***	-5.9220***	0.7543	-18.8600***
	(9.48)	(11.16)	(-4.20)	(0.47)	(-3.58)
Controls	Yes	Yes	Yes	Yes	Yes
Week FEs	0.3758	0.3395	0.2513	0.2729	0.1823
Adj. R-squared	199087	199087	187975	192432	45151
N	-0.4359***	-0.7799***	0.3286**	0.3667**	2.8635***

Panel B
Dependent variable: Next 9-day *OIB*

	(1)	(2)	(3)	(4)	(5)
Investor type:	**All**	**Individual investor**	**Foreign investors**	**Others**	**Securities investment trusts**
PTV	-0.4076***	-0.7445***	0.3962***	0.5033***	2.8066***
	(-11.60)	(-13.62)	(2.61)	(3.11)	(6.77)
STV	-0.0773***	-0.0870**	0.3777***	-0.2602*	0.2766
	(-2.69)	(-2.07)	(3.36)	(-1.82)	(0.71)
RTV	2.5892***	5.2259***	-6.7329***	0.2950	-16.9821***
	(7.16)	(9.88)	(-4.43)	(0.17)	(-3.30)
Controls	Yes	Yes	Yes	Yes	Yes
Week FEs	Yes	Yes	Yes	Yes	Yes
Adj. R-squared	0.3716	0.3127	0.2445	0.2444	0.1336
N	199026	199026	193418	194044	64482

Panel C
Dependent variable: Next 12-day *OIB*

	(1)	(2)	(3)	(4)	(5)
Investor type:	**All**	**Individual investor**	**Foreign investors**	**Others**	**Securities investment trusts**
PTV	-0.3696***	-0.6796***	0.3970***	0.4770***	2.8537***
	(-11.10)	(-13.26)	(2.68)	(2.97)	(6.95)
STV	-0.0768***	-0.0757*	0.3635***	-0.1914	0.3261
	(-2.78)	(-1.91)	(3.30)	(-1.34)	(0.81)
RTV	2.2920***	4.7043***	-6.6842***	-0.4283	-17.9913***
	(6.64)	(9.43)	(-4.59)	(-0.25)	(-3.55)
Controls	Yes	Yes	Yes	Yes	Yes
Week FEs	Yes	Yes	Yes	Yes	Yes
Adj. R-squared	0.3914	0.3296	0.2570	0.2597	0.1335
N	200752	200752	195385	196004	68377

Panel D
Dependent variable: Next 2-week *OIB*

	(1)	(2)	(3)	(4)	(5)
Investor type:	**All**	**Individual investor**	**Foreign investors**	**Others**	**Securities investment trusts**
PTV	-0.2928***	-0.5374***	0.3773***	0.4987***	2.3018***
	(-9.78)	(-11.85)	(2.69)	(3.30)	(6.01)
STV	-0.0744***	-0.0597*	0.3247***	-0.1931	0.4430
	(-3.02)	(-1.71)	(3.18)	(-1.46)	(1.18)
RTV	1.8853***	3.8698***	-6.4566***	-0.8587	-17.4692***
	(6.07)	(8.61)	(-4.71)	(-0.54)	(-3.64)
Controls	Yes	Yes	Yes	Yes	Yes
Week FEs	Yes	Yes	Yes	Yes	Yes
Adj. R-squared	0.4404	0.3743	0.2822	0.2991	0.1480
N	200796	200796	196359	196613	75072

This table reports the estimates generated by fitting variations on Eq. (4.12). In all specifications, the dependent variable is *OIB*, which measures a stock's OIB over the next 5-day (Panel A), 7-day (Panel B), 12-day (Panel C), and 2-week period (Panel D); this is constructed by aggregating orders across all investors (column 1) or only across individual investors (column 2), foreign investors (column 3), others (column 4), and securities investment trusts (column 5). Each regression equation includes the following control variables: *LOIB*, *WRet*, *MRet*, *HYRet*, *Turnover*, *Vol*, *Size*, *BM*, *CRO*, and *52WHMAX*. All the variables are as defined in Table 4.1. The sample period is from May 15, 2013 to March 28, 2018. The t-statistics in parentheses are based on standard errors clustered by stock and week. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table C5 Panel regressions: Behavioural-theory values and next-week *OIB* based on order value

	(1)	**(2)**	**(3)**	**(4)**	**(5)**
Investor type:	All	Individual investors	Foreign investors	Others	Securities investment trusts
PTV	-0.3379***	-0.5963***	0.3520**	0.4328***	2.4801***
	(-11.83)	(-13.93)	(2.60)	(3.23)	(7.35)
STV	-0.0561**	-0.0567*	0.3281***	-0.2035*	-0.0122
	(-2.53)	(-1.80)	(3.33)	(-1.78)	(-0.04)
RTV	2.5976***	4.6135***	-5.8578***	-0.5474	-13.4303***
	(8.91)	(11.15)	(-4.57)	(-0.39)	(-3.17)
Controls	Yes	Yes	Yes	Yes	Yes
Week FEs	Yes	Yes	Yes	Yes	Yes
Adj. R-squared	0.4701	0.4206	0.2966	0.3442	0.2238
N	201633	201633	194516	196135	57741

This table reports the estimates generated by fitting variations on Eq. (4.12). In all specifications, the dependent variable is *OIB*, which measures a stock's OIB in week t; this is constructed by aggregating the values of all orders (= price × number of shares) across all investors (column 1) or only across individual investors (column 2), foreign investors (column 3), others (column 4), and securities investment trusts (column 5). Each regression equation includes the following control variables: *LOIB*, *WRet*, *MRet*, *HYRet*, *Turnover*, *Vol*, *Size*, *BM*, *CRO*, and *52WHMAX*. All the variables are as defined in Table 4.1. The sample period is from May 15, 2013 to March 28, 2018. The t-statistics in parentheses are based on standard errors clustered by stock and week. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table C6 Behavioural-theory values and next-week *OIB* based on orders placed during regular trading hours

