A Prospect Theory Model for Predicting Cryptocurrency Returns *

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Abstract

This paper investigates the risk and return properties of a trading strategy for the cryptocurrency market. The main predictive power for portfolio formation comes from a simple prospect theory model that only uses price information readily available. The dataset consists of a large body of cryptocurrencies from 2014 to 2020. I find a strong outperformance over the market, even after controlling for known predictors. Factor regressions with a cryptocurrency three-factor model further reveal significant alphas. Robustness test emphasize the legitimacy of the strategy. On average, cryptocurrencies with a high (low) prospect theory value earn low (high) subsequent returns. Interestingly, traders in the cryptocurrency market seem to assess the attractiveness of cryptocurrency in a way described by prospect theory. Mechanical tests of the model show that probability weighting is a main driver behind this assessment. Cryptocurrencies with a high prospect theory value tend to be highly positively skewed. This skewness could be the reason why the cryptocurrency seems attractive to traders, similar to lottery-like gambles.

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1 Introduction

Barberis et al. (2016) developed a model based on prospect theory (Kahneman and Tversky (1979) and Tversky and Kahneman (1992)) that allow them to describe the attitude of investors towards risk in the stock market better than a standard expected utility framework. Their storyline is framed around US stock investors and their behaviour when analyzing stocks in a intuitive way: Investors inform themselves about a stock by looking at the price chart. Then they mentally represent the historical return distribution of that stock and evaluate that distribution in a way described by prospect theory. Thus investors form an opinion about the future price development of that stock. In that sense, every stock at any given time in the dataset can be attributed a prospect theory value. Investors tilt their portfolio towards high prospect theory value stocks and away from low prospect theory stocks. On average, the price of high prospect theory value stocks will rise and thus those stocks will earn low subsequent returns. The price on low prospect theory value stocks on the other hand will fall and those stocks will earn high subsequent returns on average. In a nutshell, their hypothesis is that the prospect theory value predicts future stock returns with a negative sign in the cross-section. Barberis et al. (2016) use US stock data but also find international evidence in support of their hypothesis. They report a significant risk-adjusted outperformance of their model with excess returns of up to 1.35% and monthly alphas of up to 1.3% for long-short portfolios. Furthermore, they show that these results are stronger for small cap stocks, illiquid stocks and stocks with high idiosyncratic volatility. Their explanation for that is that making investments according to prospect theory is a more accurate descriptive of individual (retail) investors behaviour than of a institutional investors behaviour. This is because institutional investors mostly follow a more sophisticated investment approach. Institutional investors have better and faster access to data and can run complex (quantitative) models on their systems.

There are two main takeaways out of all this for financial (portfolio management) research: A) The prospect theory value works as a predictive signal for stocks and B) the framework of how investors look at investment information and mentally process that information and ultimately make decisions based on that can be well described by prospect theory. Thus, it is worth to further adapt the framework to other asset classes and markets because what works for stocks ought to also work for other assets that are bought and sold by (individual) investors. Otherwise, we would have to take the results of Barberis et al. (2016) with a grain of salt and we would need to ask why only stock investors evaluate and invest according to this framework. Furthermore, if an investor were to invest in multiple asset classes, it would be even harder to rationalize the fact that he or she evaluates stocks according to prospect theory but for instance bonds according to an other framework, e.g. standard utility. By adapting the same methodology to other asset classes not only helps us understand the behaviour of investors in other asset classes and markets better (and hopefully yields a strong predictive signal for those assets) but also increases the credibility of the entire framework of Barberis et al. (2016).

Since cryptocurrencies are very volatile in nature, large intraday swings can occur at any time and thus large gains as well as losses are perceived to be more "normal" or usual than in other asset classes. The trend in cryptocurrency prices has certainly been positive over the years and at the hype of the bubble late 2017, many retail investors jumped the bandwagon. *FOMO* (fear of missing out) and herding are typical behavioural biases observed in the cryptocurrency market. This is further accelerated by the lack of any sort of fundamental values in cryptocurrencies that would revert prices back to some fundamental anchor. An investor in the cryptocurrency market mostly only observes market factors, i.e. data on prices, volumes and market capitalizations but not fundamental values like accounting or economic data. Given all this, the level of sophistication of investment decisions made in the cryptocurrency market shouldn't be as high as in other asset classes. The market is still very young, to some extent unregulated and many financial intermediaries are still afraid to enter it. Individual investors play a big role in the cryptocurrency market.

This paper adopts the approach of Barberis et al. (2016) and applies it on the cryptocurrency market. The hypothesis I want to test in this paper is the following: Investors in the cryptocurrency market look at price charts to inform themselves about a cryptocurrency. They mentally represent the historical return distribution and form an opinion on the attractiveness of the cryptocurrency. The make this evaluation according to prospect theory. They invest into cryptocurrency that appear attractive according to prospect theory and disinvest out of cryptocurrencies that appear unattractive according to prospect theory. In doing so, high prospect theory value cryptocurrencies tend to be overbought and overpriced earning low subsequent returns on average in the cross-section. Low prospect theory value cryptocurrencies tend to be underbought and underpriced earning high subsequent returns on average in the cross-section. All in all, the prospect theory value predicts future cryptocurrency returns with a negative sign in the cross-section.

This paper does not only contribute to the vast literature on behavioural portfolio management and adds another piece to the puzzle of the Barberis et al. (2016) framework by adapting it to an other asset class and market. It also adds to the young field of research on cryptocurrencies. A few recent papers were published on models to price cryptocurrencies but this paper ought to be the first one to use a behavioural finance approach. Yermack (2015) is an early paper that tried to answer the question whether or not Bitcoin is a real currency. What followed were papers on cryptocurrency pricing models (see Weber (2016); Biais et al. (2020); Biais et al. (2019); Chiu and Koeppl (2019); Cong and He (2019); Cong et al. (2019); Cong et al. (2020); Sockin and Xiong (2020); Schilling and Uhlig (2019), Abadi and Brunnermeier (2018); Routledge et al. (2018); Shen et al. (2019); Liu et al. (2019); Liu et al. (2020)) and papers about investing in cryptocurrencies (see Liu and Tsyvinski (2018); Hubrich (2017); Borri (2019); Borri and Shakhnov (2019); Hu et al. (2019); Makarov and Schoar (2020); Li and Yi (2019)).

I collect a very large sample of cryptocurrencies going back as far as 2014. Since I'm working with daily data, I compute a prospect theory value for every cryptocurrency at every single point in time (i.e every day). This yields a time-series of prospect theory values for each cryptocurrency that allows me to do the time-series, factor and panel regressions. I closely follow the methodology of Barberis et al. (2016). They provide a well-thought all around empirical testing scheme for the prospect theory value. This also allows me make comparisons to the stock market. In order to properly asses the risk-adjusted returns of the strategy, I develop and employ a cryptocurrency one and three-factor model. The factors are a cryptocurrency market factor, a size factor and a momentum factor. For the regression analysis, I run regressions of the daily return on the prospect theory value and a set of controls.

I expect similar results as in the study from Barberis et al. (2016) on the stock market, because I believe that retail (individual) stock market investors don't differ greatly from cryptocurrency investors in the way how they evaluate the investment given the information that is readily available to them. Therefore, I expect that the prospect theory value of a cryptocurrency significantly predicts subsequent cryptocurrency returns with a negative sign. Furthermore, I expect that a long-short zero investment portfolio yields significant alphas when analyzing the performance in a factor model setting.

The results actually do confirm my hypothesis and my expectations for the most part. I show that the prospect theory value of a cryptocurrency predicts future returns with a negative sign. It seems that cryptocurrency investors mentally represent the return distribution of a cryptocurrency and then evaluate this distribution in a way described by prospect theory. Empirical findings show that investors clearly favour high over low prospect theory value cryptocurrencies and invest accordingly. This leads to high prospect theory value cryptocurrencies being overbought and earning low subsequent returns and vice versa. Under prospect theory, gambles with a high mean return, a low volatility (because of loss aversion) and gambles that are positively skewed are favoured (because of the probability weighting). It turns out that cryptocurrencies with a high prospect theory value tend to have a higher mean return, lower volatility and are more positively skewed than the average. This may explain why investors deem high prospect theory value cryptocurrencies attractive and invest into them. Overall these results bring more legitimacy to the prospect theory value as a significant factor in asset pricing. Practitioners should update their valuation models accordingly.

This paper is organized as follows: Section 2 gives an overview over the most important steps behind prospect theory and shows how the prospect theory value is computed. Section 3 derives the cryptocurrency factor model that is later used to do a proper risk-adjusted performance analysis. Section 4 entails the main empirical analysis including descriptive statistics and data, time-series, factor and regression analysis, robustness tests and it sheds some light on the mechanics of the prospect theory value. Finally, section 5 concludes.

