Explaining cryptocurrency returns: A prospect theory perspective[†]

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Abstract

We investigate 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.

JEL classification codes: G11, G12, G41

Keywords: prospect theory, behavioural asset pricing, cryptocurrency, cross-section of returns

[†]We thank Larisa Yarovaya and participants at the Cryptocurrency Research Conference 2021 for helpful comments and suggestions.

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Declaration of interest: None

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* reviews the related literature and develops our hypotheses. Section *3* describes the data, illustrates how the PT value of a cryptocurrency is constructed, and describes the control variables. Section *4* details and discusses the main results of the empirical analysis. Section *5* summarises further analyses and robustness tests, and Section *6* concludes.

2. Literature review and hypotheses development

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. 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.[1] 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

[1] 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.

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.

2.3. 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.

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.

3. Data description and variables

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.[2] 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.[3] 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.[4] The number of active cryptocurrencies over the sample period is plotted in *Figure 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.

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[2] 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.
[3] 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.
[4] 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.

<Please insert *Figure 1* here>

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.[5] 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*).

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 Online Appendix). Our

[5] 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.

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.[6]

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.[7] 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:

$$PTV = \sum_{i=-m}^{n} \pi_i \, v(r_i) \tag{1}$$

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

$$v(r_i) = \begin{cases} r_i^{\alpha} & \text{if } r_i \geq 0 \\ -\lambda(-r_i)^{\beta} & \text{if } r_i < 0 \end{cases} \tag{2}$$

[6] 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 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 Online Appendix shows that our results are robust to the length of the time window used in the *editing* phase.

[7] The cryptocurrency market index is constructed as the value-weighted price of the active cryptocurrencies in the sample. Table A11 in the Online Appendix 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).

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

$$\pi_i = \begin{cases} w^+\left(\frac{n-i+1}{52}\right) - w^+\left(\frac{n-i}{52}\right) & \text{for } 0 \leq i \leq n \\ w^-\left(\frac{m+i+1}{52}\right) - w^-\left(\frac{m+i}{52}\right) & \text{for } -m \leq i < 0 \end{cases} \tag{3}$$

with

$$w^+(p) = \frac{p^\gamma}{(p^\gamma + (1-p)^\gamma)^{\frac{1}{\gamma}}}, \quad w^-(p) = \frac{p^\delta}{(p^\delta + (1-p)^\delta)^{\frac{1}{\delta}}} \tag{4}$$

being the probability weighting functions.[8]

Eqs. (2) to *(4)* contain five parameters, namely α, β, λ, γ and δ. We set them equal to the values that *Tversky and Kahneman* (*1992*) estimated based on their laboratory experiments: $\alpha = \beta = 0.88$, $\lambda = 2.25$, $\gamma = 0.61$, $\delta = 0.69$.[9] 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. (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

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

[9] 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 *4.8* we repeat our analysis using a set of country-specific parameter estimates and show that the results are robust.

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.

3.3. Control variables and summary statistics

< Please insert *Table 1* here>

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 1*.

To mitigate the impact of outliers, we winsorise all variables at the 1st and 99th percentiles separately for each week. *Table 2* presents a set of average cross-sectional summary statistics.[10] 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).

< Please insert *Table 2* here>

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

4. Empirical Analysis

4.1. Cross-sectional relationship between *PTV* and future returns

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.[11] 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.[12]

Table 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-

[11] 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.
[12] 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.

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-weighted ones, which suggests that the predictive power of PT is more pronounced among small market-cap cryptocurrencies.[13]

< Please insert *Table 3* here>

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:

$$Return_{i,t} = \beta_0 + \beta_1 PTV_{i,t-1} + \beta_2 Beta_{i,t-1} + \beta_3 Size_{i,t-1} + \beta_4 Mom_{i,t-1} + \beta_5 Rev_{i,t-1} + \beta_6 Illiq_{i,t-1} + \beta_7 Lt\_rev_{i,t-1} + \beta_8 Vol_{i,t-1} + \beta_9 Ivol_{i,t-1} + \beta_{10} Max_{i,t-1} + \beta_{11} Min_{i,t-1} + \text{Time FE} + e_{i,t} \quad (5)$$

where $Return_{i,t}$ represents cryptocurrency i's log return in excess of the risk-free rate in week t,

[13] 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 Online Appendix).

and the regressors are as defined in *Table 1*. To address the dependence in the error term, we estimate two-way clustered standard errors by cryptocurrency and week.[14]

We initially estimate *Eq. (5)* without any control variables (column 1 of *Table 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 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.[15] 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.

