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Prospect Theory in the Cryptocurrency Market

Bachelor's thesis

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Declaration of Authorship

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Prague, May 3, 2023

Kristyna Coufalova

Abstract

This thesis investigates the potential of cumulative prospect theory to explain future cryptocurrencies' returns. Moreover, the study aims to determine whether the predictive power of cumulative prospect theory value persists when cumulative prospect theory value is computed by plugging the percentage form of return (for instance, 5%) instead of the decimal form (for instance, 0.05). Using a rolling sample of 200 cryptocurrencies with the highest market capitalisation for each month from March 2017 to March 2023, we found that regardless of using returns in percentage or decimal form, the cumulative prospect theory value function produces comparative abnormal portfolio returns and confirms the hypothesis that cryptocurrencies with high (low) cumulative prospect theory value earn low (high) subsequent returns.

JEL Classification	G11, G12, G41
Keywords	Prospect theory, Cumulative Prospect Theory, Cryptocurrency, Behavioural Economics

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Abstrakt

Tato práce zkoumá potenciál kumulativní prospektové teorie k vysvětlení budoucích výnosů kryptoměn. Navíc, studie zkoumá, zda předpovědní síla hodnoty kumulativní prospektové teorie přetrvá, i když se hodnota kumulativní prospektové teorie vypočítá z procentuální formy výnosu (například 5%) místo desetinné formy výnosu (například 0,05). Použitím rolujícího vzorku 200 kryptoměn s nejvyšší tržní kapitalizací pro každý měsíc od března 2017 do března 2023 jsme zjistili, že, bez ohledu na použití výnosů v procentuální nebo desetinné formě, kumulativní prospektová teorie produkuje srovnatelné abnormální výnosy portfolia a potvrzuje tak hypotézu, že kryptoměny s vysokou (nízkou) hodnotou kumulativní prospektové teorie generují nízké (vysoké) následné výnosy.

Klasifikace JEL	G11, G12, G41
Klíčová slova	Prospektová teorie, Kumulativní prospektová teorie, Kryptoměna, Behaviorální ekonomie

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Acronyms

PT Prospect Theory

CAPM Capital Asset Pricing Model

AR Autoregressive Model

Bachelor’s Thesis Proposal

Author	Kristýna Coufalová
Supervisor	PhDr. Jiří Kukačka, Ph.D.
Proposed topic	Prospect Theory in the Cryptocurrency Market

Research Question and Motivation

An assumption about how investors evaluate risk is an essential component of any model of asset prices. While the expected utility theory is still the prevailing paradigm for modelling decision-making under risk, a growing body of evidence suggests that investors’ behaviour deviates from what the expected utility theory predicts.

Barberis *et al.* (2016) constructed an empirical test in which they try to investigate whether some investors in the stock market invest according to cumulative prospect theory (Tversky & Kahneman 1992). The main objective of this study was to test the following hypothesis: the stock with high (low) prospect theory values will have low (high) subsequent returns. They employed two main approaches, decile sorts and the Fama-MacBeth methodology, and found empirical evidence supporting their hypothesis. Moreover, they found that this prediction holds primarily for stocks with a lower market capitalisation as individual investors there are more likely to base their investment decision on the prospect theory thinking.

Using a similar methodology, Thoma (2020) tested whether some investors in the cryptocurrency market invest according to cumulative prospect theory and also found empirical support. Moreover, Chen *et al.* (2022) employed a different approach than Thoma (2020) to test whether this hypothesis holds in the cryptocurrency market and added further evidence in favour of prospect theory in the cryptocurrency market.

However, to test the hypothesis prospect theory value of a given stock or cryptocurrency must be computed. All mentioned studies use stock/cryptocurrency returns in decimal form (i.e., when the return is 50%, they plug into the function 0.5 to compute prospect theory value). As Barberis (2013) noted, there are several challenges when applying prospect theory the main one being that, in any given context, it is often unclear how to define precisely what a gain or loss is.

Barberis *et al.* (2016) did not provide any evidence of why they used a decimal form of returns rather than a percentage form to compute prospect theory value. Therefore, the aim of this thesis is to investigate whether the hypothesis laid by Barberis *et al.* (2016) and tested on the cryptocurrency market by Thoma (2020) and Chen *et al.* (2022) holds in the cryptocurrency even for a different approach to the computation of prospect theory value (i.e., even if the prospect theory value is computed by plugging percentage form of return rather than decimal form).

As opposed to Thoma (2020) and Chen *et al.* (2022) who made one large sample of cryptocurrencies for the entire period of investigation, I will do a rolling sample of 200 cryptocurrencies with the highest market capitalisation for each month from 01.03.2017 and 28.02.2023. Moreover, both Barberis *et al.* (2016) and Thoma (2020) use as base parameters of prospect theory derived from (Tversky & Kahneman 1992), which are more than 30 years old. This thesis will use these parameters and parameters based on recent research.

Hypotheses

> Hypothesis #1: Some investors in the cryptocurrency market invest according to cumulative prospect theory, i.e., they evaluate their investment into cryptocurrencies just by looking at cryptocurrencies' price charts which they evaluate by prospect theory (with percentage form). These investors invest in the attractive cryptocurrencies (have high prospect theory value) and disinvest in cryptocurrencies that are unattractive (have low prospect theory value), which results in the high prospect theory value cryptocurrencies being overbought, and the low prospect theory value cryptocurrencies being underbought. In short, the prospect theory value predicts future cryptocurrency returns with a negative sign.

Methodology

The full sample of cryptocurrencies covers the time span from 01.03.2017 to 28.02.2023. To identify whether the prospect theory (PT) value of cryptocurrency historical return predicts the future cryptocurrency return with a negative sign, I proceed as follows.

First, I download historical data for every cryptocurrency that will appear at least once in my sample. Then, for each cryptocurrency for each day, I will compute all values that I need, such as beta, min, max, a standard deviation of returns (Jia *et al.* 2020), and, most importantly, PT value. Next, I filter these cryptocurrencies in my data set with monthly portfolios.