2 Prospect Theory Model

This section gives an overview of the main elements behind the prospect theory value that is used for the empirical analysis as the primary signal for portfolio creation. This signal is derived from the cumulative prospect theory (CPT) model of Tversky and Kahneman (1992)[1]. Barberis et al. (2016) derived a prospect theory value function for return generating assets based on the historical return distribution of that asset. The functional form as well as the parameter values found in experiments for risk aversion (convexity and concavity), loss aversion and probability weighting from Tversky and Kahneman (1992) are used to calibrate the model (see below). In order to understand the mechanics behind the prospect theory value, some basic understanding of prospect theory is needed. Hens and Bachmann (2008) and Barberis et al. (2016) give an excellent primer of the topic and the following overview is largely based on their work. In prospect theory, the utility function is given by

$$\sum_{i=-m}^{n} \pi v(x_i) \tag{1}$$

$v(.)$ is called the value function and π is defined as

$$\pi_i = \begin{cases} w^+(p_i + ... + p_n) - w^+(p_{i+1} + ... + p_n) & for \; 0 \leq i \leq n \\ w^-(p_{-m} + ... + p_i) - w^-(p_{-m} + ... + p_{i-1}) & for \; -m \leq i \leq 0 \end{cases} \tag{2}$$

whereas $w^+(.)$ / $w^-(.)$ are called the probability weighting functions. In contrast, the standard expected utility for an individual is given by

$$\sum_{i=-m}^{n} p_i U(W + x_i) \tag{3}$$

[1]The original version of the prospect theory was developed in Kahneman and Tversky (1979). However, the original model has the limitation that it can only adhere to gambles with two non-zero outcomes. Most studies use the enhanced model - cumulative prospect theory - by Tversky and Kahneman (1992) that doesn't have those limitations any longer. For the sake of brevity, I only use the term *prospect theory* but I'm actually referring to the cumulative prospect theory.

When looking at the prospect theory utility function, there are four main differences to the expected utility function. Firstly, value in prospect theory is defined as gains and losses (to some reference point; could be zeros), whereas in expected utility, values are final wealth levels. Second of all, the utility function in the expected utility framework is differentiable everywhere while in prospect theory, the function has a kink at the origin (reference point) as shown in the left panel of figure 1. This kink is basically what is known as *loss aversion*, i.e. a person is more sensitive to losses than to gains of the same size or in other words: the disutility of a loss is larger than the utility of a gain with the same monetary size. The bigger the kink, the larger the degree of loss aversion. Thirdly, $v(.)$ is only concave over gains (and convex over losses) whereas $U(.)$ in the standard expected utility framework is is usually concave for all values. The left panel of figure 1 shows the concave/convex nature of curvature. Lastly, the probability space mapped to the state space is non-objective, i.e. individuals use transformed (subjective) probabilities. Those transformed probabilities are generated from a weighting function. Consequently, the weighting functions produce probabilities that leads individuals to overweight the tails of a distribution. This is shown in the right plot of figure 1, where the degree of overweight varies with the degree of the distortion.

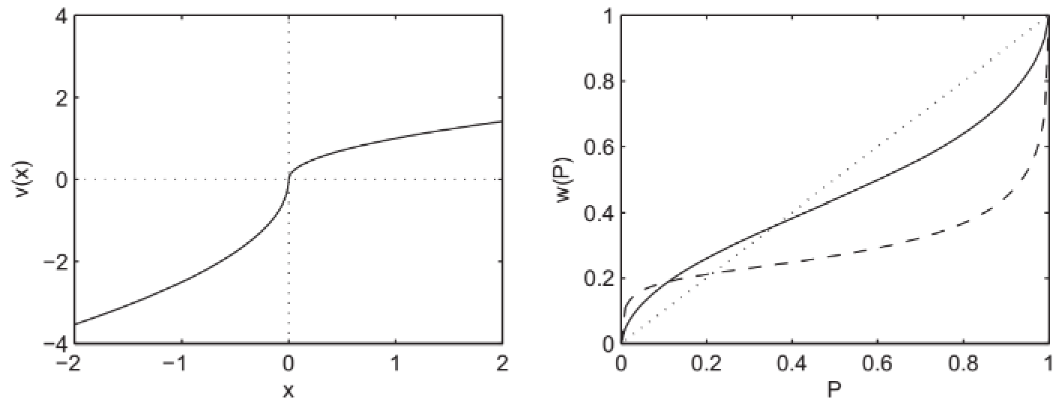

Figure 1
The value and probability weighting functions
The left plot shows the value function from Tversky and Kahneman (1992) with $\alpha = 0.5$ and $\lambda = 2.5$. This function is divided into a gains and losses part, whereas those gains and losses are evaluated from a reference point (here: Zero). The right plot depicts the probability weighting functions with different degrees of distortion (dashed line is $\delta = 0.4$, solid line is $\delta = 0.65$ and dotted line is $\delta = 1$).

The functional form of Tversky and Kahneman (1992) for the value function is defined as:

$$v(x) = \begin{cases} x^{\alpha} & for\ x \geq 0 \\ -\lambda(-x)^{\alpha} & for\ x < 0 \end{cases} \tag{4}$$

α is the parameter that captures the risk-aversion. The value function becomes linear for $\alpha = 1$ and lower values for α lead a more concave/convex curvature, i.e. more risk-aversion. λ captures the degree of loss aversion, i.e. the kink. The bigger the λ, the more loss averse the individual is. The functional form of Tversky and Kahneman (1992) for the probability weighting functions are given by:

$$w^{+}(P) = \frac{P^{\gamma}}{(P^{\gamma} + (1-P)^{\gamma})^{\frac{1}{\gamma}}} \qquad w^{-}(P) = \frac{P^{\delta}}{(P^{\delta} + (1-P)^{\delta})^{\frac{1}{\delta}}} \tag{5}$$

γ and δ are the distortion parameter that define the degree of probability weighting. The lower the values for γ and δ, the higher the degree of distortion, i.e. the more individuals overweight the tails of a distribution. In experiments, Tversky and Kahneman (1992) estimated the following values for the four parameters:

$$\begin{aligned} \alpha &= 0.88 \\ \lambda &= 2.25 \\ \gamma &= 0.61 \\ \delta &= 0.69 \end{aligned} \tag{6}$$

Since the prospect theory value for portfolio formation is derived from the historical return distribution, a clear definition is needed as to what is actually meant by that. Analogue to Barberis et al. (2016), it is assumed that investors form an opinion about a cryptocurrency by looking at the historical return distribution depicted in form of a price chart. Most investors look at charts on www.coinmarketcap.com, mentally process that chart and form an opinion on the attractiveness of the asset depicted in that chart. The price charts from www.coinmarketcap.com are available in a standardized way for intraday, one week, one month, three months, one year and year-to-date time windows. Other website with free cryptocurrency data feature mostly the same kind of price charts. For the construction of the prospect theory value, the window that is used for the historical distribution is one month, i.e. investor look at the 30 day price chart and use that for their mental representation. This is because 30 days is the standard price chart. As to the question of the choice of data frequency of the actual price data, only daily and hourly price data really makes sense in order to have enough data points for the construction of the prospect theory value. Since hourly data is not that readily available for a large body of currencies, I take daily data. Lastly, a definition of returns is needed. The choices are between raw returns, returns in excess of the risk-free rate or returns in excess of the market return. While the price chart depicts raw returns, an investor likely has some sort of understanding as to how the cryptocurrency market as a whole is performing. This overall market performance might even be the driver behind his desire to invest in cryptocurrencies in the first place. The magnitude of the market performance should also influence the assessment of attractiveness of a specific cryptocurrency's historical return distribution. If a cryptocurrency performs very well over a specific time but the overall market also performs similarly, then that cryptocurrencies performance is somewhat put into perspective. The notion of a risk-free rate may be a little abstract for a retail investor because the trade-off between investing in a risk-free asset or investing in a risky asset is actually not that realistic for him or her. The alternative to the risky asset is mostly cash for retail investors. What's more is that the daily risk-free rate is essentially zero nowadays anyway making it redundant. Thus, returns are defined as returns in excess of the market return. In summary, for the main analysis, the historical return distribution of a cryptocurrency is defined as the daily returns in excess of the market return over the last 30 days. In robustness tests, other windows for construction of the prospect theory value and other return measures are tested and reported. The results are mostly similar to the main setting.

In short, people mentally represent a cryptocurrency's historical return distribution in the form that they are most familiar with when research a cryptocurrency: the price chart. Based on that price chart, they analyze the cryptocurrency in a way described by prospect theory and form an opinion on the future return distribution, i.e. people calculate the respective prospect theory value. Then, they invest according to their prospect theory value assessment. In order to do empirical work, a formal model to calculate the prospect theory value is needed (that serves as a proxy for the mental process described above). To this end, in a first step, the daily returns in excess of the market over the last 30 days of a specific cryptocurrency are sorted in increasing order, i.e. the most negative return over the last 30 days is first and the most positive return over the last 30 days is last one in that order. $n = 30 - m$ is the amount of positive returns and m is the amount of negative returns for a specific look-back period. The sorted historical return distribution is given by

$$(r_{-m}, \frac{1}{30}; r_{-m+1}, \frac{1}{30}; ...; r_{-1}, \frac{1}{30}; r_1, \frac{1}{30}; ...; r_{n-1}, \frac{1}{30}; r_n, \frac{1}{30}) \tag{7}$$

whereas r_{-m} is the lowest and r_n the highest return in the given look-back period of 30 days. Furthermore, every return over the last 30 days has the same probability of occurrence, i.e. $\frac{1}{30}$. Putting this together with CPT from Tversky and Kahneman (1992), the prospect theory value (PV) of this distribution is defined as

$$\begin{aligned} PV = & \sum_{j=-m}^{-1} v(r_j)\left[w^{-}(\frac{j+m+1}{30}) - w^{-}(\frac{j+m}{30})\right] \\ & + \sum_{j=1}^{n} v(r_j)\left[w^{+}(\frac{n-j+1}{30}) - w^{+}(\frac{n-j}{30})\right] \end{aligned} \tag{8}$$

with the functional forms for $v(r_j)$, w^- and w^+ defined in expressions (4) and (5) and parameter estimates from Tversky and Kahneman (1992) as shown in expression (6)[2].