	(1)	(2)	(3)	(4)	(5)
Investor type:	All	Individual investors	Foreign investors	Others	Securities investment trusts
PTV	-0.2023***	-0.5119***	0.3538***	0.4726***	2.4838***
	(-7.15)	(-11.30)	(2.60)	(3.45)	(7.40)
STV	-0.1147***	-0.1113***	0.3433***	-0.2567**	-0.0057
	(-5.32)	(-3.27)	(3.43)	(-2.16)	(-0.02)
RTV	1.8405***	3.8897***	-5.9164***	-0.0089	-13.4356***
	(6.27)	(8.47)	(-4.58)	(-0.01)	(-3.18)
Controls	Yes	Yes	Yes	Yes	Yes
Week FEs	Yes	Yes	Yes	Yes	Yes
Adj. R-squared	0.2952	0.3216	0.2962	0.3215	0.2236
N	201631	201631	194435	195917	57678

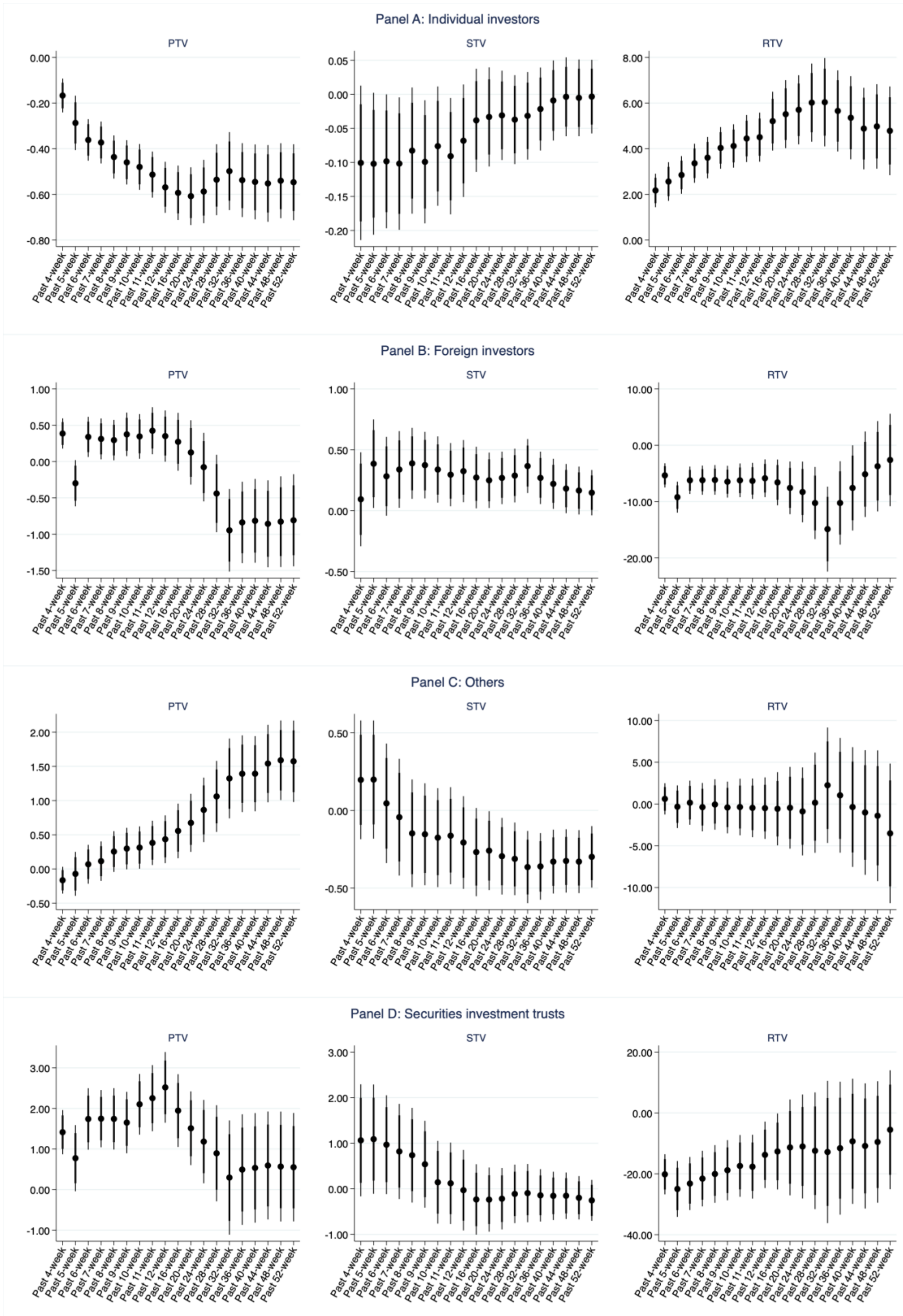
This table reports the estimates generated by fitting variations on Eq. (4.12). In all specifications, the dependent variable, *OIB*, measures a stock's OIB in week t, which is constructed by aggregating only orders placed during regular trading hours (i.e., from 9:00 am to 1:30 pm). In column 1, orders originating from all investors are included in the construction of *OIB*, whereas in column 2 (3, 4, 5) only orders originating from individual investors (foreign investors, others, securities investment trusts) are taken into account. Each regression equation includes the following control variables: *LOIB*, *WRet*, *MRet*, *HYRet*, *Turnover*, *Vol*, *Size*, *BM*, *CRO*, and *52WHMAX*. All the variables are as defined in Table 4.1. The sample period is from May 15, 2013 to March 28, 2018. The t-statistics in parentheses are based on standard errors clustered by stock and week. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table C7 Behavioural-theory values and next-week *OIB* based on executed orders