Each day from 01.03.2017 to 28.02.2023, I rank all cryptocurrencies in my data set with monthly portfolios on their PT value a group them into deciles. Decile 1 corresponds to cryptocurrencies with the lowest PT value and decile 10 corresponds to cryptocurrencies with the highest PT value. For each day and for each decile corresponding to a particular day, I will compute the mean return of that decile. In the final step, I use these decile returns as input to the autoregression model of the first order, as well as to factor regression, the CAPM (Sharpe 1964; Lintner 1965). The results of these models reveal whether the model investors in the large capitalisation cryptocurrency market invest according to cumulative prospect theory.

Contribution

This thesis adds further testing evidence to the prospect theory value framework in the cryptocurrency market and adds another approach for testing the prospect theory. Moreover, it ought to enhance valuation models that incorporate predictors based on human behaviour and psychology, leading to advancements in financial research.

Literature Review

This bachelor's thesis is built on several main sources. The first one is Tversky & Kahneman (1992) in which a new version of prospect theory is examined – it incorporates cumulative functional and extends the theory to uncertain as well as risky prospects with any number of the outcome. This is needed because in the cryptocurrency market outcomes are uncertain and more than two outcomes are possible. The second, most important one, is Barberis *et al.* (2016), which seeks to explain whether Cumulative Prospect Theory is present in the stock market. Prior to Barberis *et al.* (2016), the most known paper which deals with prospect theory and stock prices but only in the one-period economy is Barberis & Huang (2008).

Outline

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Core bibliography

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Author

Supervisor

Chapter 1

Introduction

An assumption about how investors evaluate risk is an essential component of any model of asset prices. While the prevailing paradigm for modelling decision-making under risk is expected utility theory, increasing evidence suggests that investor behaviour often deviates from what is predicted by expected utility theory.

In their work, Barberis *et al.* (2016) investigate whether some stock market investors evaluate risk according to the cumulative prospect theory (Tversky & Kahneman 1992) rather than the expected utility. They developed a model of asset prices based on cumulative prospect theory and tested a hypothesis that some investors think about stocks in terms of stock's historical return distributions and in addition that these investors evaluate stock's return distributions according to cumulative prospect theory; this means that some investors form an opinion about the future price development of particular stock simply by looking at the stock's historical price chart, which they evaluate according to cumulative prospect theory. Cumulative prospect theory is a theory of decision-making under risk and uncertainty that consists of two parts: the value function and the probability weighting function. The value function describes how individuals perceive gains and losses, with a greater sensitivity to losses than gains. The probability weighting function describes how individuals subjectively evaluate probabilities, overweighting low probabilities and underweighting high probabilities. In the model settings, it means that cumulative prospect theory value can be calculated for every stock in our sample on any given day. Barberis *et al.* (2016) wanted to find out whether a stock with a high (low) cumulative prospect theory value would yield a low (high) subsequent return. Their prediction was, therefore, that in the cross-section, a stock's cumulative prospect theory value will predict the stock's subsequent return with a negative sign. To test this hypothesis, they used decile sorts and the Fama-MacBeth methodology (Fama & MacBeth 1973). Through both approaches, they found empirical evidence for this prediction in the U.S. stock market and the majority of almost fifty national markets. They also confirmed the hypothesis that prospect theory value's predictive power is greater among low market capitalisation stocks and stocks with high idiosyncratic volatility.

Thoma (2020) applied a similar methodology as Barberis *et al.* (2016) to test whether the prediction about cumulative prospect theory (that the cryptocurrency's cumulative prospect theory value will predict the cryptocurrency's subsequent return with a negative sign) also holds in the cryptocurrency market. He showed that the prediction holds even after controlling for known predictors, such as small minus big and the winners minus losers factor. Moreover, Chen *et al.* (2022) tested the Barberis *et al.* (2016) hypothesis on cryptocurrency as well and found that it holds, to be precise, that on average, after controlling for a large number of factors that influence expected return, when the cumulative prospect theory value of a cryptocurrency increases by one cross-sectional standard deviation, its next-week return decreases by 0.71% compared to other cryptocurrencies. Furthermore, they found that all components of cumulative prospect theory have an impact on the explanation of cryptocurrency investors' behaviour; most strikingly, the concavity/convexity of value function has the largest effect among these two components. This is in contrast with Barberis *et al.* (2016), who found that the probability weighting component accounts for a significant part of prospect theory's predictive power. These discrepant findings will also be of interest in this study.

As mentioned above, cumulative prospect theory consists of two parts, the value function and the weighting function. The weighting function represents subjective values of probabilities, so the arguments of the function are true probabilities, and outputs are subjective probabilities. Therefore, the range of arguments is only a close interval [0,1], and there is no possibility for ambiguity. Only different parameters of the function can be set. In contrast, the value function and its parameters were derived from experiments with monetary payoffs and losses. The first ambiguous thing is that sometimes parameters were estimated from experiments based on payoffs in EUR, other times from experiments based on payoffs in USD and many other currencies. Therefore, it is clear that when the exchange rates are not equal to one, the estimated parameters of the value function will be different. Secondly, there is no study that would estimate the value function parameters from experiments based on payoffs in percentage returns, but despite this Barberis *et al.* (2016) used in their study percentage change of price of a stock and plugged that into the value function. Moreover, we found that all Barberis *et al.* (2016), Thoma (2020), and Chen *et al.* (2022) used the decile returns to compute cumulative prospect theory value (i.e., when the return is 20%, they plug into the function 0.2 to compute cumulative prospect theory value). As Barberis (2013) noted, there are several challenges when applying prospect theory, the main one being that, in any given context, it is often unclear how to define precisely what a gain or loss is. Barberis *et al.* (2016) did not provide any evidence of why they used a decimal form of returns rather than a percentage form to compute cumulative prospect theory value.