3 Factor Models

In order to properly asses the risk and return of a PV-based investment strategy, some form of risk-adjusted performance measure is needed to make comparison with other strategies meaningful. The most common factor model used in financial literature for stock returns is the Fama and French (1992) three factor model, which could be seen as an enhancement of the CAPM model (Sharpe (1964); Lintner (1965*a*); Lintner (1965*b*); Mossin (1966)). The three factors used to describe the cross-section of stock returns are the the *market* factor (market excess return), the *size* (Small Minus Big) and *value* (High Minus Low) factors. Later, the three factor model was enhanced by a *momentum* (Winners Minus Loosers) factor (Carhart, 1997) and *investment* (Conservative Minus Aggressive) and *profitability* (Robust Minus Weak) factors (Fama and French, 2015). Those factors capture most of the variation in the cross-section of expected stock returns as shown by the respective authors. They have emerged as the standard factor models for the stock market asset pricing literature. As to other asset classes, factor models for the currency, commodity and corporate bond markets were provided by Lustig et al. (2011), Szymanowska et al. (2014) and Bai et al. (2019), respectively.

Cryptocurrencies and stocks share some statistical similarities, e.g. leptokurtosis (Chan et al., 2017), heteroskedasticity (Gkillas and Katsiampa, 2018) and long-memory (Phillip et al., 2019).

[2]In section 4.5, other values for the parameters γ and δ are tested in order to stress the effect of probability weighting.

However, cryptocurrencies and stocks are different in a way that there are no fundamental data for cryptocurrencies and the factors mentioned above are mostly driven by fundamentals. To show this, Gregoriou (2019) reports significant alphas in cryptocurrency regressions on the Fama and French (1992) factors. Furthermore, Liu and Tsyvinski (2018) obtain similar results of cryptocurrencies having no exposure to common stock, currency, commodities and macroeconomic factors. Thus, a cryptocurrency-specific factor model is needed in order to properly assess the risk and return properties of a PV-based investment approach. What those factors are and how they are calculated is derived below.

Since there are no fundamental data for cryptocurrencies as there are with other asset classes, I focused on factors that can be built only with price, volume or market capitalization data. Liu et al. (2019) show that three factors - cryptocurrency market excess return, size and momentum - capture the cross-section of expected cryptocurrency returns. They show 9 significant long-short strategies for cryptocurrencies and that those three factors account for all the variation in the returns of those strategies. Similar results were developed by Liu et al. (2020), Li and Yi (2019) and Shen et al. (2019). Therefore, I constructed a market excess return, a size and a momentum factor. Data and its sources are defined in detail in section 4.1. I follow the same approach in building the factors as in Fama and French (1992). The daily cryptocurrency market excess return (CMKT) aka market factor is:

$$CMKT = MKT - Rf \tag{9}$$

The cryptocurrency market return - MKT - is calculated as the value-weighted daily return of all coins in the dataset. The risk-free rate - Rf - is the daily yield of one-month Treasury bills. For the size factor (SMB) and momentum (WML) factors, I do a double sorting approach. For the SMB factor, every day, coins are sorted into three size groups by their market capitalization in USD, analogue to Liu et al. (2019): bottom 30% (small), middle 40% (middle) and top 30% (big). For the WML factor, all coins are sorted into three momentum groups based on their 21 days momentum (look-back period analogue to Liu et al. (2019)): bottom 30% (loosers), middle 40% (middle) and top 30% (winners). Then I form value-weighted portfolio for each of the group combinations and calculate the returns of said portfolios: Small-Loosers, Small-Middle, Small-Winners, Middle-Loosers, Middle-Middle, Middle-Winners, Big-Loosers, Big-Middle and Big-Winners. Then, SMB and WML are defined as:

$$\begin{aligned} SMB =& 1/3 * (Small\text{-}Loosers + Small\text{-}Middle + Small\text{-}Winners) \\ &- 1/3 * (Big\text{-}Loosers + Big\text{-}Middle + Big\text{-}Winners) \end{aligned} \tag{10}$$

$$\begin{aligned} WML =& 1/2 * (Small\text{-}Winners + Big\text{-}Winners) \\ &- 1/2 * (Small\text{-}Loosers + Big\text{-}Loosers) \end{aligned} \tag{11}$$

Putting all this together yields two different factor models: The crypto one factor model (Crypto CAPM) with the CMKT (market) factor and the crypto three factor model (analogue to Fama and French (1992)) with an additional SMB (Size) and WML (momentum) factor. The regression models for those two factor models are then defined as

$$R_t^i - Rf_t = \beta_0^i + \beta_1^i \cdot (MKT_t - Rf_t) + \epsilon_t^i \tag{12}$$

for the one factor model and

$$R_t^i - Rf_t = \beta_0^i + \beta_1^i \cdot (MKT_t - Rf_t) + \beta_2^i \cdot SMB_t + \beta_3^i \cdot WML_t + \epsilon_t^i \tag{13}$$

for the three factor model.

4 Empirical Analysis

This section presents the results of the empirical analysis. The goal of the analysis as stated in section 1 is to find out whether or not a simple prospect theory model can described the way traders assess the attractiveness of cryptocurrencies and whether a trading strategy based on that model leads to a risk-adjusted outperformance after controlling for known predictors. Since a big portion of the empirical analysis of PV has been conducted for the stock market by Barberis et al. (2016), I mostly follow their approach and testing mechanics.

4.1 Data

All the data comes from www.coingecko.com by using their free standard API[3] solution. www.coingecko.com is a information platform for cryptocurrency prices that collects it's data from various exchanges and it into a readily available, standardized and clean form. Outliers are detected by an algorithm and dealt with accordingly. The prices are calculated using a global volume-weighted average price formula, i.e. the prices on www.coingecko.com are averaged over all exchanges in the same way that www.coinmarketcap.com does it. For listing a cryptocurrency on www.coingecko.com, the cryptocurrency needs to be traded on at least one public exchange with a REST API in place and with information on price and volume available. Furthermore, the volume obviously needs to be non-zero in order to determine the price at any given time. Both active and defunct cryptocurrencies are listed, therefore rendering any survivorship bias non-existent.

I collect daily closing prices in USD of all cryptocurrencies listed on www.coingecko.com, both active and defunct ones at the time of collection. Furthermore, I collect daily volume and market capitalization data for the same cryptocurrencies, both also denominated in USD. The full sample covers the timespan from 01.01.2014 to 31.01.2020. I require that all coins must at least have a market capitalization of 1'000'000 USD or greater. Secondly, I exclude cryptocurrencies with a price history shorter than 183 trading days (half a year). Thirdly, I exclude coins with prices that are below 0.01 USD. I calculate daily log returns on all remaining cryptocurrencies and exclude any observations with daily returns bigger than 1500%. The final sample after filtration yields a total of 1'313 cryptocurrencies.

Summary statistics of all the variables used in my analysis are reported in table 1. Panel A reports means and standard deviations while panel B shows pairwise correlations. PV - the main variable of interest for this paper - is the prospect theory value of the historical return distribution of a cryptocurrency as defined in expression (8) in section 2. *Ret* is the daily log return of a cryptocurrency in excess of the market return. The market return is defined in section 3. *Mom* is the momentum of a cryptocurrency and defined as the cumulative daily log excess return over the last 30 days. *Size* is the log market capitalization in USD. *Beta* is a cryptocurrency's beta of the returns over the last 30 days as stated by the one factor model. The approach is the same as for stocks: Daily log returns in excess of the risk-free rate are regressed on the daily

[3] Application programming interface

cryptocurrency market excess returns, see also expression (12) in section 3. The risk-free rate is the daily yield of one-month Treasury bills. Data on the risk-free rate are gathered from Kenneth French's Website[4]. *Vol* is the average daily log dollar volume over the last 30 days in USD. *Sd Vol* is the standard deviation of the daily log dollar volume over the last 30 days. Both variables - *Vol* ahd *Sd Vol* were identified by Liu et al. (2019) as significant controls for cryptocurrency returns in the cross-section. Since many cryptocurrencies suffer from a high degree of illiquidity, market impact is certainly an issue for some cryptocurrencies. Thus I include *Illiq* as a measure of illiquidity from Amihud (200), scaled by 10^{-14}. This measure serves as a rough measure for the price impact. Since it only needs data on returns and volume, calculating it for this analysis is achievable given the dataset. Higher values of *Illiq* indicate a higher degree of illiquidity of an asset when compared to an asset with a lower *Illiq*. *Skew* is the skewness of the daily excess returns over the last 30 days. *Kurt* is the excess kurtosis of the daily excess returns over the previous 30 days. I expect cryptocurrency returns to be highly skewed and to feature fat tails. The probability weighting in the prospect theory model captures the overweighting of those tails and the attractiveness of an asset depends to some degree on the skewness of its returns when looking at it from the view of a prospect theory investor. It could be those extremes of the return distribution that people might - or might not - find appealing. Thus, I also include *Min* and *Max*, which are the maximum and the negative of the minimum daily log excess return over the last 30 days, similar to Bali et al. (2011). Lastly, *Sd* is defined as the standard deviation of a cryptocurrencies daily excess returns over the previous 30 days.