Column 3 (*Table 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*).[16]

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[14] *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.

[15] 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).

[16] Table A5 in the Online Appendix 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.

The skewness-related variables appear in columns 9-12 of *Table 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 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 4*.[17]

< Please insert *Table 4* here>

4.2. Time-series relationship between *PTV* and future returns

Next, we use panel regressions similar to *Eq. (5)* but with cryptocurrency FE to exploit the second dimension of our dataset. By removing the variation across cryptocurrencies and

[17] 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.

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 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 result lends support to *H2*.[18] According to our preferred equation (column 7 of *Table 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%.[19]

Based on the estimates in column 10 of *Table 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.

< Please insert *Table 5* here>

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 ($= excess\ return_{i,t} -$

[18] Table A6 in the Online Appendix 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.
[19] 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).

$\widehat{Beta_{i,t}} \times market\ excess\ return_t$) as the dependent variable. In both instances, the estimates reveal that our results are robust (see columns 1-2 of Table A8 in the Online Appendix).

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. (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 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.[20] Our preferred model (column 7 of *Table 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.[21]

< Please insert *Table 6* here>

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

[20] 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 Online Appendix). 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 Online Appendix).

[21] 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 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.

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.

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 7*, are to a large extent consistent with our expectations. The coefficients on the interaction terms $PTV \times Size$ and $PTV \times Age$ are statistically significant at the 5% level, and the coefficients on the interaction terms $PTV \times Vol$ and $PTV \times Ivol$ 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, the coefficient on the interaction term *PTV*×*Illiq* is negative as expected but not statistically significantly different from zero.

< Please insert *Table 7* here>

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* 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.[22]

[22] 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 Online Appendix). Considering that for several of these sectors the number

<Please insert *Figure 2* here >

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 8*. Column 7, where all three components are active, represents the benchmark and is identical to column 7 of *Table 6*. In column 1 (*Table 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* (γ, δ) and *CC* (α, β) equal to 1 in *Eqs. (2)* and *(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 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

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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.

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.

< Please insert *Table 8* here>

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:

$$EU = \sum_{i=-m}^{n} \frac{1}{52} \frac{(1 + R_i)^{1-\theta}}{1 - \theta} \tag{6}$$

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 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.

< Please insert *Table 9* here>

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 Online Appendix). 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 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 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.

<Please insert *Figure 3* here>

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 Online Appendix, 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).

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.

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Tables and Figures

Table 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. 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.

Table 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.

Table 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 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.

Table 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 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 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 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 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.