Therefore, the aim of this thesis is to investigate whether the hypothesis laid by Barberis *et al.* (2016) and tested on the cryptocurrency market by Thoma (2020) and Chen *et al.* (2022) holds in the cryptocurrency even for a different approach to the computation of prospect theory value (i.e., even if the prospect theory value is computed by plugging the percentage form of return into the value function rather than the decimal form). This will contribute to understanding how investors evaluate risk in the cryptocurrency market, more specifically, whether the different forms of returns have such a large impact on cumulative prospect theory value that the Barberis *et al.* (2016) hypothesis would not hold.

To test this, we will use a rolling sample of 200 cryptocurrencies with the highest market capitalisation for each month from March 2017 to March 2023 to prevent the influence of micro-cap cryptocurrencies and also to prevent survivor and hindsight bias. Moreover, this approach enables to use only equal-weighted form of returns.

It is worth noting that both Barberis *et al.* (2016) and Thoma (2020) used cumulative prospect theory parameters derived from Tversky & Kahneman (1992) work, which are more than 30 years old, to be precise they varied parameters of the weighting function component but not the value function component. However, this thesis will not solely rely on these parameters but will also consider parameters based on recent research, such as (Brown *et al.* 2021; Walasek *et al.* 2018; Rieger *et al.* 2016). This approach will ensure that the analysis is up-to-date and reflects the current understanding of investors' risk evaluation.

To conclude, the two main hypotheses which will be tested in this study are the following:

> **Hypothesis #1**: Some investors in the cryptocurrency market invest according to cumulative prospect theory, i.e., they evaluate their investment into cryptocurrencies just by looking at cryptocurrencies' price charts which they evaluate by cumulative prospect theory (with a decimal form of cryptocurrencies' return). These investors invest in the attractive cryptocurrencies (have high cumulative prospect theory value) and disinvest in cryptocurrencies that are unattractive (have low cumulative prospect theory value), which results in the high prospect theory value cryptocurrencies being overbought, and the low prospect theory value cryptocurrencies being underbought. In short, the cumulative prospect theory value predicts future cryptocurrency returns in excess of the market with a negative sign.
>
> **Hypothesis #2**: Hypothesis #1 holds not only for the decimal form of cryptocurrencies' return but also for the percentage form.

To test these hypotheses, we use the equal-weighted simple form of cryptocurrencies' return and proceed with the following structure of analysis. Chapter 2 reviews existing literature to provide context and build on previous research. Chapter 3 outlines the prospect theory model structure and discuss in more detail the reasoning behind hypothesis #2, while Chapter 4 explains the data collection method and variables construction. In Chapter 5 is described the methodology of an analytical part. The crucial part of the study is in Chapter 6, where returns in both percentage and decimal form are tested, and the analytical findings either confirm or disprove the hypotheses. To ensure the validity of the results, robustness checks are carried out in Chapter 7, where different forms of returns are tested. Moreover, in Chapter 7 are discussed the main drivers of the prospect theory model. Finally, Chapter 8 concludes the study's findings.

Chapter 2

Literature Review

This section comprehensively overviews prospect theory, covering its key elements and related concepts. As this thesis contrasts prospect theory with expected utility theory, we will also explore the historical roots of decision theory, which can be traced back to the expected value and expected utility theory. The last section will review the applications of prospect theory in the financial markets.

2.1 Origins of Decision Theory

Generally, the origin of decision theory is seen in the correspondence on probability between Pascal and Fermat, which is dated to 1654 (David 1998). In these correspondence lists, Pascal and Fermat claimed that when a person is making a decision, he or she should choose the option with the highest expected value. The expected value is simply the value of an outcome multiplied by the probability of that outcome, as can be seen below:

$$E(X) = \sum_{i=1}^{n} P(X_i) \cdot X_i, \tag{2.1}$$

where $P(X_i)$ is a probability that outcome i occurs, X_i is value of an outcome i, and $\sum_{i=1}^{n} P(X_i) = 1$.

However, the expected value maximisation is often problematic as it does not allow decision-makers to exhibit their preferences, such as risk-seeking. This gave rise to further developments. In 1738, a Swiss mathematician, Daniel Bernoulli, proposed that people evaluate options by their utility function, which is their subjective value assigned to each outcome, rather than the objective value of each outcome (Glimcher 2014). In spite of this, the modern formulation of expected utility theory is credited to von Neumann *et al.* (1944). This process is called expected utility maximisation. The expected utility be written as:

$$E(U(X)) = \sum_{i=1}^{n} P(X_i) \cdot U(X_i), \tag{2.2}$$

where $\sum_{i=1}^{n} P(X_i) = 1$ and $U(X_i)$ represents the utility from obtaining outcome X_i. The expected utility relies on four main axioms: completeness, transitivity, continuity, and substitution. But later on, these axioms were called into question by, for example, the "Allais Paradox" (Allais 1953; 1979).

2.2 Prospect Theory and Cumulative Prospect Theory

Evidence of deviations from expected utility theory led to a non-normative form of expected utility theory called prospect theory. Kahneman & Tversky (1979) tried to merge several well-known deviations from the expected utility theory into a single theory of choice, the prospect theory. Here, it must be pointed out that many other different models were conducted to incorporate these deviations from the expected utility theory, such as Regret Theory (Loomes & Sugden 1982), and Disappointment Theory (Gul 1991), however, none of them incorporated all deviations. This first version of prospect theory has some limitations; for example, it can be applied only to risky prospects, in which probabilities are known to the decision maker, and not to uncertain[1] prospects, in which probabilities are not known to the decision maker, and it can be applied only to gambles with at least to non-zero outcomes. In contrast, cumulative prospect theory can be applied to both risky and uncertain prospects and to any finite number of outcomes. Although cumulative prospect theory is an advancement of prospect theory, its fundamental elements remain the same. Therefore, we will only describe in detail cumulative prospect theory.