Table 1
Summary Statistics

A. Means and standard deviations

	PV	Ret	Mom	Size	Beta	Vol	Sd Vol	Illiq	Skew	Kurt	Min	Max	Sd
Mean	-0.07	-0.004	-0.11	16.16	0.94	12.16	11.79	1.45	0.36	2.56	0.22	0.25	0.09
Sd	0.06	0.134	0.44	2.17	0.90	3.36	3.55	188.18	1.01	3.52	0.31	0.32	0.11

B. Correlations

	PV	Ret	Mom	Size	Beta	Vol	Sd Vol	Illiq	Skew	Kurt	Min	Max	Sd
PV	1.00												
Ret	0.12	1.00											
Mom	0.52	0.20	1.00										
Size	0.28	0.04	0.12	1.00									
Beta	0.06	0.01	0.06	0.08	1.00								
Vol	0.31	-0.00	0.06	0.79	0.07	1.00							
Sd Vol	0.25	0.00	0.07	0.72	0.08	0.92	1.00						
Illiq	-0.01	0.00	-0.01	-0.01	-0.01	-0.02	-0.02	1.00					
Skew	0.35	0.08	0.34	0.10	0.04	0.12	0.14	-0.01	1.00				
Kurt	-0.06	0.01	0.07	-0.04	0.01	0.00	0.03	0.02	0.32	1.00			
Min	-0.83	-0.04	-0.12	-0.21	-0.02	-0.26	-0.20	0.01	-0.18	0.29	1.00		
Max	-0.57	0.03	0.17	-0.18	-0.00	-0.22	-0.15	0.00	0.23	0.41	0.85	1.00	
Sd	-0.78	-0.01	0.04	-0.21	-0.03	-0.27	-0.20	0.00	0.02	0.26	0.93	0.93	1.00

Note: Panel A of this table shows means and standard deviations of each variable used in the empirical analysis. Panel B shows the correlations of these variables with each other, respectively. The means, standard deviations and correlations are calculated from the cross-section day by day. Reported here are the time-series averages of these daily statistics. The full sample covers the timespan from 01.01.2014 to 31.01.2020 (T=2'222) for a wide range of cryptocurrencies (N=1'313). All data was collected from www.coingecko.com using a standard API. *PV* is the prospect theory value of a cryptocurrencies historical return distribution as defined in section 2 in expression (8). *Ret* is the daily log return in excess of the market. *Mom* is the cumulative excess return over the last 30 days. *Size* is the log market capitalization. *Beta* is a cryptocurrency's beta of the returns over the last 30 days as stated by the one factor model defined in expression (12) in section 3. *Vol* is the average daily log dollar volume over the last 30 days. *Sd Vol* is the standard deviation of the daily log dollar volume over the last 30 days. *Illiq* is the measure of illiquidity from Amihud (200), scaled by 10^{-14}. *Skew* is the skewness of the daily excess returns over the last 30 days. *Kurt* is the excess kurtosis of the daily excess returns over the previous 30 days. *Min* and *Max* are the maximum and the negative of the minimum daily log excess return over the last 30 days, similar to Bali et al. (2011). *Sd* is the standard deviation of a cryptocurrencies daily excess returns over the previous 30 days.

[4]https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

According to Barberis et al. (2016), the prospect theory value of an investment is increasing in the investment's mean, decreasing in the investment's volatility, i.e the potential of high losses (because of loss aversion), and increasing in the investment's skewness (because of probability weighting). The correlations from panel B of table 1 suggest to a first approximation that this is indeed the case in the data. In the cross-section of all the cryptocurrencies in the dataset, PV is positively correlated with past return measures (*Ret* and *Mom*), negatively correlated with the past volatility measures and measures of high gains and losses (*Sd*, *Min*, *Max* and *Kurt*) and positively correlated with past skewness measure (*Skew*). Furthermore, high PV cryptocurrencies have a tendency to have a higher market capitalization (*Size*) and a higher dollar volume (*Vol*). A reason for this could be that larger cryptocurrencies with a higher trade volume tend to be less volatile.

4.2 Time-Series Analysis

In order to test the hypothesis of this paper, i.e. that the prospect theory value (PV) of a cryptocurrencies historical return distribution predicts future performance in the cross-section with a negative sign, I analyse the performance with a decile sorting approach analogue to Barberis et al. (2016). In section 4.4, I follow a regression based approach to test the hypothesis.

For each day in the sample between 01.02.2014 to 31.01.2020, I sort cryptocurrencies into decile portfolios based on their PV value, from lowest to highest, at the beginning of the day and compute the returns of each decile portfolio for that day, i.e. the following 24 hours. The decile portfolio returns are calculated both equal-weighted (EW) and value-weighted (VW). Daily returns are in excess of the daily market return. In the end, this procedure yields a time-series of daily returns for every decile portfolio. Based on each time-series for every decile portfolio, average returns are computed and reported in table 2. Furthermore, I report one-factor alphas and three-factor alphas for all decile portfolios, again both equal-weighted and value-weighted. The one-factor alpha is derived from the cryptocurrency CAPM shown in expression (12), whereas the three-factor alpha enhances the one-factor model by a size and momentum factor, as outlined in expression (13) in section 3. On the right hand side of table 2, in the last column, average returns, one-factor and three-factor alphas are reported for the *low minus high* portfolio that goes long into the cryptocurrencies in the bottom decile and short into the cryptocurrencies in the top decile (i.e. the long-short portfolio). This means, that this zero-cost investment strategy buys low PV cryptocurrencies and sells short high PV cryptocurrencies. Results in this last column are particularly of interest because it allows to directly make statements as to whether PV predicts subsequent cryptocurrency returns with a negative sign, i.e. if high PV cryptocurrencies earn low subsequent returns and vice versa. If the returns of the *low minus high* portfolio are significantly positive, the hypothesis is validated. The results reported in table 2 indeed do validate the hypothesis. Both value-weighted and equal-weighted, average daily excess returns of the long-short portfolio are highly significant with 5.2% (VW) and 2.1% (EW) respectively. Furthermore, alphas are highly significant too, with 5.2% (VW) and 2.1% (EW) for the one-factor model and 5.3% (VW) and 2.2% (EW) for the three-factor model, respectively. The fact that returns and alphas are bigger for value-weighted than for equal-weighted portfolios suggests that the prospect theory value has more predictive power for larger cryptocurrencies with a higher market capitalization (size). One possible explanation for this is that historically, larger cryptocurrencies tend to have slightly higher average returns.

Figure 2 shows the results from table 2 graphically to some extent. The top chart plots the daily three-factor alphas for every decile portfolio that was formed based on PV, both for returns calculated on an equal-weight and value-weight basis. Every day, cryptocurrencies are sorted into deciles based on their prospect theory value. Based on the time series of the average returns, three-factor alphas are calculated for each decile and plotted. The vertical axis is the daily alpha in % while the horizontal axis corresponds to the decile portfolio in ascending order. The main message, which can be seen at a first glance is, that the two graphs decrease almost monotonically from lowest to highest decile. The bottom chart brings a new time dimension to the table. The charts plots three-factor alphas of a long-short portfolio that buys cryptocurrencies in the lowest PV decile and sells cryptocurrencies in the highest PV decile at t-1. The vertical axis shows daily alphas in % whereas the horizontal axis shows the time lag between the PV signal and the start of return measurement in days. Returns are again computed on both value-weight and equal-weight basis. It becomes clear that PV retains its predictive power well after the first day in case of value-weighted returns. PV calculated from returns between t-30 and t-1 not only have a high significant predictive power for returns in t but also beyond the first day in days t+1, t+2 up until t+6 at minimum for returns computed with value-weights. However, for equal-weighted returns, the predictive power of PV is basically zero after the first day. What's more is that the predictive power of PV is the highest in the first day and then almost monotonically decreases the next days.