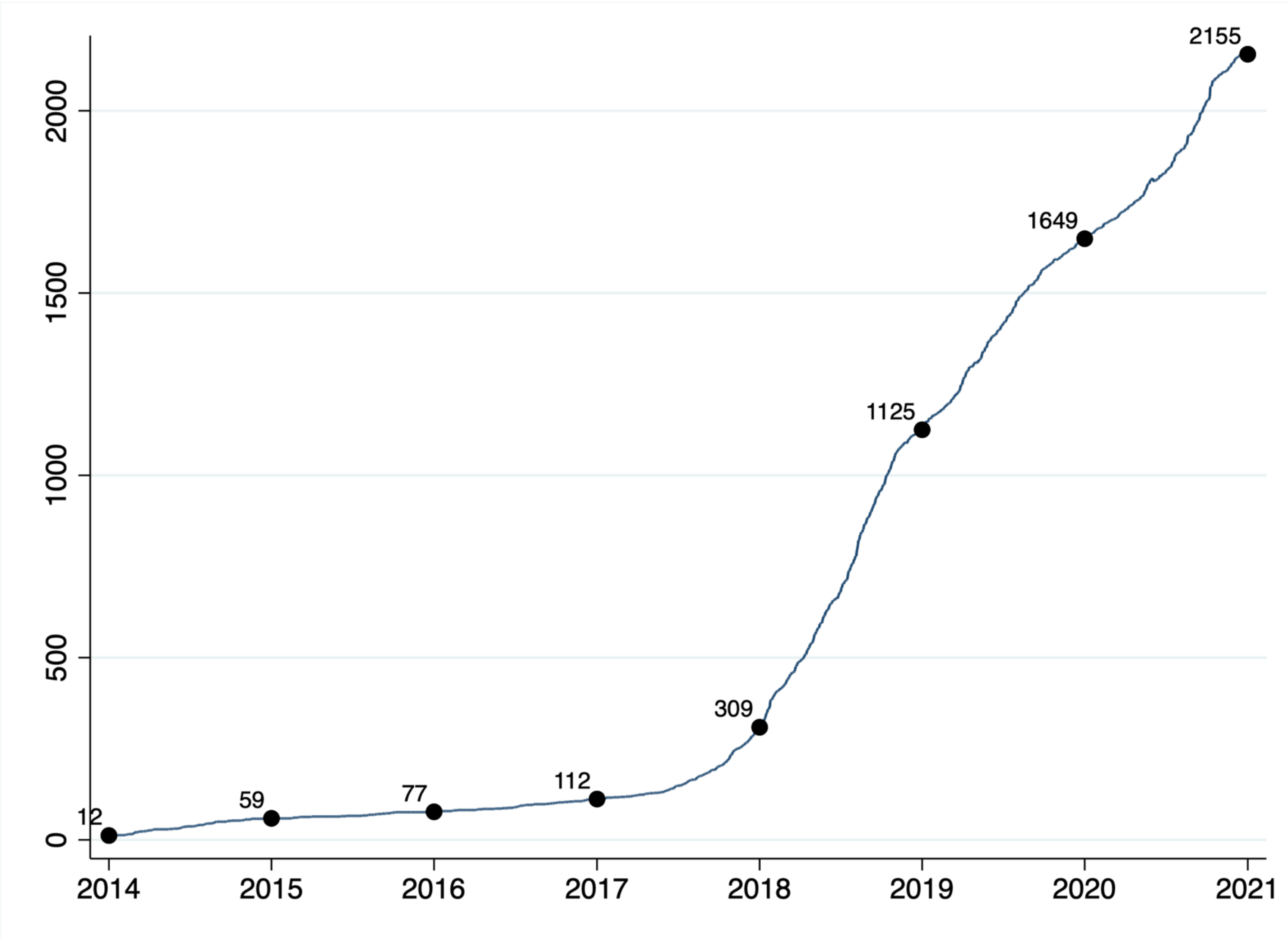
Table 9. *PTV* vs. expected utility value