To get an idea of how cumulative prospect theory works, consider the following example. Let us have a gamble with m losses $x_{-m}, ..., x_{-1}$ and their respective probabilities $p_{-m}, ..., p_{-1}$, n gains $x_1, ..., x_n$ with their probabilities $p_1, ..., p_n$, and an outcome of 0, x_0 , with its respective probability p_0. The sum of all probabilities of this gamble is 1. This gamble can be rewritten as

[1] ambiguous

$$(x_{-m}, p_{-m}; ...; x_{-1}, p_{-1}; x_0, p_0; x_1, p_1; ...; x_n, p_n). \tag{2.3}$$

The final value of this gamble for an individual is

$$\sum_{i=-m}^{n} \pi_i v(x_i), \tag{2.4}$$

and is derived by the following procedure. Value function, $v(.)$, is defined as

$$v(x) = \begin{cases} x^\alpha & \text{for} \quad x \geq n \\ -\lambda(-x)^\beta & \text{for} \quad x < 0, \end{cases} \tag{2.5}$$

where x is a monetary gain or loss, λ determines the degree of loss aversion, the higher the lambda, the higher the sensitivity to losses, α determines the curvature of the value function for gains, and β determines the curvature of the value function for losses. $\lambda > 0$, $\alpha, \beta \in (0, 1)$.

Decision weight of prospect i, π_i, is defined as

$$\pi_i = \begin{cases} w^+(p_i + ... + p_n) - w^+(p_{i+1} + ... + p_n) & , \quad 0 \leq i \leq n \\ w^-(p_{-m} + ... + p_i) - w^-(p_{-m} + ... + p_{i-1}) & , \quad -m \leq i \leq 0, \end{cases} \tag{2.6}$$

where w^+ and w^- are probability weighting function; w^+ corresponds to a probability of gain and w^- corresponds to a probability of loss. Both w^+ and w^- are strictly increasing functions from a unit interval into itself and holds that $w^+(0) = w^-(0) = 0$, and $w^+(1) = w^-(1) = 1$.

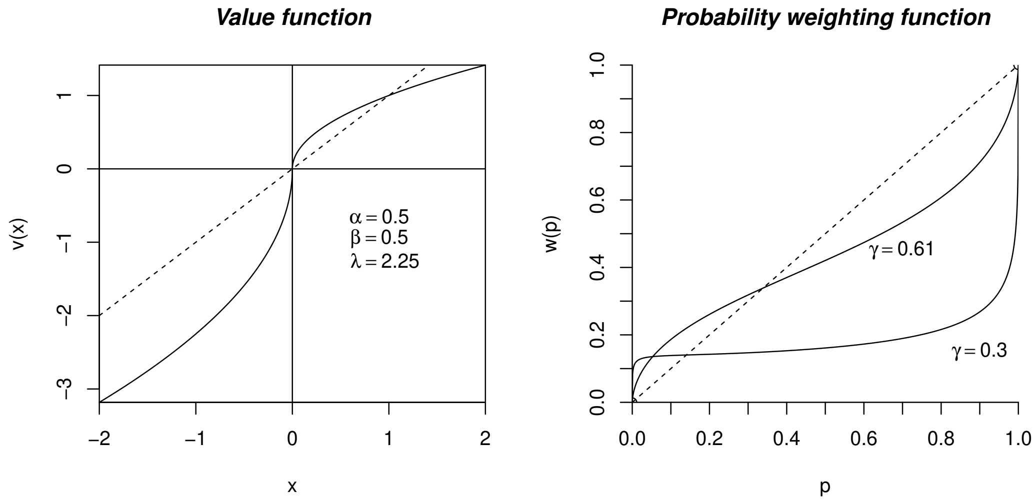
$$w^+(p) = \frac{p^\gamma}{(p^\gamma + (1-p)^\gamma)^{\frac{1}{\gamma}}}, \tag{2.7}$$

$$w^-(p) = \frac{p^\delta}{(p^\delta + (1-p)^\delta)^{\frac{1}{\delta}}}, \tag{2.8}$$

where $\gamma, \delta \in (0, 1)$. For $0 \leq i \leq n$, the decision weight π_i is linked to a positive outcome, indicating the difference between the events "the outcome is at least as good as x_i" and "the outcome is strictly better than x_i". For $-m \leq i \leq 0$, the decision weight π_i is linked to a negative outcome, indicating the difference between the events "the outcome is at least as bad as x_i" and "the outcome is strictly worse than x_i". The graphical representation of the prospect theory value function and weighting function is shown in Figure 2.1.

On the other hand, the standard expected utility of a given gamble of an

Figure 2.1: Prospect theory value and weighting functions



Note: The left figure shows the value function v(x) from (Tversky and Kahneman, 1992) with parameters $\alpha = 0.5$, $\beta = 0.5$ and $\lambda = 2.25$ and reference point equal to zero. The parameters α and β were chosen lower than in (Tversky and Kahneman,1992) to highlight the nature of the function. The right figure shows the probability weighting function for different parameters of distortion. The dashed line in both figures represents a simple linear function $f(x) = x$.

individual is defined as

$$\sum_{i=-m}^{n} p_i \cdot U(W + x_i), \tag{2.9}$$

where W is an individual's current state of wealth, function U is the individual's utility function, x_i is a monetary gain or loss, and p_i is a probability of x_i.

The prospect theory utility function differs from the expected utility function in four main properties. First, in prospect theory, value is defined as gains and losses relative to a reference point (which could be zero), while in expected utility, values refer to final wealth levels, i.e. to $W + x_i$. Second, the utility function in the expected utility framework is differentiable everywhere, but in prospect theory, there is a kink at the origin, reference point, that represents loss aversion. This means that people are more sensitive to losses than gains of the same size, or in other words, the disutility of a loss is greater than the utility of a gain of the same monetary value. The size of the kink determines the degree of loss aversion. Third, the concavity of the prospect theory function only applies to gains and convexity to losses, while the standard expected utility function is usually concave for all values. Last, the probability space in prospect theory is subjective, meaning individuals use transformed probabilities generated from a weighting function and do not use actual probabilities as it is in expected utility. This leads to a greater emphasis on the tails of a distribution. Hereafter, we will write only prospect theory when referring to cumulative prospect theory, as it this the only one used from now on.