	(1)	(2)	(3)	(4)
Investor type:	Individual investors	Foreign investors	Others	Securities investment trusts
PTV	-0.3226***	0.8179***	0.5487***	2.4907***
	(-8.72)	(5.35)	(3.32)	(7.60)
STV	0.0078	0.1970*	-0.4576***	-0.0912
	(0.28)	(1.74)	(-3.03)	(-0.26)
RTV	1.6485***	-5.3627***	-0.7063	-13.0100***
	(5.13)	(-3.98)	(-0.40)	(-3.03)
Controls	Yes	Yes	Yes	Yes
Week FEs	Yes	Yes	Yes	Yes
Adj. R-squared	0.2612	0.1841	0.1561	0.2188
N	201572	193314	179665	58643

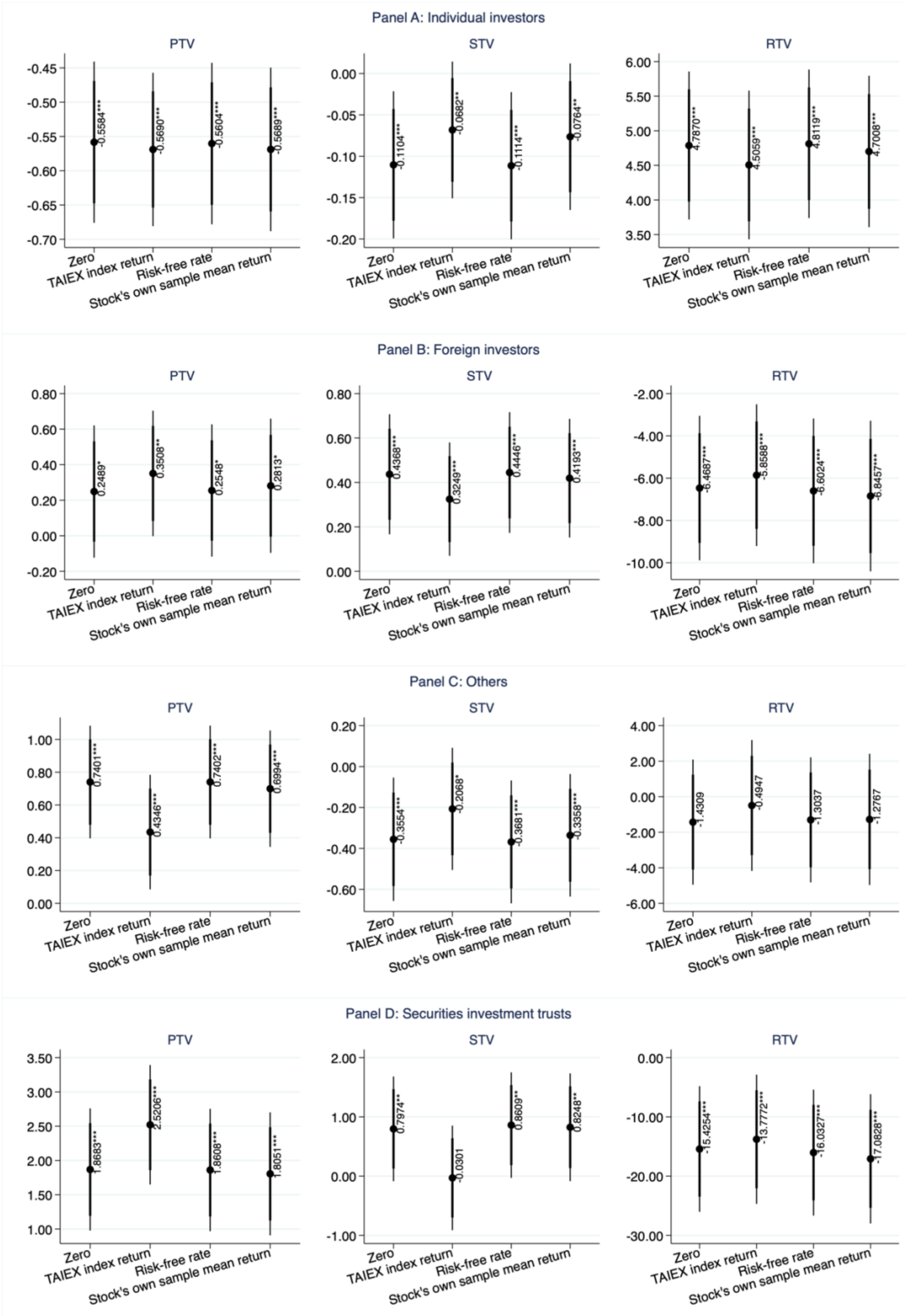
This table reports the estimates generated by fitting variations on Eq. (4.12). In all specifications, the dependent variable is *OIB*, which measures a stock's OIB in week t. This is constructed by aggregating the volume of all executed orders originating from individual investors (column 1), foreign investors (column 2), others (column 3), and securities investment trusts (column 4). Each regression equation includes the following control variables*:* *LOIB*, *WRet*, *MRet*, *HYRet*, *Turnover*, *Vol*, *Size*, *BM*, *CRO*, and *52WHMAX*. All the variables are as defined in Table 4.1. The sample period is from May 15, 2013 to March 28, 2018. The t-statistics in parentheses are based on standard errors clustered by stock and week. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Figure C1 Behavioural-theory values and next-week *OIB*: Alternative look-back window lengths