	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

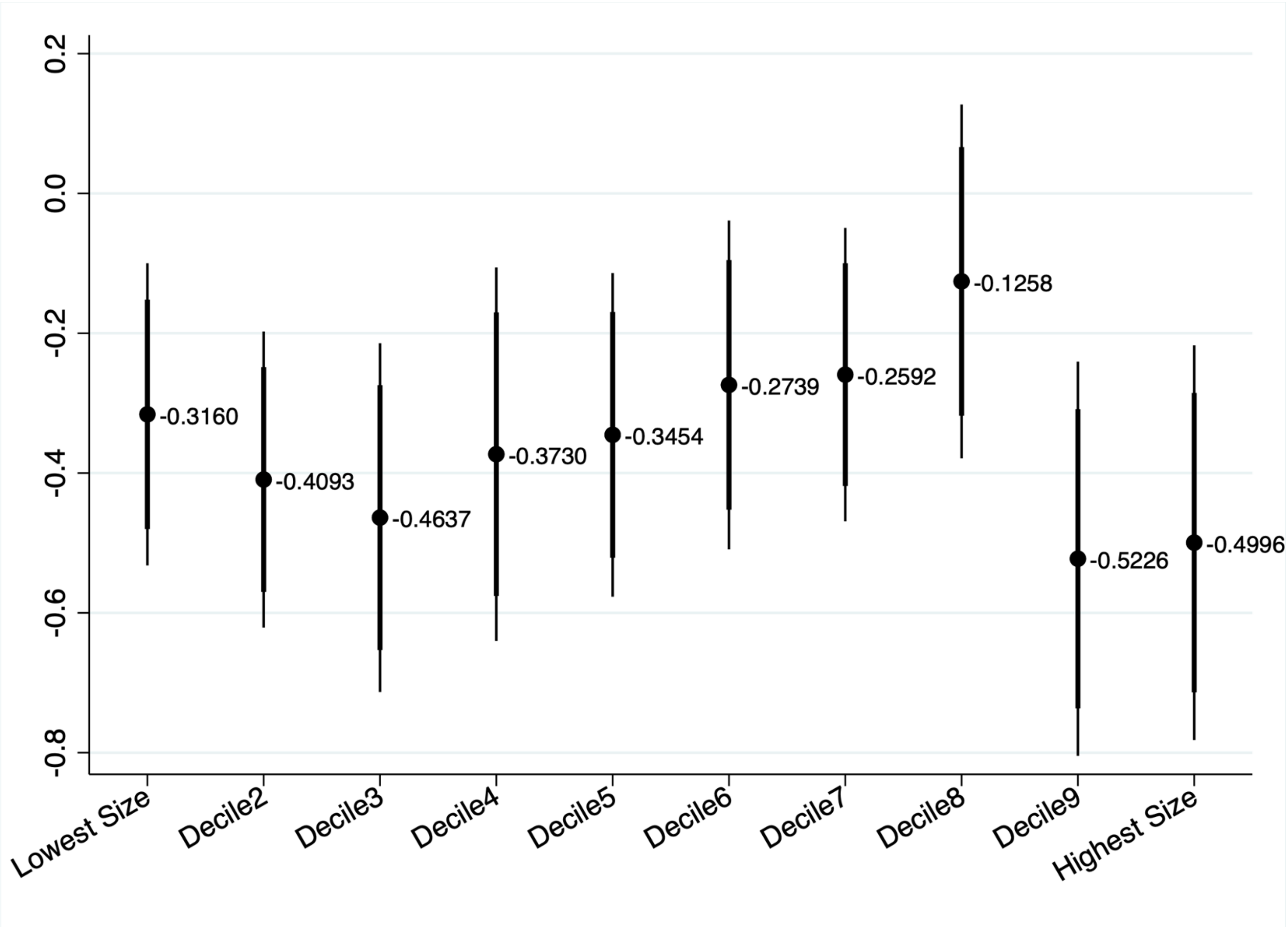
This table reports estimates of panel regressions with two-way FE (cryptocurrency and week). Only the relevant coefficients are displayed. In all specifications, the dependent variable is the one-week-ahead excess return of the given cryptocurrency, and the controls are *Size*, *Mom*, *Rev*, *Illiq*, *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 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.