2.3 Chronological Development of Prospect Theory's Applications in Finance

Since the publication of Tversky & Kahneman (1992), many attempts have been made to apply this concept to the financial market. One of the first highly influential papers was Benartzi & Thaler (1995) which provided empirical evidence that prospect theory, especially loss aversion, with narrow framing, which occurs when an individual evaluates risk in isolation from other risks, can explain the famous equity premium puzzle in the US.

Subsequently, Ding *et al.* (2004) in his study applied prospect theory to analyse how analysts' forecasts affect stock returns. Even though he did not incorporate prospect theory in the model, he provided empirical evidence supporting prospect theory's application in financial markets.

Later on, Barberis & Huang (2008) investigated how the concept of probability weighting applies to stock market investing. They showed that when investors are faced with lottery-like payoffs, their probability weighting can result in the overvaluation of high-volatility stocks and the undervaluation of low-volatility stocks.

Kliger & Levy (2009), by analysing data on options on S&P 500 found both economical and statistical evidence of non-linear probability weighting and loss aversion. Moreover, they showed that cumulative prospect theory prevailed over both expected utility theory and rank-dependent expected utility theory in terms of the model's overall fit.

In another study on the application of prospect theory in asset pricing, Zhang & Semmler (2009) provided empirical evidence of prospect theory in asset pricing using time-series data and a loss aversion model. The study tested the hypothesis that investors exhibit loss aversion, which can lead to the equity premium puzzle, where stocks have higher expected returns than bonds, even though they are riskier. He found that the loss aversion model based on prospect theory can explain the equity premium puzzle better than other asset pricing models. The study contributed to the literature on prospect theory and its application in asset pricing, highlighting the importance of loss aversion in explaining the behaviour of investors and the pricing of assets.

Afterwards, Kothiyal *et al.* (2014) conducted an experimental study to assess the predictive power of prospect theory in decision-making under ambiguity. The authors discovered that prospect theory was more effective than expected utility theory in describing ambiguous decision-making behaviour. Moreover, they found that prospect theory performed better than alternative theories for predicting decisions under uncertainty.

Many more studies deal with either implementation or investigation of prospect theory; however, we just picked the most important ones for this research. Despite numerous studies contributing to the understanding of prospect theory's application in finance, Barberis (2013) identifies several challenges in applying the theory. One of the main difficulties is the lack of clarity in defining a gain or loss precisely in different contexts.

These findings led Barberis *et al.* (2016) to use a comparable methodology as in Benartzi & Thaler (1995) and, with some modifications, apply it to the stock market. The accuracy of these hypotheses was subsequently examined in other markets, such as the corporate bonds market (Zhong & Wang 2018), the foreign exchange currency market (Xu *et al.* 2020), and the cryptocurrency market (Thoma 2020; Chen *et al.* 2022).

2.4 Prospect Theory and its Applications in the Cryptocurrency Market

As for the prospect theory in the cryptocurrency market, the literature dealing with this topic is scarce. A notable one is a study by Al-Mansour (2020), which, by using multiple regression analysis, revealed that the herding theory factors, prospect theory, and heuristic theory significantly impact investors' investment decisions in the cryptocurrency market; however, did not use the sorting of cryptocurrencies according to Prospect Theory (PT) value.

The second notable study is Ababio (2019). This study aimed to investigate whether investors could enhance the value of their investment portfolios by investing in behaviorally driven assets within the international equity and cryptocurrency markets (a small group of cryptocurrencies sorted by PT value). The findings indicate that investing in assets with significantly lower PT values can increase the likelihood of adding value to investment holdings for investors.

2.5 Summary of Literature Review

To conclude, an increasing number of studies incorporate not only isolated parts of prospect theory, such as probability weighting or loss aversion but also try to merge all aspects together. However, until today, there still does not exist a single and unified approach for applying prospect theory, and much more research and literature, especially in cryptocurrency, is needed. As Barberis (2013) notes, the best way to tackle this question-and the main approach researchers are taking-is to derive the predictions of prospect theory under various plausible definitions, which is exactly what this study is about.

Chapter 3

Prospect Theory Model Structure

In this chapter, the prospect theory model's components are explored regarding their relevance in constructing the prospect theory value model. Specifically, consideration is given to the appropriate time periods and parameters that are suitable for use in the prospect theory model. Moreover, in Section 3.3 is discussed in more detail the reasoning behind hypothesis #2.

3.1 Window for Construction of Return Distribution

According to hypothesis #1, the majority of people look at price charts of cryptocurrencies to inform themselves about the coin's historical price. Most used cryptocurrencies' price charts are simple and freely available websites which do not require setting up an account to access their services, such as coinmarketcap.com, coingecko.com, livecoinwatch.com, coinbase.com, crypto.com, and coincodex.com. On the homepage of these websites is displayed a list of cryptocurrencies arranged in descending order by market capitalisation, i.e. the first cryptocurrency is the one with the highest market capitalisation. For each cryptocurrency, several variables are shown, including a 7-day percent change, and, most importantly, a price chart for the last 7 days. These 7-day price charts are colour-coded, with green indicating a positive weekly percentage change and red indicating a negative one. Another important feature is that all price changes are also coloured either green or red by the same principle. These features affect human behaviour; one of the possible consequences can be anchoring bias, which occurs when people rely too much on the first information they see when making decisions. For example, Jia *et al.* (2022)

found a strong positive cross-sectional association between a form of anchoring and future cryptocurrency returns. In the context of this case, anchoring can occur when some investors fixate on a trend and its colour and perceive it as significant and base their subsequent decisions and actions around that reference point. This would be in line with hypothesis #1 and hypothesis #2 about prospect theory value. Therefore, one of the periods of study's interest is 7 days.