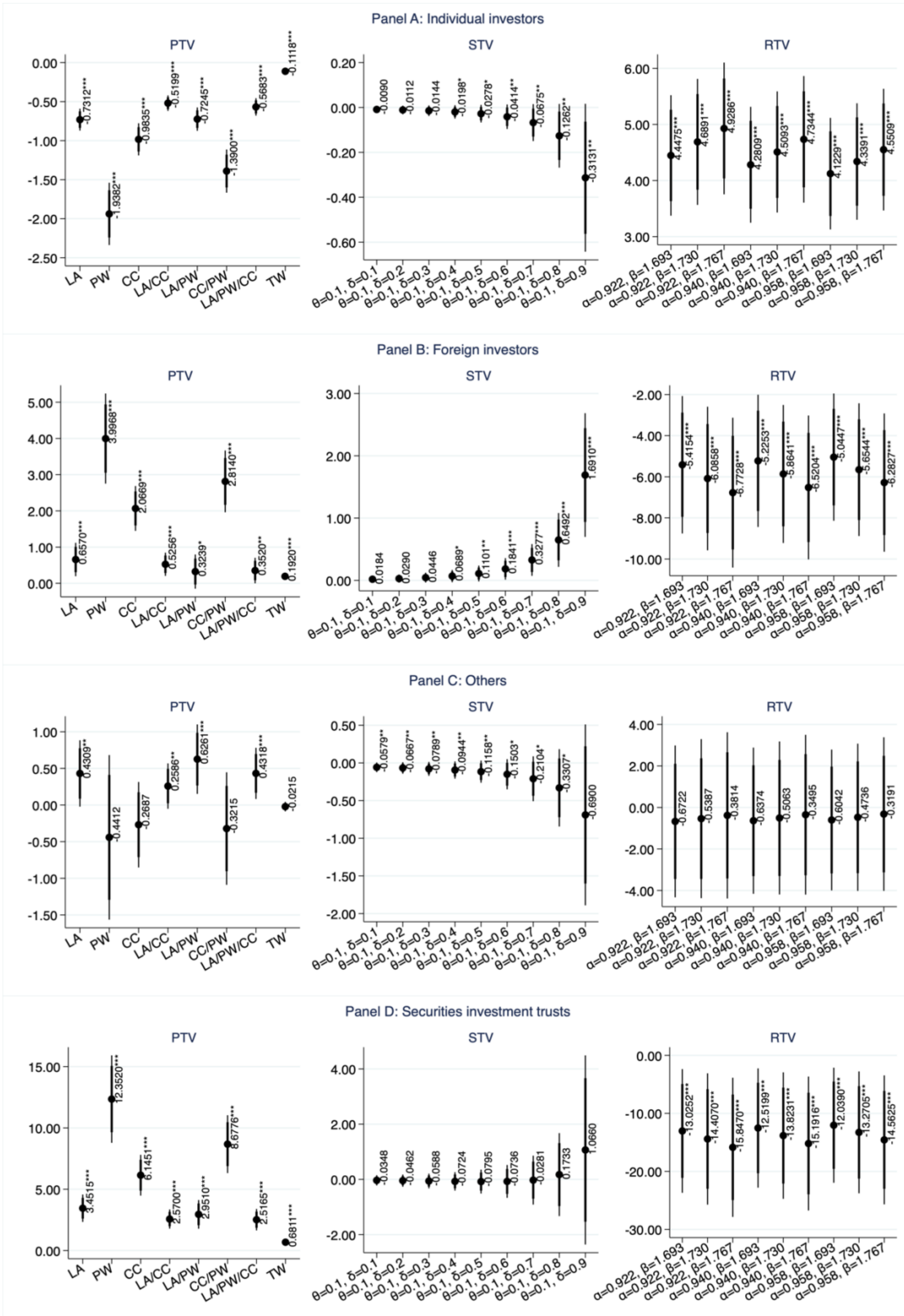
This figure plots the point estimates and the 95% and 99% confidence intervals of the coefficients on *PTV*, *STV*, and *RTV*, where the latter three variables are constructed under alternative look-back window lengths. All estimates are obtained by fitting Eq. (4.12). In all specifications, the dependent variable is *OIB*, which measures a stock's OIB in week t. This is constructed by aggregating all orders originating from individual investors (Panel A), foreign investors (Panel B), others (Panel C), and securities investment trusts (Panel D). *PTV*, *STV*, and *RTV* are the prospect theory value, salience theory value, and regret theory value of a stock's historical weekly return distribution from week t-j to week t-1, respectively, where j varies between 4 and 52 (with gaps) across specifications. For example, the label "Past 52-week" on the x-axis indicates that we measure a stock's *PTV*, *STV*, and *RTV* based on its historical weekly return distribution from week t-52 to week t-1. Each regression equation includes the following control variables: *LOIB*, *WRet*, *MRet*, *HYRet*, *Turnover*, *Vol*, *Size*, *BM*, *CRO*, and *52WHMAX*, which are defined in Table 4.1. The sample period is from May 15, 2013 to March 28, 2018. The confidence intervals are computed with double clustered (stock and week) standard errors.

Figure C2 Behavioural-theory values and next-week OIB: Alternative reference points and counterfactuals