Figure 1. Number of active cryptocurrencies over time



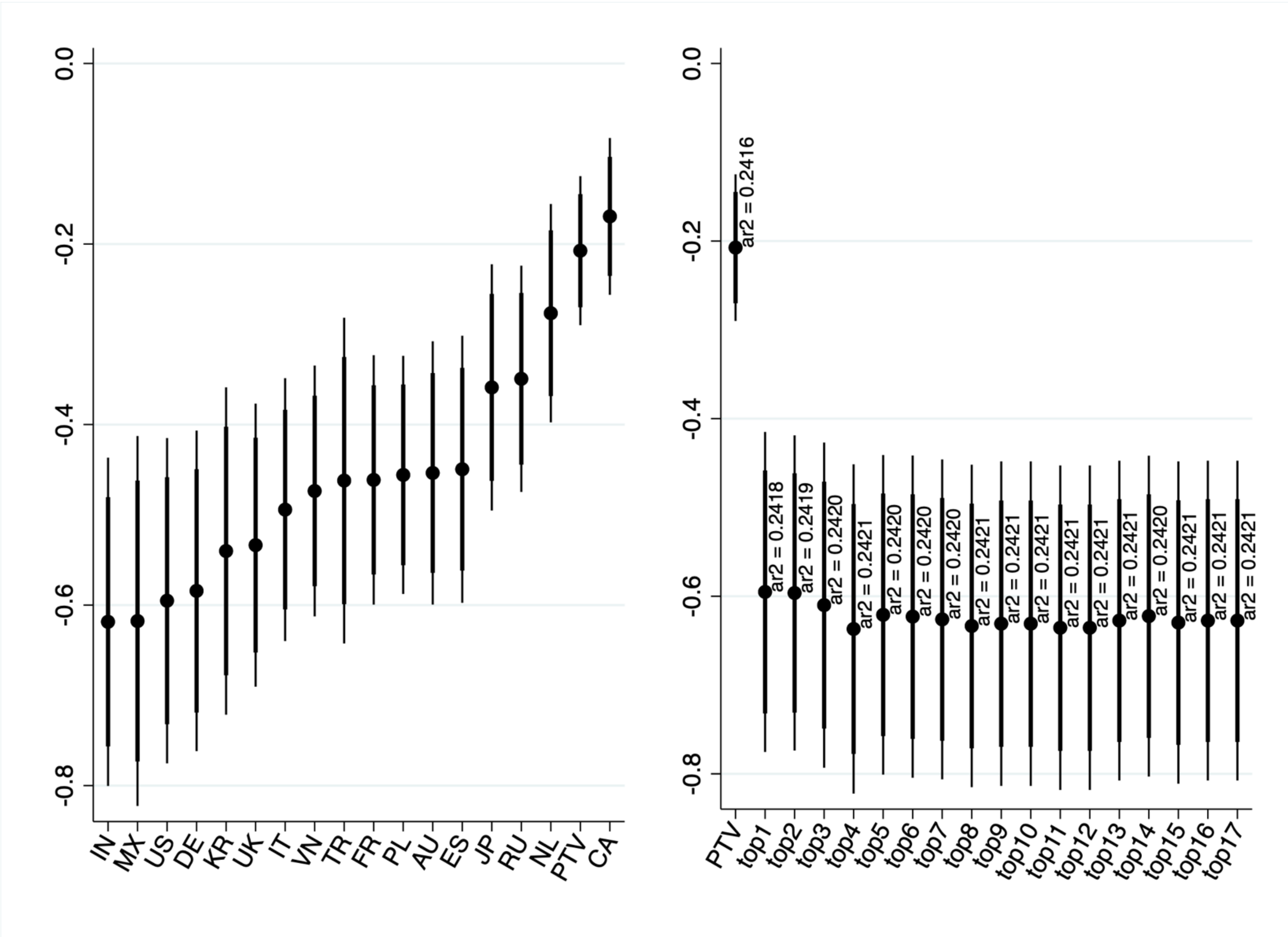
This figure plots the number of active cryptocurrencies in our dataset between the start and the end of our sample period, which runs from January 1, 2014 to December 31, 2020. The labels along the solid line show the number of active cryptocurrencies on January 1 of each year, with the exception of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

Figure 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 1. The confidence intervals are based on standard errors clustered by cryptocurrency and week.

Figure 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.

Online Appendix for

“Explaining cryptocurrency returns: A prospect theory perspective”

Abstract

In this Online 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 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 4.1.2 of the main paper.

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

Column 3 of Table 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 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.[23] 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.

[23] 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.

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 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 *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*).[24] 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

[24] 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).

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.