When one of the cryptocurrencies from the list is clicked, a price chart and other detailed information about the cryptocurrency are displayed. Again, the graph is of the biggest interest. All websites listed above show price charts for the last 24 hours as a default. The other options offered are 7 days, 14 days, 1 month, 3 months, 1 year, and the whole period of existence. Although, as cryptocurrencies are known for their high volatility (Klein *et al.* 2018; Corbet *et al.* 2018), which means that their prices can fluctuate rapidly and dramatically in short periods of time, it is reasonable to test both hypotheses on shorter periods of time. Therefore, it would be sensible to test the hypothesis with prospect theory value created from the past 1 day, 7 days, 14 days, and 30 days return of the cryptocurrency.

Unfortunately, hourly or minute data are not available to download for free; thus, we will do analysis only with daily data, to be exact, the daily close price of cryptocurrencies. Moreover, we are technologically constrained so we can choose only a limited number of periods. Due to these facts, we will test whether my hypothesis holds only for two PT construction windows: 7 days and 14 days.

3.2 Choice of Parameters

Next, we will set preference parameters α, λ, γ, and δ. Even though Thoma (2020) work closely follows the methodology of Barberis *et al.* (2016) and applies it to the cryptocurrency market, the work lacks different choices of parameters of prospect theory; Thoma (2020) has done tests with different choices of parameters of weighting function but left the parameters of value function constant and did not examine other parameter values. In order to find an alternative set of parameters for this study, the same methodology as in (Barberis *et al.* 2021) will be employed.

A classical and most-known set of parameters is

$$\begin{aligned}\alpha &= 0.88,\\ \beta &= 0.88,\\ \gamma &= 0.61,\\ \delta &= 0.69,\\ \lambda &= 2.25,\end{aligned} \tag{3.1}$$

which was estimated by Tversky & Kahneman (1992); values of those parameters represent the median participant in their experiment. However, this experiment was done with a small number of participants and is more than 30 years old. Since 1992, a lot of experiments have been conducted to estimate the true values of parameters. Given that results of this study are heavily dependent on the values of these preference parameters, it would be inappropriate to derive these parameters only from one study.

In an international survey, Rieger *et al.* (2016) found strong, systematic, and statistically significant differences in prospect theory parameters among 53 countries worldwide and also revealed that different degrees of probability weighting are associated with different economical situations, cultural differences, and gender. They also found that α and β are statistically different, α being less than β. For gains, the mean country-level estimate is $\alpha = 0.46$; for losses, the mean estimate is $\beta = 0.58$. The rest mean estimates are $\gamma = 0.5$, $\delta = 0.81$, and $\lambda = 1.73$.

Booij *et al.* (2009) computed the mean of parameter estimates from the large body of previous studies and experiments and found that the mean parameter estimates are $\alpha = 0.69$, $\beta = 0.86$, $\gamma = 0.69$, $\delta = 0.72$, and $\lambda = 2.07$. Moreover, they conducted their own experiment and estimated the following values of parameters:$\alpha = 0.859$, $\beta = 0.826$, and $\lambda = 1.58$. Many more studies and meta-analyses were conducted to estimate these parameters; however, it is out of the scope of this work to compare them all. Mostly, the estimates of α and β range from 0.4 to 0.9, with α being less or equal to β in most cases. Therefore, I will set parameters as an approximate mean of them: $\alpha = 0.65$, $\beta = 0.75$. In a large body of studies, parameters γ and δ move around the original parameters measured by Tversky & Kahneman (1992); therefore, we will not change these parameters.

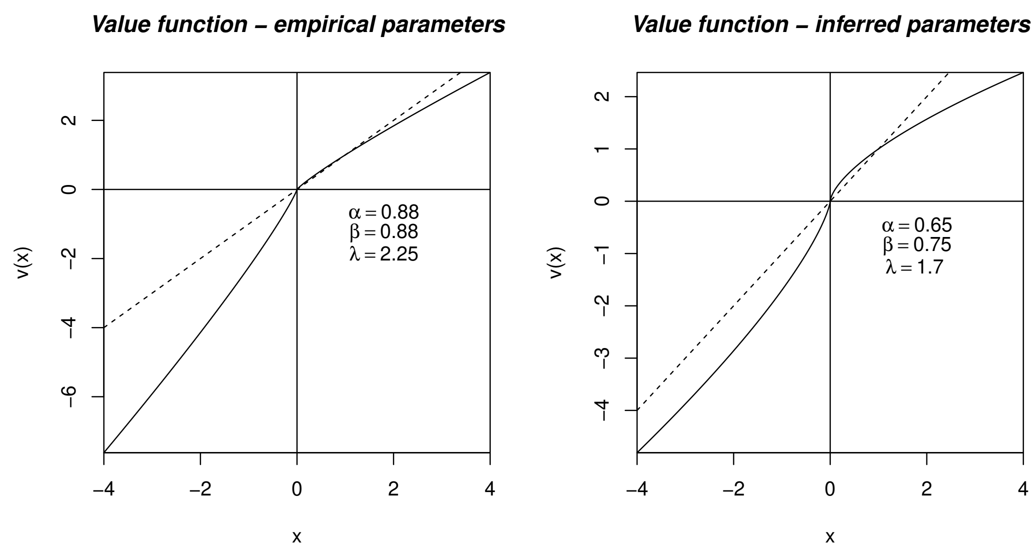
As for the loss aversion parameter λ, Walasek *et al.* (2018) in a random-effect meta-analysis found a median of λ equal to 1.31, 95% CI $[1.10, 1.53]$. In contrast, in a meta-analysis of empirical estimates of loss-aversion, Brown *et al.* (2021) found that the aggregate-level mean λ is 1.955 with 95% CI $[1.824, 2.104]$ and the median λ is 1.545. Therefore, to respect all these results, we will set $\lambda = 1.7$.

To summarise, we will use the following set of parameters as a base set for the data analysis

$$\begin{aligned} \alpha &= 0.65, \\ \beta &= 0.75, \\ \gamma &= 0.61, \\ \delta &= 0.69, \\ \lambda &= 1.70 \end{aligned} \tag{3.2}$$

and call this set "inferred parameters". However, to have some comparable benchmark with previous works, such as Thoma (2020), we will perform all the tests even with the original parameters from (Kahneman & Tversky 1979). In Figure 3.1 is provided a graphical representation of these two sets of parameters.