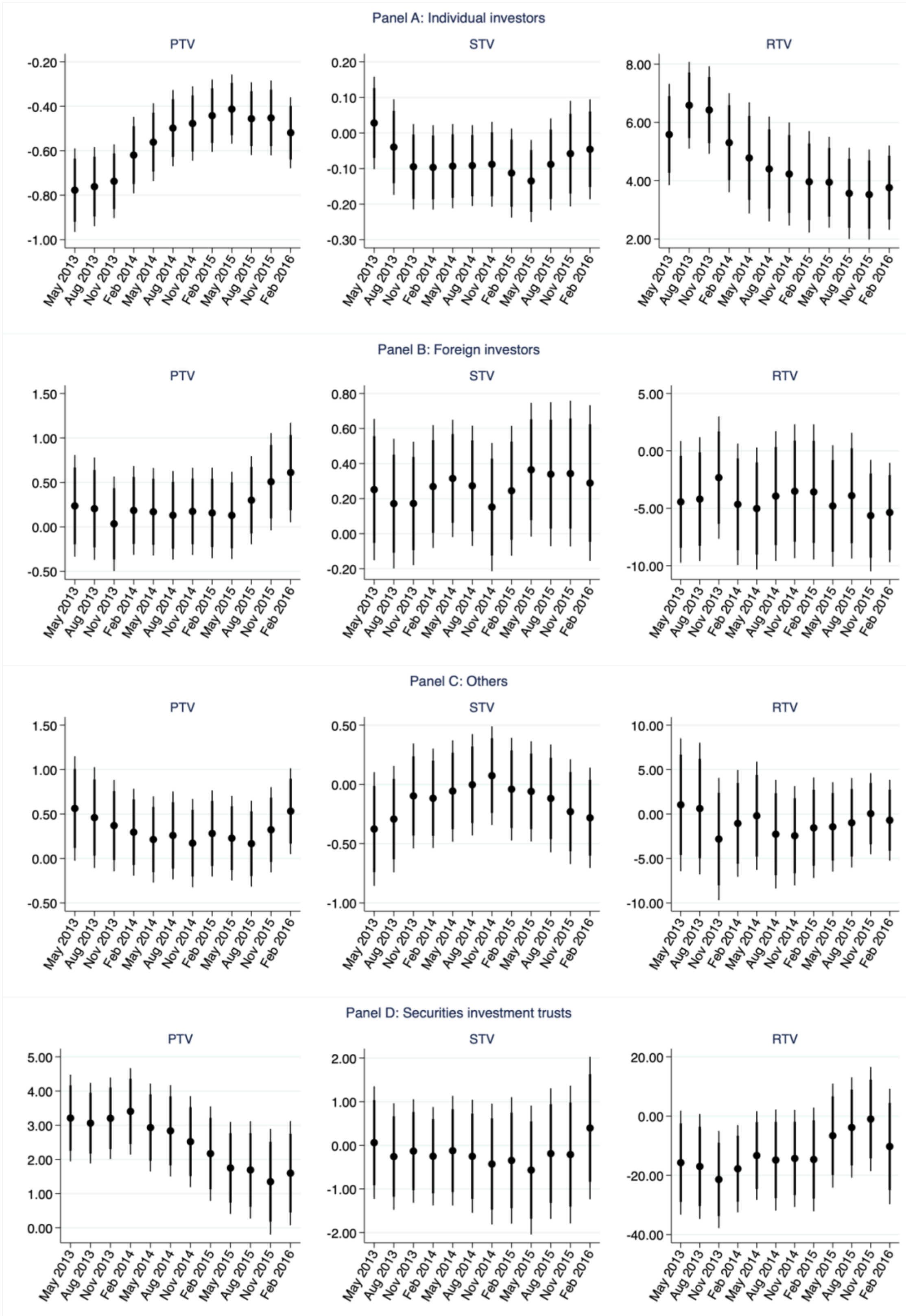
This figure plots the point estimates and the 95% and 99% confidence intervals of the coefficients on *PTV*, *STV*, and *RTV*, where the latter three variables are constructed on the basis of alternative reference points or counterfactuals. All estimates are obtained by fitting Eq. (4.12). In all specifications, the dependent variable is *OIB*, which measures a stock's OIB in week t. This is constructed by aggregating all orders originating from individual investors (Panel A), foreign investors (Panel B), others (Panel C), and securities investment trusts (Panel D). *PTV*, *STV*, and *RTV* are the prospect theory value, salience theory value, and regret theory value of a stock's historical weekly return distribution from week t-12 to week t-1, respectively. What varies across specifications is the reference point or counterfactual against which investors are assumed to evaluate a stock's return. We consider four possible reference points or counterfactuals: the return on the Taiwan capitalisation-weighted stock market index (TAIEX), zero, the risk-free rate of return, and the stock's own sample mean return. Each regression equation includes the following control variables: *LOIB*, *WRet*, *MRet*, *HYRet*, *Turnover*, *Vol*, *Size*, *BM*, *CRO*, and *52WHMAX*, which are defined in Table 4.1. The sample period is from May 15, 2013 to March 28, 2018. The confidence intervals are computed with double clustered (stock and week) standard errors.

Figure C3 Behavioural-theory values and next-week OIB: Alternative parameter values