Tables and Figures

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 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 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

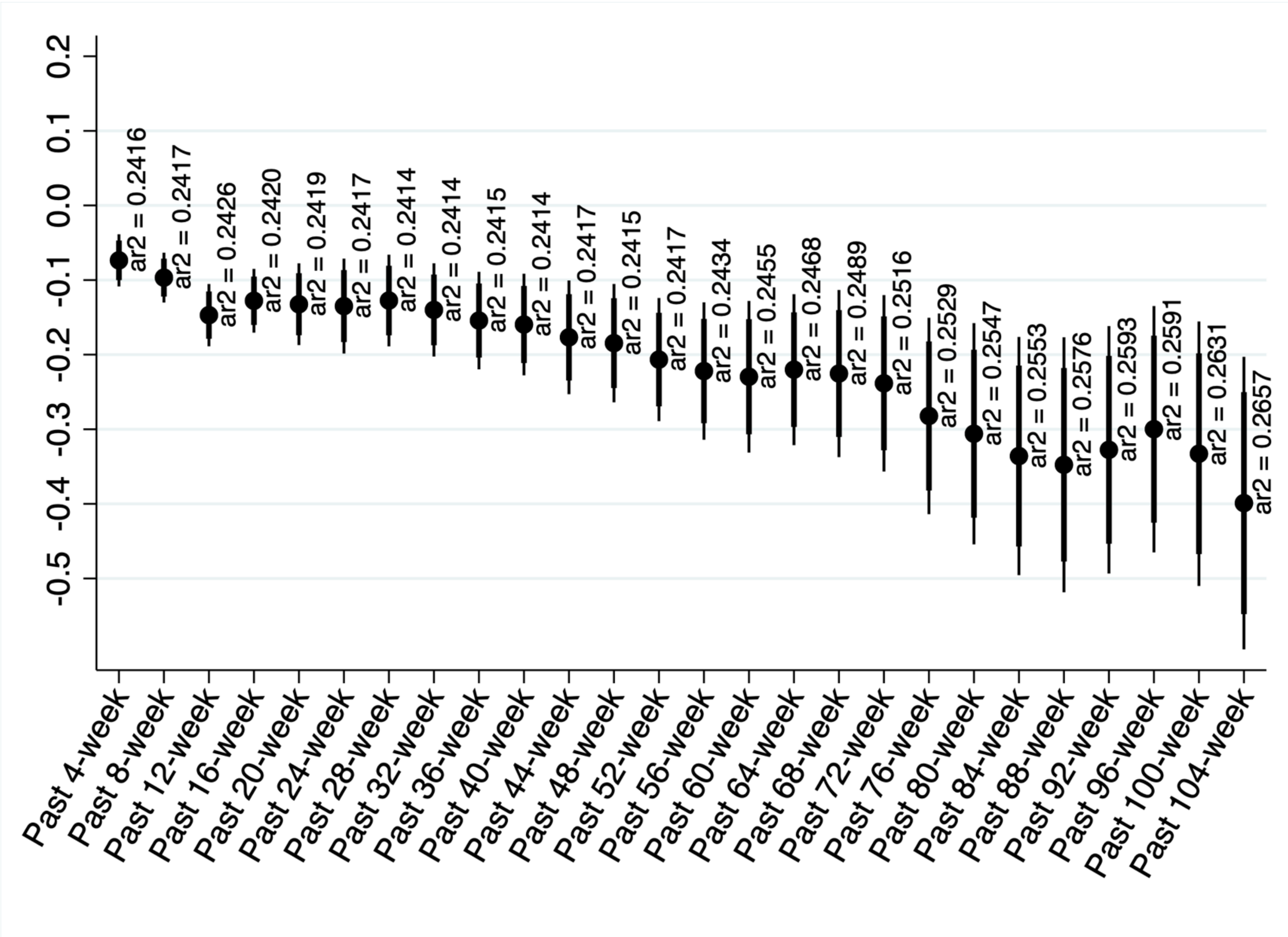
This table reports estimates of panel regressions with two-way FE (cryptocurrency and week). In all specifications, the dependent variable is the one-week-ahead excess return of the given cryptocurrency. In column 1, the *PTV* variable is constructed under the assumption that, instead of evaluating the 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