Table 2
Portfolio Analysis

		P1 Low PV	P2	P3	P4	P5	P6	P7	P8	P9	P10 High PV	PV Low-High Portfolio
Excess Return	VW	**5.150**	**0.476**	**0.319**	0.101	0.026	**-0.312**	**-0.208**	-0.073	-0.124	-0.041	**5.191**
		(8.61)	(2.55)	(2.48)	(0.41)	(0.21)	(-2.89)	(-2.14)	(-0.89)	(-1.58)	(-0.66)	(8.58)
	EW	**1.120**	**-0.319**	**-0.250**	**-0.337**	**-0.371**	**-0.599**	**-0.485**	**-0.462**	**-0.513**	**-0.976**	**2.096**
		(5.00)	(-2.49)	(-2.43)	(-3.02)	(-4.20)	(-7.40)	(-6.34)	(-5.81)	(-7.33)	(-7.73)	(8.09)
One-Factor Alpha	VW	**5.118**	**0.490**	**0.328**	0.094	0.305	**-0.307**	**-0.202**	-0.070	**-0.129**	-0.042	**5.157**
		(8.69)	(2.63)	(2.55)	(0.38)	(0.12)	(-2.85)	(-2.12)	(-0.86)	(-1.68)	(-0.70)	(8.67)
	EW	**1.138**	**-0.299**	**-0.239**	**-0.327**	**-0.363**	**-0.584**	**-0.473**	**-0.449**	**-0.501**	**-0.959**	**2.094**
		(5.11)	(-2.35)	(-2.32)	(-2.93)	(-4.12)	(-7.29)	(-6.25)	(-5.72)	(-7.18)	(-7.59)	(8.11)
Three-Factor Alpha	VW	**5.221**	**0.805**	**0.497**	**0.801**	**0.305**	-0.058	0.014	**0.156**	-0.076	**-0.115**	**5.332**
		(9.09)	(3.91)	(3.41)	(2.94)	(2.65)	(-0.47)	(0.13)	(1.79)	(-0.83)	(-1.84)	(9.23)
	EW	**1.188**	**-0.243**	-0.154	-0.105	**-0.218**	**-0.418**	**-0.361**	**-0.324**	**-0.427**	**-0.990**	**2.174**
		(4.88)	(-1.71)	(-1.38)	(-0.84)	(-2.14)	(-4.56)	(-4.43)	(-3.88)	(-5.40)	(-7.82)	(7.96)

Note: This table summarizes average daily excess returns and alphas of decile portfolios constructed using PV, i.e. the prospect theory value of a cryptocurrencies historical returns, as stated in section 2. Every day, cryptocurrencies are sorted into deciles based on their PV values. Portfolios are both calculated as value-weighted (VW) and equal-weighted (EW). Returns are calculated in excess of the market return. The one-factor alpha is derived from the cryptocurrency CAPM , whereas the three-factor alpha enhances the one-factor model by a size and momentum factor, as outlined in section 3. Returns and alphas are in %.The sample runs from 01.02.2014 to 31.01.2020. Robust t-statistics are in parentheses and bold typefaces indicate significance at the 10%-level.

Lastly, factor regression analysis show that the majority of the returns cannot be explained by either the one-factor nor by the three-factor model, hence the highly significant alphas as shown in table 2 beforehand. Table 3 summarizes the factor loading of both models. This table shows the factor loadings from regressions of both value-weighted (VW) and equal-weighted (EW) returns of the long-short portfolios. The one-factor model is the cryptocurrency CAPM , whereas the three-factor model enhances the one-factor model by a size and momentum factor, as outlined in section 3. Only the size factor in case of value-weighted returns is significant with -1.112. Size and PV do comove, as also seen in table 1. High PV cryptocurrencies tend to be larger cryptocurrencies. The larger cryptocurrencies are the ones that are more frequently traded, i.e. have a higher volume. This could be because those cryptocurrencies feature a better access to trading via crypto exchanges[5]. Many retail investors trade what they have easy access

[5]Especially in the beginning of the rise in cryptocurrencies in until 2018, there have been just a handful of exchanges and those exchanges mostly only offered trading in the largest few cryptocurrencies in terms of their

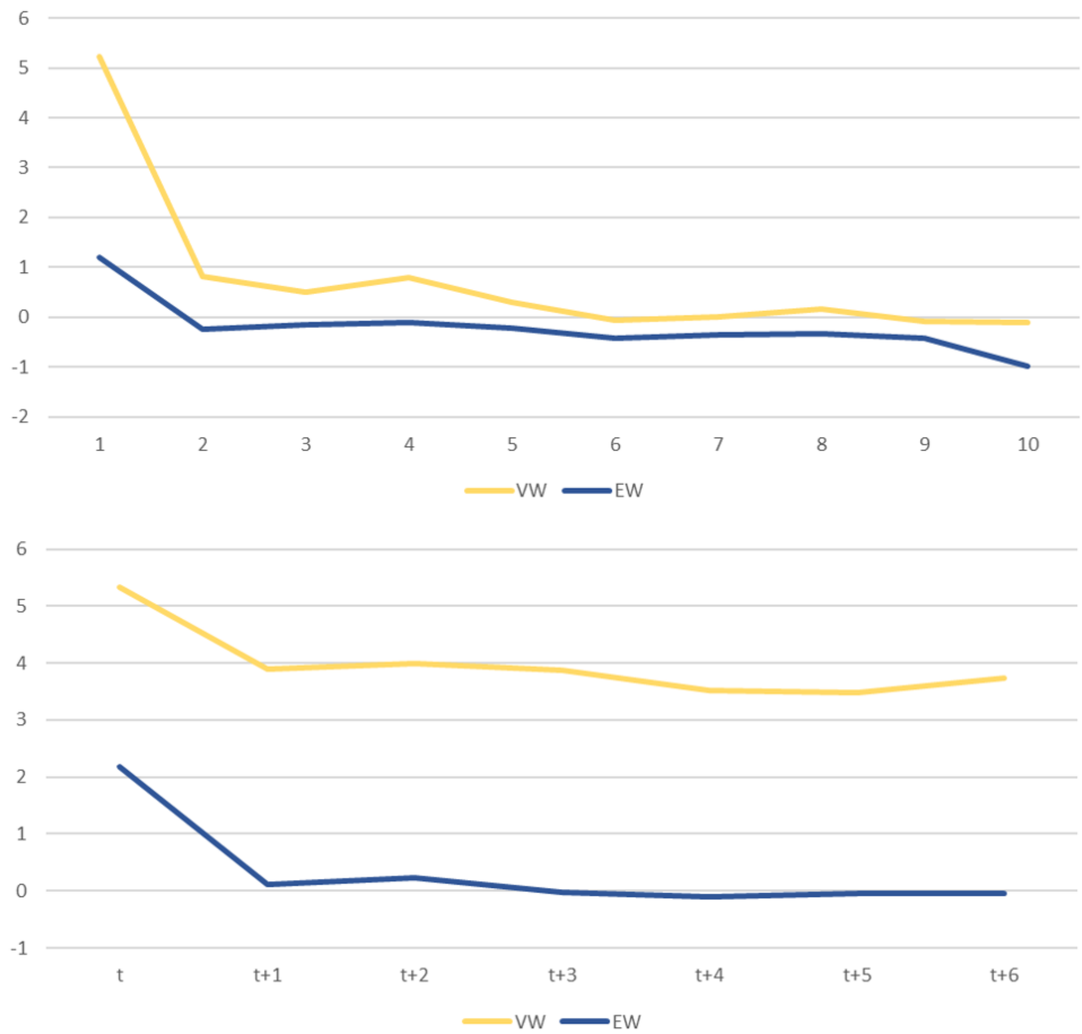

Figure 2
Alphas of PV deciles and performance of long-short portfolios over time
The top plot shows three-factor alphas for decile portfolios that were formed based on PV. Every day, cryptocurrencies are sorted into deciles based on their prospect theory value of their historic return distribution. Based on the time series of the average returns, three-factor alphas are calculated for each decile and plotted here. Returns are calculated on both equal-weight and value-weight basis. The vertical axis is the daily alpha in % while the horizontal axis corresponds to the decile portfolio in ascending order. The bottom plot shows three-factor alphas of a long-short portfolio that buys cryptocurrencies in the lowest PV decile and sells cryptocurrencies in the highest PV decile a t-1. The vertical axis shows daily alphas in % whereas the horizontal axis shows the time lag between the PV signal and return measurement in days. Returns are again measured on both value-weight and equal-weight basis.

to[6] and what seems appealing to them when they go to their exchange of choice. Thus, size highly comoves with volume as shown in table 1. Interestingly, the momentum factor cannot explain the returns of the long-short portfolio at all, which shows that PV does far more than just capture the momentum effect, i.e. herding. One could argue that when people look at the price chart, they see the (positive and negative) momentum of a cryptocurrency and herding leads them to invest and disinvest into and out of those cryptocurrencies with a high/low momentum, increasing the momentum even further. This would be especially the case if the asset is usually traded at a very high frequency (hourly and 24/7) and at a high turnover (going in and out very fast), which is actually the case for cryptocurrencies. However, this analysis shows that PV is able to capture the behaviour of investors far better than just momentum. Prospect theory seems to be able to explain the investment choice made by investors better, i.e. probability weighting and loss aversion seem to bring something additional to the table that is relevant when assessing investment choices made by individuals in the cryptocurrency market. What becomes abundantly clear is that PV leads to significant alphas when using it as a investment signal for a zero-investment portfolio and neither the one- nor the three-factor model is able to explain the returns in the cross-section in a satisfactory manner. Even beyond the first day of portfolio creation, PV retains its predictive power.