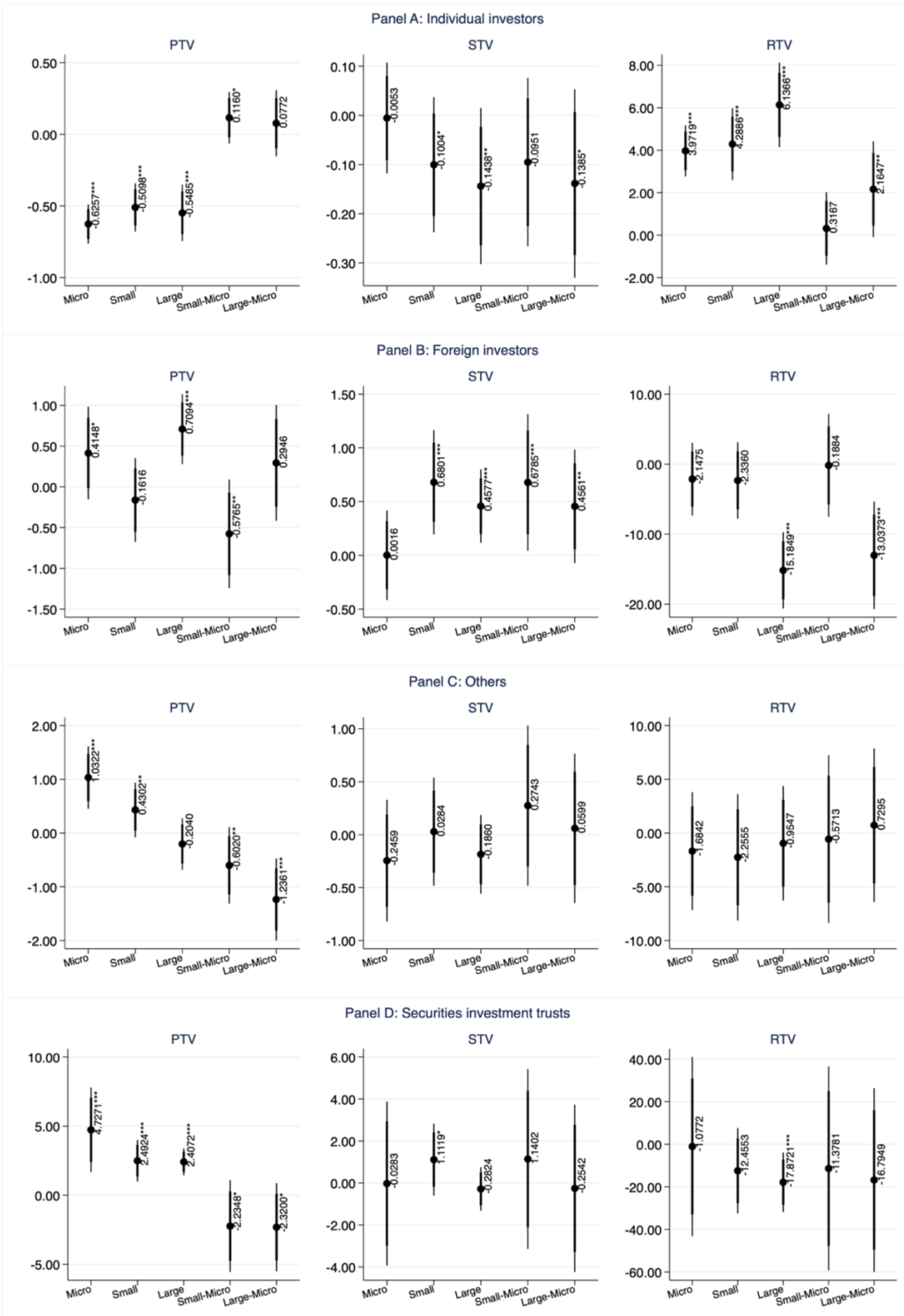
This figure plots the point estimates and the 95% and 99% confidence intervals of the coefficients on *PTV*, *STV*, and *RTV*, where the latter three variables are constructed using alternative parameter values. All estimates are obtained by fitting Eq. (4.12). In all specifications, the dependent variable is *OIB*, which measures a stock's OIB in week t. This is constructed by aggregating all orders originating from individual investors (Panel A), foreign investors (Panel B), others (Panel C), and securities investment trusts (Panel D). *PTV*, *STV*, and *RTV* are the prospect theory value, salience theory value, and regret theory value of a stock's historical weekly return distribution from week t-12 to week t-1, respectively. What varies across specifications are the values of the parameters that underlie the construction of the *PTV*, *STV*, and *RTV* variables. In the case of *PTV*, the "LA" label indicates that only the loss aversion component of PT is active (i.e., $c = d = 1$, $\lambda = 2.25$, $\gamma = 1$, $\rho = 1$), the "PW" label indicates that only the probability weighting component is active (i.e., $c = d = 1$, $\lambda = 1$, $\gamma = 0.61$, $\rho = 0.69$), and the "CC" label indicates that only the concavity/convexity component is active (i.e., $c = d = 0.88$, $\lambda = 1$, $\gamma = 1$, $\rho = 1$). Analogously, "LA/CC" indicates that $c = d = 0.88$, $\lambda = 2.25$, $\gamma = 1$, $\rho = 1$, "LA/PW" indicates that $c = d = 1$, $\lambda = 2.25$, $\gamma = 0.61$, $\rho = 0.69$, "CC/PW" indicates that $c = d = 0.88$, $\lambda = 1$, $\gamma = 0.61$, $\rho = 0.69$, and "LA/PW/CC" indicates that $c = d = 0.88$, $\lambda = 2.25$, $\gamma = 0.61$, $\rho = 0.69$. Lastly, "TW" indicates that *PTV* is constructed using the Taiwan-specific PT parameter values estimated by *Rieger et al.* (*2017*): $c = 0.26$, $d = 0.49$, $\lambda = 1.33$, $\gamma = \rho = 0.71$. In the case of *STV*, we hold θ constant at 0.1 and let the salience distortion parameter δ vary between 0.1 and 0.9. In the case of *RTV*, we let the values of α and β increase or decrease by one standard deviation (*Bleichrodt et al., 2010*). Each regression equation includes the following control variables: *LOIB*, *WRet*, *MRet*, *HYRet*, *Turnover*, *Vol*, *Size*, *BM*, *CRO*, and *52WHMAX*, which are defined in Table 4.1. The sample period is from May 15, 2013 to March 28, 2018. The confidence intervals are computed with double clustered (stock and week) standard errors.

Figure C4 Behavioural-theory values and next-week *OIB*: Rolling-window regressions