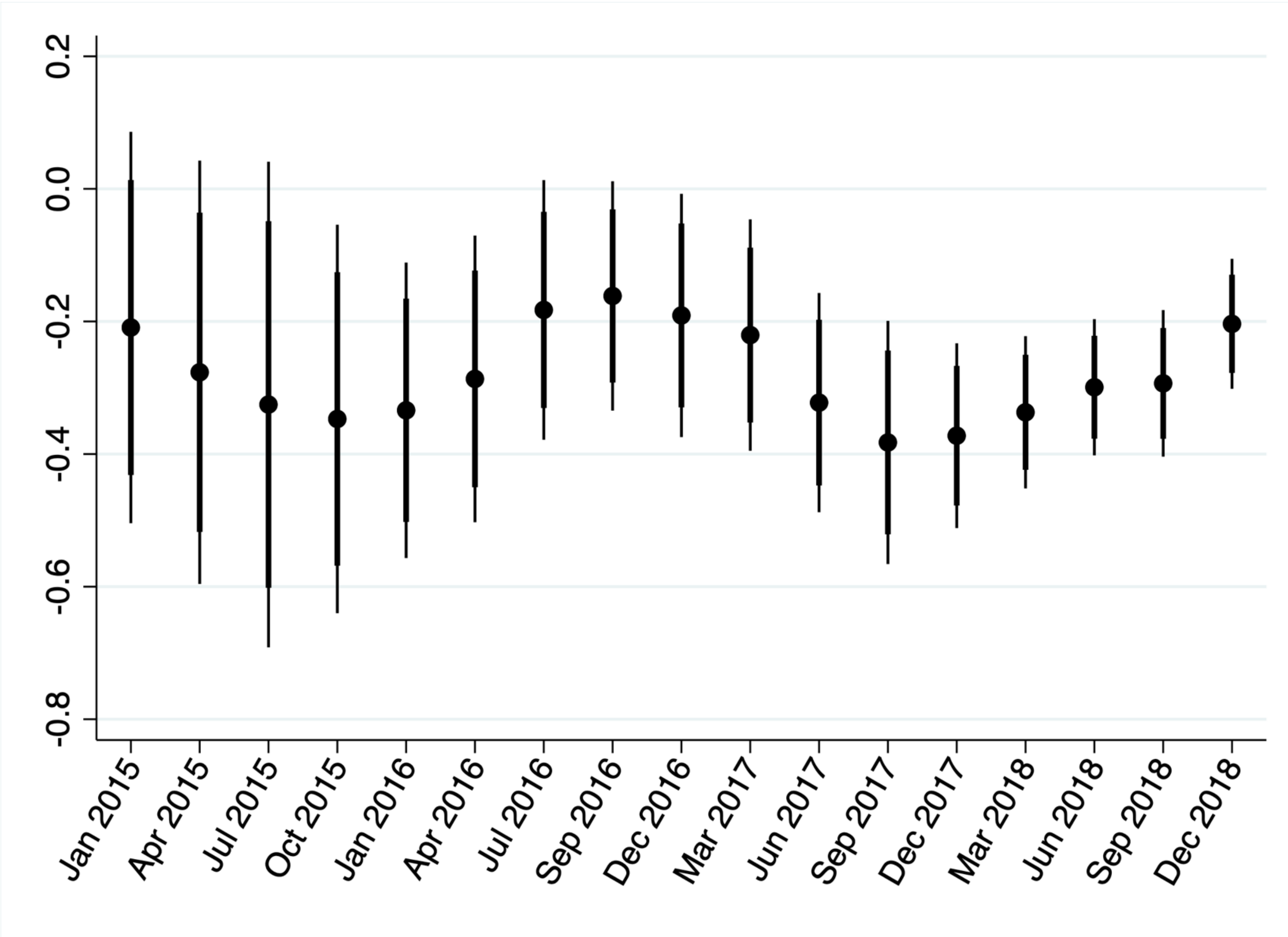
This table presents estimates of panel regressions with two-way FE (cryptocurrency and week). In all specifications, the dependent variable is the one-week-ahead excess return of the given cryptocurrency. *PTV*, which is the PT value of a cryptocurrency's historical return distribution from week t-52 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* (*HighBitcoinWikiSearch*) 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 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 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 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.

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