Table 3
Factor Loadings

Model	Return Base	Rm-Rf	SMB	WML
One-Factor Model	VW	0.163 (0.88)		
One-Factor Model	EW	-0.005 (-0.07)		
Three-Factor Model	VW	-0.503 (-1.45)	**-1.112** (-2.47)	0.016 (0.07)
Three-Factor Model	EW	-0.129 (-1.02)	-0.214 (-1.48)	-0.040 (-0.50)

Note: This table shows factor loadings from regressions of both value-weighted (VW) and equal-weighted (EW) returns of long-short portfolios. Every day, all cryptocurrencies are sorted into deciles based on their PV value. The long-short portfolios buy cryptocurrencies in the bottom decile and short cryptocurrencies in the top decile. The one-factor model is the cryptocurrency CAPM , whereas the three-factor model enhances the one-factor model by a size and momentum factor, as outlined in section 3. The sample runs from 01.02.2014 to 31.01.2020. Robust t-statistics are in parentheses and bold typefaces indicate significance at the 10%-level.

4.3 Robustness

In a next step, I vary certain parameters and tweak settings for signal and portfolio creation in order to assess the robustness of PV as a trading signal. As shown before, the crypto market return MKT is calculated as the value-weighted daily return of all underlying coins. Since returns of the each asset are computed in excess of the crypto market return for the portfolio creation, results of the portfolio analysis already shows some resilience because the trend in cryptocurrency prices in recent years is taken into account accordingly by deducting the market return. However, further robustness tests show a very high level of resilience of PV as a trading signal when changing certain parameters.

Table 4 summarizes those robustness tests. Firstly, the sample is basically split into a two with a 60%/40% split and the analysis is done for every subperiod on its own. The first subperiod from 2014 to late 2017 was a period that saw an enormous uprising in crypto market capitalizations and ultimately prices. The second subperiod from late 2017 to early 2020 features a large downturn and markets that trended sideways for a longer period of time. Alphas remain highly significant and quite large for both subperiods. Again, alphas for value-weighted returns are

market capitalizations.

[6]This is to some extent because of the lack of maturity of the entire cryptocurrency market. The user experience has just not been that good in the first 8 years since the beginning of bitcoin in 2010 and thus access and tradability have been an issue. However, recently more and more traditional banks offer trading in cryptocurrencies to their clients and also institutional investors come into the market leading to a maturation of the entire cryptocurrency space.

larger than for equal-weighted returns. Secondly, I vary the length of the construction window the PV. Previously, this has been 30 days and for robustness sake, I also calculate PV using a window of 60 and 90 days. In both cases, alphas remain highly significant for value-weighted and equal-weighted returns. Next I use raw returns instead of excess returns for the computation of PV. Alphas are almost identical to the setup with excess returns and of course also significant. Then I skip a day between the calculation of PV and the measuring of portfolio returns to see if the reversal effect is only short term for one day. The value-weighted alpha remains highly significant whereas the equal-weighted alpha becomes insignificant. This shows that on average, for smaller cryptocurrencies, the reversal effect disappears afters the first day. Lastly, I calculate a simple price momentum strategy that buys the winners in the top decile portfolio and sells the losers of the bottom decile portfolio. The lookback windows is 30 days to make it comparable to the PV strategy. Both alphas are highly significant albeit smaller than the alpha of the PV strategy for value-weighted returns. However, the alpha for the equal-weighted return for the momentum strategy is much larger than the PV counterpart. It seems that among smaller cryptocurrencies, a significant momentum effect is present. This makes it even more fascinating since I show that the momentum factor fails to explain the variation in PV as seen in table 3.

Table 4
Robustness

		VW	EW
Subperiods	01.02.2014 - 31.08.2017	**4.426**	**2.165**
		(5.55)	(5.13)
	01.09.2017 - 31.01.2020	**5.277**	**2.260**
		(5.80)	(10.71)
PV Construction Window	Past 60 Days	**4.940**	**1.460**
		(8.77)	(5.58)
	Past 90 Days	**4.471**	**1.237**
		(7.96)	(4.52)
Other Return Measure	Raw Returns	**5.338**	**2.129**
		(9.19)	(7.93)
Skip a Day		**3.897**	0.111
		(6.89)	(0.42)
Momentum	Past 30 Days	**4.669**	**5.132**
		(10.03)	(20.38)

Note: This table shows regression results for various robustness checks. The results presented are three-factor alphas in % of long-short portfolios that buy (short) cryptocurrencies in the lowest (highest) PV decile on a daily basis. Returns are measured on a value-weighted (VW) and equal-weighted (EW) basis. The first two robust checks split the sample into two subperiods. The two consecutive robust checks alternate the construction window for the PV value. Thirdly, PV is computed using raw returns. Next, a day is skipped between measuring PV signals and measuring returns. Lastly, instead of using PV values as signals for portfolio formation, a simple price momentum signal with a lookback window of 30 days is employed. The entire sample runs from 01.02.2014 to 31.01.2020. Robust t-statistics are in parentheses and bold typefaces indicate significance at the 10%-level.

4.4 Regression Analysis

Next I perform a battery of panel regressions. In all regressions, *Ret*, which is the daily log return in excess of the market, serves as the dependent variable. The goal is to analyze the significance of PV as a signal even after controlling for predictors of returns. In other words, to test the hypothesis that PV has predictive power for subsequent returns even when including controls. The panel methodology employed here allows this setting while yielding robust t-statistics due to clustering.

Panel A of Table 5 reports those empirical findings in the following logic: Column (1) through Column (8) are results of one regression each while adding another control variable to the mix one by one. The plain vanilla regression without controls is reported in column (1), where *Ret* is regressed on PV alone. Then one by one, controls, as defined in section 4.1, are added. Those controls are: momentum (*Mom*), market capitalization (size), the beta (*Beta*), volume (*Vol*), standard deviation of volume (*Sd Vol*), illiquidity (*Illiq*), skewness (*Skew*), kurtosis (*Kurt*), minimum (*Min*) and maximum (*Max*) returns, respectively. Results show that the hypothesis is supported by the data even with controls, i.e PV predicts subsequent returns with a negative sign. High (low) PV cryptocurrencies earn low (high) subsequent returns on average in the sample. PV retains it's significant predictive power from column (1) through (8). As shown in section 4.5, past returns of high PV cryptocurrencies are highly positively skewed. Therefore, it is even more interesting that adding *Skew* as a control does not the coefficient of PV in magnitude and statistical significance.

While PV is highly significant, the size of the coefficient is smaller to other variables like skewness, size or volume. To some extent, this is in line with Barberis et al. (2016). They argue, that the construction of PV is constrained by prior theory whereas other variables like the aforementioned ones are not. What is meant by that is that PV is computed using the exact functional form proposed by Tversky and Kahneman (1992), including exactly the same parameter values. Thus, the significance of the predictive power of PV is rather high given those constraints. PV never falls below a significance level of 1%, even when adding *Skew* as a control. t-statistics are calculated in a very robust way by clustering standard errors along two dimensions, which should eliminate fixed and temporary (time-decaying) time and firm[7] effects according to Petersen (2009). Regarding the statistical significance of empirical studies, Harvey et al. (2016) show that because of data mining, t-statistics should be taken with a grain of salt and higher thresholds should apply when deeming something significant or not (i.e. upgrade from the standard two to three). However, they further argue that this changes when given theory and evidence dictates and motivates the tested models, as is the case in this analysis as already argued above. Thus, the robustness analysis becomes even more important in alleviating those data mining concerns. In light of all this, the very high t-statistics shown in Table 5, as well as what is shown in the time-series and the robustness analysis prior, yield more confidence when rendering a verdict on the statistical significance of PV.

[7] *Firm* here refers to the cross-sectional unit of the panel. In this study, this thus refers to a specific cryptocurrency.