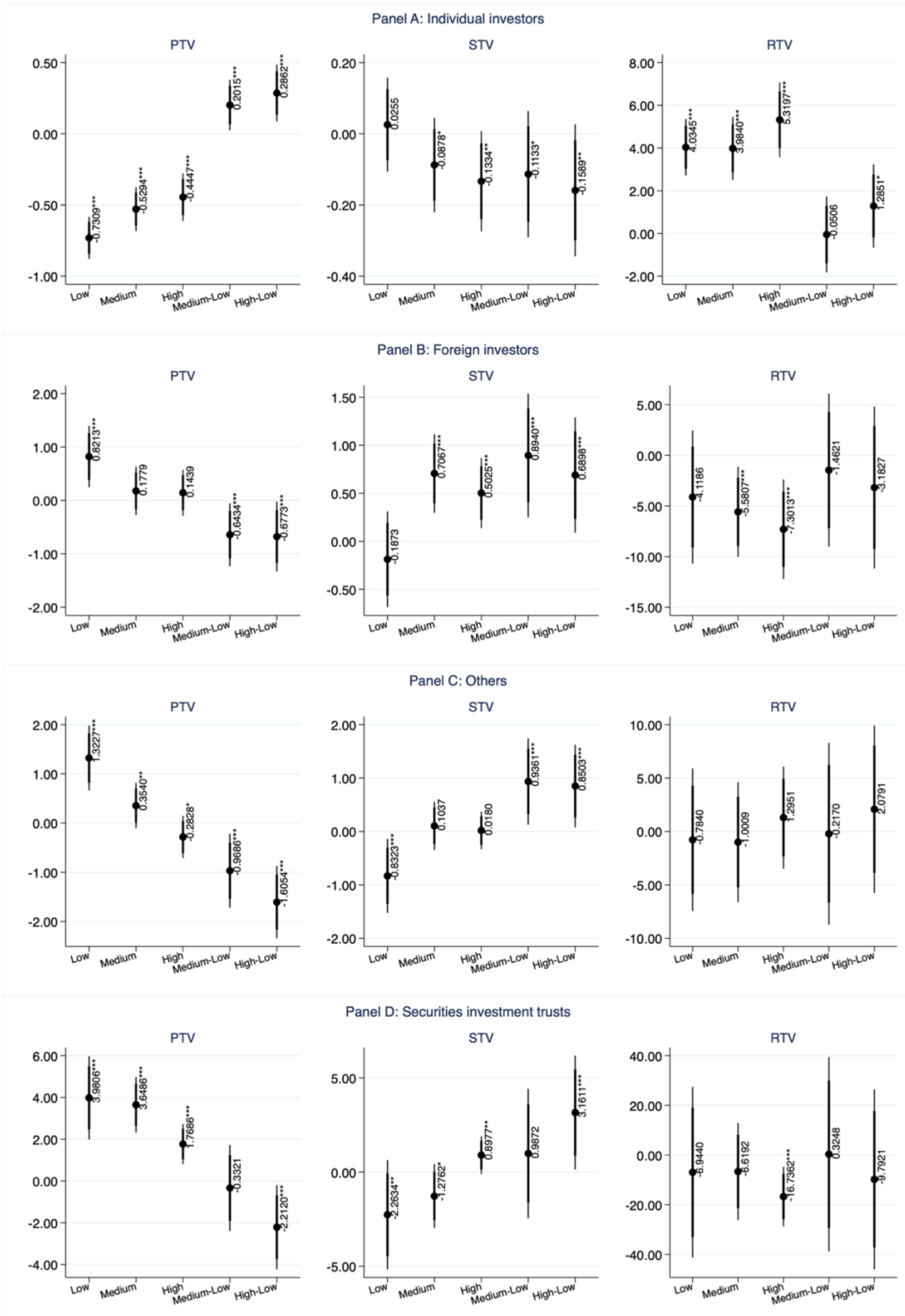
This figure plots the point estimates and the 95% and 99% confidence intervals of the coefficients on PTV, STV, and RTV from rolling-window regressions. All estimates are obtained by fitting Eq. (4.12). In all regressions, the dependent variable is OIB, which measures a stock's OIB in week t. This is constructed by aggregating all orders originating from individual investors (Panel A), foreign investors (Panel B), others (Panel C), and securities investment trusts (Panel D). PTV, STV, and RTV are the prospect theory value, salience theory value, and regret theory value of a stock's historical weekly return distribution from week t-12 to week t-1, respectively. 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 date of the rolling window. For example, "May 2013" indicates that the first regression is based on data from May 2013 to May 2015. Each regression equation includes the following control variables: *LOIB*, *WRet*, *MRet*, *HYRet*, *Turnover*, *Vol*, *Size*, *BM*, *CRO*, and *52WHMAX*, which are defined in Table 4.1. The confidence intervals are computed with double clustered (stock and week) standard errors.

Figure C5 Behavioural effects by size segment: Micro-cap, small-cap, and large-cap