Figure 3.1: Prospect theory value functions with the examined parameters



Note: The right figure shows the value function $v(x)$ from (Tversky & Kahneman 1992) with parameters $\alpha = 0.88$, $\beta = 0.88$ and $\lambda = 2.25$ and reference point equal to zero. The left figure shows the value function $v(x)$ from (Tversky & Kahneman 1992) with another set of parameters chosen for the study. The dashed line in both figures represents a simple linear function $f(x) = x$. The length of the x-axis is in both graphs fixed; however, the length of the y-axis differs.

Let us take a closer look at what these different sets of parameters could mean for the results of the study. For instance, suppose we consider a value of 5 with a reference point of 0. Empirical parameters represent this as 4.122, while inferred parameters represent it as 2.847. A value of -5 with a reference point of 0 is viewed as -9.274 by empirical parameters and as -5.684 by inferred parameters. Similarly, a value of 0.5 with a reference point of 0 is viewed as 0.543 by empirical parameters and as 0.637 by inferred parameters, while a value of -0.5 with a reference point of 0 is viewed as -1.22 by empirical parameters and as -1.01 by inferred parameters.

It is worth noting that we are dealing with percentages in hypothesis #2. The different parameters of the value function play a crucial role in shaping the value function in the interval [-1,1]. Additionally, we assume the framing effect, meaning that people evaluate each cryptocurrency return separately, and we use a reference point equal to zero. Therefore, it is important to examine how the values between -3.485 (the first quartile of percentage returns) and 3.232 (the third quartile of percentage returns) are evaluated according to the value function.

As shown in Figure 3.1, the shape of the two value functions differs significantly, and therefore we expect some differences in the results as well. Table 3.1 provides an overview of the main properties of the cryptocurrency's daily percentage returns to highlight that the majority of cryptocurrencies' returns are in a range on which have different sets of value function parameters considerable influence. Furthermore, examining the distribution of cryptocurrencies' returns will provide a useful visualisation of what outputs we can expect from the value function.

Table 3.1: Explanatory data analysis: cryptocurrency daily percentage return

Min	First Quartile	Median	Mean	Third Quartile	Max
-96.587	-3.485	-0.128	0.353	3.232	1357.864

Table 3.1 shows that the first quartile (Q1) is -3.485%, and the third quartile (Q3) is 3.232%. Therefore, the IQR is calculated as follows:

$$IQR = Q3 - Q1 = 3.232\% - (-3.485\%) = 6.717\%.$$

This means that the middle 50% of the data falls within a range of 6.717% centred around the median value of -0.128%. In other words, the daily percentage returns for cryptocurrencies were within the range of -3.485% to 3.232% for half of the observations, which is much smaller than the range between the minimum and maximum values of 1454.451%. This indicates that the majority of daily returns fall within a relatively narrow range, while there are extreme values (outliers). Therefore, we expect the parameters of the value function to have a significant impact on the PT value construction.

It is also important to note that the mean daily percentage return for cryptocurrencies was 0.353%. This means that, on average, cryptocurrencies experienced a small positive daily return during the period analysed. However, the large difference between the mean and median values indicates that the distribution of daily returns is right-skewed, with some extremely high returns on certain days that pull the mean up.

3.3 Scaling

Before moving on to the last section, we would like to discuss one really important issue and the main focus of this study that has not received much attention yet – the scale of the prospect theory value function. All examined studies about prospect theory Barberis *et al.* (2016); Thoma (2020); Chen *et al.* (2022); Xu *et al.* (2020); Zhong & Wang (2018) plugged into the prospect theory's value function percentage form of return (for example, 0.25) and not in percentage form (for example, 25%). However, all studies dealing with the estimation of the prospect theory value function examined in Section 3.2 estimate prospect theory parameters through gambles where values are in monetary terms, not percentage return terms at all. There exist much more studies such as Etchart-Vincent (2004), Gonzalez & Wu (1999), Wu & Gonzalez (1996), which estimated prospect theory parameters through gambles where gains and losses offered were in USD, or Abdellaoui *et al.* (2008) where gains and losses offered were in EUR. The authors of Barberis *et al.* (2016) did not justify using decimal returns instead of percentage returns when calculating prospect theory value. This lack of clarity and reasoning in defining the arguments of the value function results in the possible choice of percentage returns as arguments to the value function. Moreover, there is a chance that the use of a percentage form of returns rather than a decimal form of returns can yield higher portfolio returns.

To better understand this thought, let us consider the following example: Imagine you have a gamble with two values: 25% return and 75% return, which can also be rewritten as 0.25 and 0.75 return. You will evaluate this game by value function with empirical parameters. When you plug 0.25 into the value function, you get approximately 0.295; when you plug in 0.75, you get approximately 0.776. When you plug 75 into the value function, you get approximately 44.67 which is after division by 100 equal to 0.4467. When you plug 25 into the value function, you get approximately 16.98 which is after division by 100 equal to 0.1698. Finally, we can see that for 25% return, the re-scaled values are 0.1698 for percentage form and 0.295 for decimal form, and for 75% return, the re-scaled values are 0.776 for percentage form and 0.4467 for decimal form. Thus, it is a big difference if you plug percentage rates in decimal or percentage form. Different outputs of the value function based on both decimal and percentage returns are examined in Table 3.2.

Table 3.2: Percentage returns from value function

A. Empirical parameters										
	-100%	-95%	-50%	-5%	-1%	1%	5%	50%	95%	100%
Decimal	-2.25	-2.15	-1.22	-0.16	-0.04	0.02	0.07	0.54	0.96	1
Percents	-1.30	-1.24	-0.70	-0.09	-0.02	0.01	0.04	0.31	0.57	0.58
B. Inferred parameters										
	-100%	-95%	-50%	-5%	-1%	1%	5%	50%	95%	100%
Decimal	-1.7	-1.64	-1.01	-0.18	-0.05	0.05	0.14	0.64	0.97	1
Percents	-0.54	-0.52	-0.32	0.06	-0.02	0.01	0.03	0.13	0.19	0.20

Therefore, this is the main reason why we chose to do the analysis with both percentage form and decimal form of cryptocurrencies' returns. Moreover, both of these forms of returns will be examined with empirical and inferred parameters.