Table 5
Regression Analysis

A. PV is calculated using returns from day t-30 to day t-1

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
PV	**-0.121**	**-0.119**	**-0.137**	**-0.140**	**-0.140**	**-0.404**	**-0.437**	**-0.500**
	(-11.52)	(-8.22)	(-9.02)	(-9.09)	(-9.09)	(-12.56)	(-13.15)	(-13.87)
Mom		0.001	0.003	**0.003**	**0.003**	**0.027**	**0.029**	**0.032**
		(0.64)	(1.53)	(1.70)	(1.70)	(9.53)	(9.92)	(10.62)
Size		**-0.058**	**-0.323**	**-0.326**	**-0.326**	**-0.341**	**-0.345**	**-0.320**
		(-2.32)	(-6.51)	(-6.63)	(-6.63)	(-6.84)	(-6.75)	(-6.47)
Beta		-0.059	-0.066	-0.061	-0.060	-0.022	-0.025	-0.018
		(-0.93)	(-0.99)	(-0.90)	(-0.90)	(-0.39)	(-0.42)	(-0.31)
Vol			**0.224**	**0.328**	**0.328**	**0.272**	**0.282**	**0.280**
			(7.93)	(8.30)	(8.30)	(8.03)	(8.21)	(7.84)
Sd Vol				**-0.105**	**-0.105**	**-0.040**	**-0.060**	**-0.072**
				(-3.98)	(-3.98)	(-1.85)	(-2.93)	(-3.27)
Illiq					**0.014**	**0.015**	**0.017**	**0.013**
					(21.37)	(19.17)	(22.13)	(16.97)
Min						0.004	**0.034**	0.020
						(0.44)	(2.53)	(1.43)
Max						**-0.063**	**-0.096**	**-0.098**
						(-8.80)	(-7.43)	(-7.71)
Skew							**0.798**	**0.669**
							(5.89)	(4.89)
Kurt								**0.141**
								(8.55)
N	505’547	504’395	504’395	504’385	504’385	504’385	504’385	504’385

(Continued)

Table 5
Continued

B. PV *is calculated using returns from day t-31 to day t-2*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
PV	**-0.018**	**0.025**	0.011	0.010	0.010	**0.202**	**0.174**	**0.187**
	(-2.54)	(2.93)	(1.27)	(1.09)	(1.09)	(8.84)	(7.46)	(8.00)
Mom		**-0.007**	**-0.006**	**-0.006**	**-0.006**	-0.003	-0.001	-0.001
		(-5.01)	(-4.26)	(-4.12)	(-4.12)	(-1.56)	(-0.25)	(-0.65)
Size		**-0.147**	**-0.326**	**-0.327**	**-0.327**	**-0.357**	**-0.362**	**-0.365**
		(-5.80)	(-6.97)	(-7.01)	(-7.02)	(-7.58)	(-7.55)	(-7.60)
Beta		-0.067	-0.073	-0.071	-0.070	-0.072	-0.074	**-0.075**
		(-1.55)	(-1.63)	(-1.58)	(-1.57)	(-1.64)	(-1.63)	(-1.65)
Vol			**0.152**	**0.197**	**0.198**	**0.121**	**0.130**	**0.130**
			(6.31)	(6.78)	(6.79)	(4.06)	(4.66)	(4.61)
Sd Vol				**-0.046**	**-0.046**	0.029	0.015	0.017
				(2.73)	(-2.73)	(1.31)	(0.82)	(0.92)
Illiq					**0.013**	**0.009**	**0.011**	**0.012**
					(22.15)	(12.20)	(14.26)	(14.56)
Min						**0.105**	**0.123**	**0.126**
						(11.23)	(8.84)	(8.98)
Max						**-0.076**	**-0.099**	**-0.098**
						(-9.94)	(-7.34)	(-7.28)
Skew							**0.512**	**0.532**
							(3.84)	(3.93)
Kurt								**-0.025**
								(-2.11)
N	504'797	503'667	503'667	503'657	503'657	503'657	503'657	503'657

Note: This table shows regression results for panel regressions. *Ret*, which is the daily log return in excess of the market, is the dependent variable in all regressions. PV is the prospect theory value of a cryptocurrencies historical return distribution as defined in section 2. In panel A, PV is calculated using returns from day *t-30* to day *t-1*. In panel B, PV is calculated using returns from day *t-31* to day *t-2*. *Mom* is the cumulative excess return calculated from day *t-31* to day *t-2*. Size is the log market capitalization at *t-1*. *Beta* is a cryptocurrency's beta at *t-1* calculated with returns over the previous 30 days, as stated by the Crypto-CAPM defined in section 3. *Vol* is the average daily log dollar volume at *t-1* over the previous 30 days. *Sd Vol* is the standard deviation of the daily log dollar volume at *t-1* over the previous 30 days. *Illiq* is the measure of illiquidity from Amihud (200) at *t-1*, scaled by 10^{-16}. *Skew* is the skewness of the daily excess returns at *t-1* over the previous 30 days. *Kurt* is the excess kurtosis of the daily excess returns at *t-1* over the previous 30 days. *Min* and *Max* are the maximum and the negative of the minimum daily log excess return at *t-1* over the previous 30 days, similar to Bali et al. (2011). *Ret*, *PV*, *Mom*, *Min* and *Max* are scaled up by 100. The sample runs from 01.02.2014 to 31.01.2020. Robust (two dimensional clustering) t-statistics are in parentheses and bold typefaces indicate significance at the 10%-level.

Panel B of Table 5 show exactly the same regressions as panel A does but with one major difference: PV is lagged by one day, i.e computed using returns from day *t-31* to day *t-2*. The rest is the same; with added controls one by one from column (1) through (8). The reasoning behind this second battery of regressions is to check whether the short term reversal explains most of the excess returns and after one day of reversal, the effect would essentially disappear or even reverse again. On the other hand, exhibiting statistically significant results in this analysis would suggest that PV retains at least some of it's predictive power even beyond short term reversal on the first day after portfolio creation. To some extent is obviously linked to what is shown in figure 2, only with the added feature of testing against a set of controls that ought to influence or explain cryptocurrency returns. Bottom line, PV retains it's predictive power for subsequent returns with statistical significance in most cases. t-statistics are mostly well above the needed threshold, even when taking conservative numbers as suggested by Harvey et al. (2016). Again, even after including *Skew* as a control, PV remains significant. However, results of the coefficients are mixed up. While in the analysis before (panel A), PV had negative coefficients throughout, meaning that high (low) PV cryptocurrencies earn low (high) subsequent returns. By skipping a day between the signal creation and the measuring of returns, PV almost exclusively now has positive coefficients when adding controls. Thus, high (low) PV cryptocurrencies earn high (low) subsequent returns the day after tomorrow. This basically means that when controlling for known predictors, it seems that one of the main drivers behind returns of long-short portfolios is short term reversal of high and low PV cryptocurrencies on the day after portfolio formation. The following day however, prices of those high (low) PV cryptocurrencies tend to rise (fall) again. In summary, PV significantly predicts time-t returns at *t-1* with a negative sign and at *t-2* with a positive sign.

4.5 Prospect Theory Mechanics

In the prior chapters, empirical evidence confirms the hypothesis that PV has predictive power for cryptocurrency returns in the cross-section. The reasoning behind this is in line with Barberis et al. (2016). Albeit they argue for stocks, the same line of thinking should hold for cryptocurrencies as well. According to them, investors inform themselves about a stock by looking at price charts and mentally represent the historical return distribution. With that information, investors evaluate stocks in accordance with prospect theory and buy (sell) stocks that seem appealing (unappealing) to them under prospect theory. The appealing stocks on average become overbought and earn low subsequent returns because of the reversal. The unappealing stocks become underbought and thus earn high subsequent returns on average. The interesting question Barberis et al. (2016) they try to answer is what exactly makes a high (low) PV stock appealing (unappealing) to investors. In other words, what are the characteristics of high and low PV stocks and some of the mechanics behind the prospect theory value. Since these are indeed some of the most compelling questions surrounding this entire topic, I follow their approach in evaluating the mechanics behind PV and as to what makes certain cryptocurrencies seem appealing or unappealing under that framework.

As already argued before, gambles with a high prospect theory value are gambles with a high mean payoff, a low standard deviation (because of loss aversion the value decreases with a high standard deviation) and a high skewness (because of probability weighting the value increases with positively skewed gambles). Thus high PV cryptocurrencies should have high past returns, low past volatility and high past skewness (Barberis et al., 2016). In order to test this further, I compute averages of deciles based on PV, i.e. I sort cryptocurrencies in deciles according to their PV and calculate averages for each decile for a set of characteristics. Specifically, for every day, cryptocurrencies are sorted into deciles based on their PV values. After that, for each decile and for a list of variables, mean values of all the cryptocurrencies in that decile for a specific day are calculated and then the time-series averages of those values are reported in table 7. The results do confirm the notion of a gamble under prospect theory: Variables of past returns (*Ret* and *Mom*) and skewness (*Skew*) indeed increase monotonically from low PV to high PV deciles. The increase in skewness from low to high PV deciles is even smoother than for stocks (Barberis et al., 2016). Past volatility variables and variables that indicate high past wins and losses, i.e. standard deviation of returns (*Sd*), the minimum (*Min*) and maximum (*Max*) absolute returns decrease monotonically in PV but from decile 9 to 10 increase again slightly. This is on the other hand in line with the analysis for stocks (Barberis et al., 2016). Barberis et al. (2016) argue that there is a correlation between volatility and skewness because high PV stocks more positively skewed and more volatile than the average stock in the sample. Thus, high PV stocks are those that trade off skewness, volatility and past returns optimally, i.e. yield the highest prospect theory value to a investor that evaluates stocks according to that framework (Barberis et al., 2016). The makes also sense for cryptocurrencies and helps to explain the numbers we see in table 7.