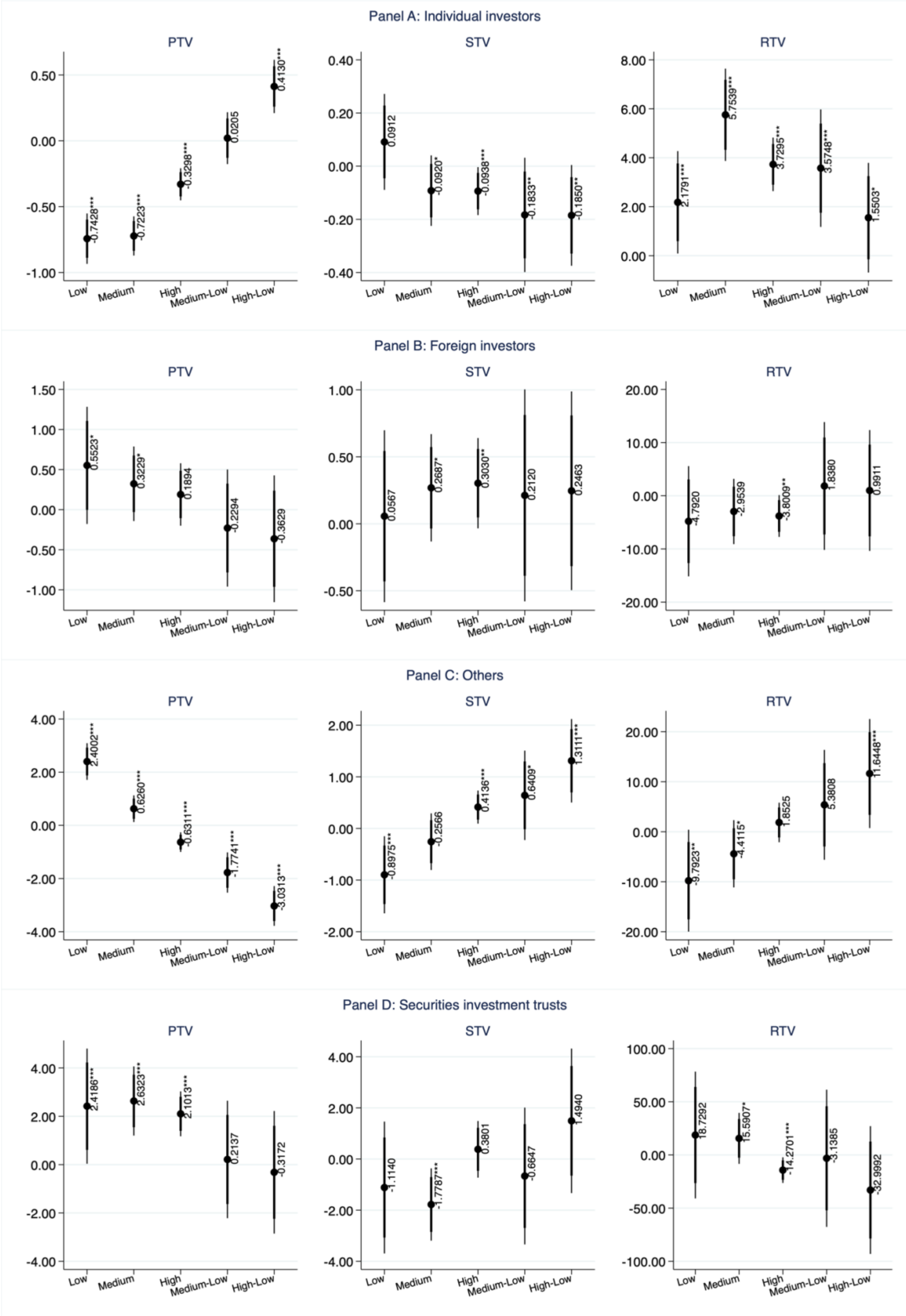
This figure plots the point estimates and the 95% and 99% confidence intervals of the coefficients on *PTV*, *STV*, and *RTV* for the micro-cap ("Micro"), small-cap ("Small"), and large-cap ("Large") market segments. At the end of each week, we sort stocks into size segments by market capitalisation: The micro-cap (small-cap, large-cap) segment consists of those stocks that account for the bottom 3% (middle 7%, top 90%) of total market capitalisation. We construct a dummy variable, *Small* (*Large*), that takes the value of 1 if a stock falls into the small-cap (large-cap) segment, and 0 otherwise. We then re-estimate regression Eq. 4.12 after adding to the model the *Small* and *Large* dummy variables, interactions between *Small* and *PTV*, *STV*, and *RTV,* and interactions between *Large* and *PTV*, *STV*, and *RTV*. In all specifications, the dependent variable is *OIB*, which measures a stock's OIB in week t. This is constructed by aggregating all orders originating from individual investors (Panel A), foreign investors (Panel B), others (Panel C), and securities investment trusts (Panel D). *PTV*, *STV*, and *RTV* are the prospect theory value, salience theory value, and regret theory value of a stock's historical weekly return distribution from week t-12 to week t-1, respectively. The control variables are *LOIB*, *WRet*, *MRet*, *HYRet*, *Turnover*, *Vol*, *Size*, *BM*, *CRO*, and *52WHMAX*, which are defined in Table 4.1. The sample period is from May 15, 2013 to March 28, 2018. The confidence intervals are computed with double clustered (stock and week) standard errors.

Figure C6 Behavioural effects by price segment: Low-price, medium-price, and high-price



This figure plots the point estimates and the 95% and 99% confidence intervals of the coefficients on *PTV*, *STV*, and *RTV* for the low-price ("Low"), medium-price ("Medium"), and high-price ("High") market segments. At the end of each week, we sort stocks into terciles by closing price: The low-price (medium-price, high-price) segment consists of those stocks that fall in the bottom (middle, top) tercile. We construct a dummy variable, *Medium* (*High*), that takes the value of 1 if a stock falls into the medium-price (high-price) segment, and 0 otherwise. We then re-estimate regression Eq. 4.12 after adding to the model the *Medium* and *High* dummy variables, interactions between *Medium* and *PTV*, *STV*, and *RTV,* and interactions between *High* and *PTV*, *STV*, and *RTV*. In all specifications, the dependent variable is *OIB*, which measures a stock's OIB in week t. This is constructed by aggregating all orders originating from individual investors (Panel A), foreign investors (Panel B), others (Panel C), and securities investment trusts (Panel D). *PTV*, *STV*, and *RTV* are the prospect theory value, salience theory value, and regret theory value of a stock's historical weekly return distribution from week t-12 to week t-1, respectively. The control variables are *LOIB*, *WRet*, *MRet*, *HYRet*, *Turnover*, *Vol*, *Size*, *BM*, *CRO*, and *52WHMAX*, which are defined in Table 4.1. The sample period is from May 15, 2013 to March 28, 2018. The confidence intervals are computed with double clustered (stock and week) standard errors.

Figure C7 Behavioural effects by turnover segment: Low-turnover, medium-turnover, and high-turnover



This figure plots the point estimates and the 95% and 99% confidence intervals of the coefficients on *PTV*, *STV*, and *RTV* for the low-turnover ("Low"), medium-turnover ("Medium"), and high-turnover ("High") market segments. At the end of each week, we sort stocks into terciles by turnover: The low-turnover (medium-turnover, high-turnover) segment consists of those stocks that fall in the bottom (middle, top) tercile. We construct a dummy variable, *Medium* (*High*), that takes the value of 1 if a stock falls into the medium-turnover (high-turnover) segment, and 0 otherwise. We then re-estimate regression Eq. 4.12 after adding to the model the *Medium* and *High* dummy variables, interactions between *Medium* and *PTV*, *STV*, and *RTV,* and interactions between *High* and *PTV*, *STV*, and *RTV*. In all specifications, the dependent variable is *OIB*, which measures a stock's OIB in week t. This is constructed by aggregating all orders originating from individual investors (Panel A), foreign investors (Panel B), others (Panel C), and securities investment trusts (Panel D). *PTV*, *STV*, and *RTV* are the prospect theory value, salience theory value, and regret theory value of a stock's historical weekly return distribution from week t-12 to week t-1, respectively. The control variables are *LOIB*, *WRet*, *MRet*, *HYRet*, *Turnover*, *Vol*, *Size*, *BM*, *CRO*, and *52WHMAX*, which are defined in Table 4.1. The sample period is from May 15, 2013 to March 28, 2018. The confidence intervals are computed with double clustered (stock and week) standard errors.

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