Table 7
Characteristic of Decile Portfolios

Portfolios	PV	Beta	Size	Mom	Illiq	Vol	Sd Vol	Max	Min	Skew	Kurt	Sd	Ret
Low PV	-0.213	0.494	12.095	-0.516	187.204	8.112	8.203	0.752	0.856	-0.265	3.827	0.227	-0.032
2	-0.115	0.638	12.779	-0.319	215.690	8.923	8.862	0.346	0.357	-0.055	2.514	0.111	-0.014
3	-0.089	0.676	13.472	-0.228	0.028	9.506	9.362	0.263	0.257	0.053	2.051	0.090	-0.011
4	-0.074	0.738	13.903	-0.173	0.008	9.975	9.789	0.232	0.210	0.167	2.033	0.080	-0.006
5	-0.064	0.783	14.379	-0.131	0.004	10.394	10.174	0.206	0.178	0.246	2.010	0.072	-0.005
6	-0.055	0.806	14.582	-0.075	16.405	10.654	10.421	0.195	0.156	0.343	2.042	0.066	-0.003
7	-0.046	0.813	14.912	-0.020	50.996	10.930	10.663	0.185	0.137	0.433	2.120	0.061	0.000
8	-0.038	0.806	15.269	0.034	0.023	11.385	11.139	0.181	0.121	0.569	2.378	0.057	0.001
9	-0.029	0.817	15.662	0.128	0.019	11.920	11.638	0.190	0.108	0.812	2.841	0.055	0.007
High PV	-0.008	0.877	16.288	0.434	0.051	12.813	12.369	0.288	0.105	1.190	4.558	0.068	0.031

Note: Every day, cryptocurrencies are sorted into deciles based on their PV values. After that, for each decile and for a list of variables, mean values of all the cryptocurrencies in that decile are calculated and the time-series averages of those values are reported in this table. Every variable is defined in section 4.1 and table 1. The sample runs from 01.02.2014 to 31.01.2020.

In case of stocks, skewness is one of the main drivers behind the high returns according to Barberis et al. (2016) because high PV stock are highly positively skewed. They show that probability weighting is mostly responsible for the predictive power of PV. To see if this is also the case for cryptocurrencies, I rerun the same regressions as in table 5 column (6) but with eleven different probability weighting parameters. The only thing that changes from one regression to the other is thus the computation of PV. Table 8 reports these results. The dependent variable, return, is again regressed on PV and a number of controls. Column (1) to (11) vary the parameters for probability weighting, γ and δ, from 0.31/0.39 to 1.31/1.39. The level of loss aversion and risk aversion (concavity and convexity) stay constant across all regressions. Column (4) with γ and δ as 0.61/0.69 is the exact same regression as in table 5 column (6). The numbers look differently because the independent variables are standardized to mean 0 and standard deviation 1 in order to make the results comparable across regressions. The table shows that the predictive power of PV on subsequent returns is highest and most significant for probability weighting parameters that are smaller than 1. The smaller the values for γ and δ, the higher then degree of distortion, i.e the higher the degree of overweighting of tails (see also figure 1). In fact, the coefficients of PV increase monotonically in absolute terms when lowering values for γ and δ (except in the most extreme case for γ and δ 0.31/0.39). For values of γ and δ above 1 that correspond to underweighting of tails, the coefficients of PV decrease in absolute terms, suggesting that the effect of PV on the subsequent return becomes smaller. In summary, skewness is a very important factor when analyzing the importance of PV for predicting future returns because in the probability weighting framework, the attractiveness of an asset is influenced by it's past skewness. This is in line with table 7. By looking at the price chart of the cryptocurrency, investors see the skewness and evaluate the asset as a gamble similar to a lottery. Since investors, especially retail investors in the cryptocurrency market, like those kind of gambles (one could even say seek such gambles in this market), they buy those cryptocurrencies that have those statistical features, leading those assets to rise in prices and earn low subsequent returns. PV seems to be able to capture what part about a investment in cryptocurrencies seems attractive and what part does not seem attractive to investors fairly well.

Table 8
Regression Analysis with different degrees of probability weighting

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
γ	0.31	0.41	0.51	0.61	0.71	0.81	0.91	1.01	1.11	1.21	1.31
δ	0.39	0.49	0.59	0.69	0.79	0.89	0.99	1.09	1.19	1.29	1.39
PV	**-2.356**	**-2.994**	**-2.977**	**-2.808**	**-2.621**	**-2.452**	**-2.306**	**-2.180**	**-2.067**	**-1.966**	**-1.873**
	(-7.36)	(-10.89)	(-12.04)	(-12.55)	(-12.83)	(-12.98)	(-13.06)	(-13.06)	(-12.99)	(-12.87)	(-12.70)
Mom	**0.596**	**0.859**	**1.114**	**1.335**	**1.514**	**1.651**	**1.747**	**1.808**	**1.839**	**1.846**	**1.835**
	(6.15)	(7.81)	(8.85)	(9.46)	(9.81)	(10.01)	(10.10)	(10.12)	(10.08)	(10.00)	(9.88)
Size	**-0.866**	**-0.852**	**-0.840**	**-0.829**	**-0.821**	**-0.814**	**-0.809**	**-0.806**	**-0.804**	**-0.804**	**-0.805**
	(-7.24)	(-7.07)	(-6.95)	(-6.84)	(-6.76)	(-6.71)	(-6.67)	(-6.66)	(-6.66)	(-6.68)	(-6.70)
Beta	-0.048	-0.034	-0.026	-0.020	-0.018	-0.018	-0.019	-0.022	-0.025	-0.029	-0.034
	(-1.16)	(-0.76)	(-0.52)	(-0.39)	(-0.34)	(-0.33)	(-0.36)	(-0.43)	(-0.52)	(-0.62)	(-0.73)
Vol	**0.867**	**0.977**	**1.037**	**1.070**	**1.087**	**1.090**	**1.083**	**1.069**	**1.050**	**1.027**	**1.003**
	(6.90)	(7.50)	(7.84)	(8.04)	(8.15)	(8.18)	(8.16)	(8.10)	(8.01)	(7.90)	(7.78)
Sd Vol	-0.057	-0.115	-0.153	**-0.182**	**-0.204**	**-0.220**	**-0.231**	**-0.236**	**-0.237**	**-0.234**	**-0.229**
	(-0.59)	(-1.19)	(-1.57)	(-1.88)	(-2.13)	(-2.34)	(-2.49)	(-2.59)	(-2.64)	(-2.65)	(-2.63)
Illiq	**0.019**	**0.021**	**0.023**	**0.025**	**0.026**	**0.027**	**0.028**	**0.029**	**0.029**	**0.029**	**0.029**
	(16.01)	(17.30)	(18.27)	(18.96)	(19.43)	(19.76)	(20.00)	(20.18)	(20.33)	(20.46)	(20.57)
Min	-0.170	**-0.868**	-0.510	0.133	**0.805**	**1.416**	**1.937**	**2.362**	**2.699**	**2.958**	**3.153**
	(-0.31)	(-1.93)	(-1.34)	(0.40)	(2.74)	(5.14)	(7.19)	(8.72)	(9.76)	(10.43)	(10.85)
Max	**-1.903**	**-1.651**	**-1.917**	**-2.352**	**-2.797**	**-3.191**	**-3.511**	**-3.754**	**-3.929**	**-4.046**	**-4.118**
	(-5.64)	(-5.45)	(-6.87)	(-8.81)	(-10.53)	(-11.72)	(-12.42)	(-12.76)	(-12.87)	(-12.85)	(-12.75)
N	504'642	504'642	504'642	504'642	504'642	504'642	504'642	504'642	504'642	504'642	504'642

Note: This table shows regression results for panel regressions with different degrees of probability weighting. *Ret*, which is the daily log return in excess of the market, is the dependent variable in all regressions. PV is the prospect theory value of a cryptocurrencies histrorical return distribution as defined in section 2. Every regression varies the probability parameters γ and δ for the PV calibration. The standard values from Tversky and Kahneman (1992) are 0.61 and 0.69, respectively. All independent variables have been normalized with mean 0 and standard deviation 1 in order to make the different models comparable. *Ret*, PV, *Mom*, *Min* and *Max* are scaled up by 100. The sample runs from 01.02.2014 to 31.01.2020. Robust (two dimensional clustering) t-statistics are in parentheses and bold typefaces indicate significance at the 10%-level.

5 Conclusion

Using data on a vast majority of cryptocurrencies, I show that the prospect theory value of a cryptocurrency predicts future returns with a negative sign. The motivation behind this stems from a first analysis that has been conducted on stock market. Similarly, cryptocurrency investors mentally represent the return distribution of a cryptocurrency and then evaluate this distribution in a way described by prospect theory. Every cryptocurrency can be attributed with a prospect theory value that serves as a signal for portfolio creation. Various tests including time-series, factor and regression analysis do indeed show that investors favour high over low prospect theory value cryptocurrencies. This leads to high prospect theory value cryptocurrencies being overbought and earning low subsequent returns in the cross-section and vice versa. This study can be seen as a first extension to the original paper by Barberis et al. (2016) because I adapt their empirical methodology closely while testing the signal for an other asset class. Hopefully, this leads to further testing of the prospect theory value framework as I believe that it is able to explain the behaviour or individual investors better than the standard expected utility framework. Ultimately, this study along with other studies around the prospect theory value ought to enhance valuation models that incorporate these kinds of predictors and therefore, lead to advancements in financial research.

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