3.4 Prospect Theory Value Construction

Based on the information presented in Sections 3.1, 3.2, and 3.3, we have eight combinations on which we will conduct the analysis: 7-day period with empirical parameters, 7-day period with inferred parameters, 14-day period with empirical parameters, 14-day period with inferred parameters, 7-day period with inferred parameters and a decimal form of returns, 14-day period with inferred parameters and a decimal form of returns, 7-day period with empirical parameters and a decimal form of returns, and 14 day period with empirical parameters and a decimal form of returns. For the explanation, a 7-day construction window will be used; for the construction of PT with a 14-day window,

Table 3.3: Combinations of inputs to prospect theory value function

Construction window	Transformation of returns	Form of returns	Parameters
7 days	Simple	Percentage	Empirical
7 days	Simple	Percentage	Inferred
7 days	Simple	Decimal	Empirical
7 days	Simple	Decimal	Inferred
14 days	Simple	Percentage	Empirical
14 days	Simple	Percentage	Inferred
14 days	Simple	Decimal	Empirical
14 days	Simple	Decimal	Inferred

Note: Table shows the eight variations of inputs to the prospect theory value function on which the study's main analysis will be conducted. These variations were selected based on the information presented in Sections 3.1, 3.2, and 3.3. In the second column is reported transformation of cryptocurrencies in order to highlight that the main analysis is conducted solely with a simple form of return and not logarithmic.

the methodology employed is identical. These combinations are summarised in Table 3.3.

If we want to compute the PT value of the cryptocurrency at time t, we need to have data on cryptocurrency returns from time $t-8$ to time $t-1$. Then, these past returns must be sorted in ascending order. Let us denote m, the number of negative returns, and $n = 7 - m$, the number of positive returns. As in Section 2.2, we label these sorted returns in ascending order, i.e. the most negative return is r_{-m}, then r_{-m+1}, through r_n, the most positive return. Finally, each of these returns is assigned an equal probability of $\frac{1}{7}$. The cryptocurrency historical distribution now has a form of:

$$(r_{-m}, \frac{1}{7}; r_{-m+1}, \frac{1}{7}; ...; r_{-1}, \frac{1}{7}; r_1, \frac{1}{7}; ...; r_{n-1}, \frac{1}{7}; r_n, \frac{1}{7}). \tag{3.3}$$

PT value of distribution 3.3 is then computed as described in Section 2.2. Therefore, PT value of distribution 3.3 has a form:

$$\begin{aligned} PT = &\sum_{i=-m}^{-1} v(r_i) \cdot \Big[w^-\Big(\frac{i+m+1}{7}\Big) - w^-\Big(\frac{i+m}{7}\Big)\Big] \\ &+ \sum_{i=1}^{n} v(r_i) \cdot \Big[w^+\Big(\frac{n-i+1}{7}\Big) - w^+\Big(\frac{n+i}{7}\Big)\Big]. \end{aligned} \tag{3.4}$$

This is the final form of PT value, which will be used as input for the analytical part.

Chapter 4

Data and Variables Description

This chapter provides a description of data collection and variables construction.

4.1 Cryptocurrency Data

All cryptocurrency data were collected directly from CoinMarketCap (2023)[Assessed on 2023-03-07] through a special function in R. CoinMarketCap is the most-referenced price-tracking website for crypto assets and offers easy access to cryptocurrency data, especially in terms of price and volume data. It aggregates information from over 230 main exchanges and provides information on name, id, symbol, reference currency [1], price open, price high, price low, price close, time of price open, time of price high, time of price low, time of price close, market capitalisation, and volume for each coin.

At CoinMarketCap historical snapshots are listed active as well as defunct (dead) cryptocurrencies that ceased to exist due to different factors, such as low liquidity or insufficient funding. Including both active and dead cryptocurrencies in the sample will alleviate survivor bias concerns.

Different than Barberis *et al.* (2016), who constructed the sample from all stocks in the CRSP universe, and Thoma (2020) and Chen *et al.* (2022), who constructed the sample from all cryptocurrencies which met certain assumptions, such as minimum value, minimal market capitalisation, and maximum daily return, we create one sample in which we pick only first 200 largest cryptocurrencies based on market capitalisation in a given month, and then we sort

[1]Reference currency for every coin in the sample is USD

out cryptocurrencies which do not meet certain assumptions; this is to prevent the influence of micro-cap cryptocurrencies.

Cryptocurrencies that are pegged to other currencies, mainly to the USD but also to the EUR, or other currencies, are excluded from the sample; this includes cryptocurrencies such as Tether, USD Coin, Binance USD, Dai, TrueUSD, Pax Dollar, USDD, and bitUSD. These cryptocurrencies are entirely removed from the sample after the portfolio formation occurs. Thus, it can happen that there will not be a full sample of the 200 most capitalised cryptocurrencies for each month.

4.2 S&P Cryptocurrency Broad Digital Market Index

For the calculation of the *beta* controlling variable (defined in Section 4.5), which will be used in the linear regression analysis, a measure of the cryptocurrency market performance is needed. S&P Cryptocurrency Broad Digital Market Index was chosen as a representative for the market due to its broad market representability and data availability. We download data from S&P Dow Jones Indices (2023)[Assessed on 2023-03-07]. The S&P CBDMI is an index launched by S&P Dow Jones Indices and tracks the performance of a diverse group of cryptocurrencies. The index includes more than 240 coins that meet specific criteria, such as a minimum market capitalisation and liquidity threshold. The index is market capitalisation-weighted, with each coin's weight determined by its market capitalisation relative to the total market capitalisation of all coins included in the index. The index is rebalanced on a quarterly basis to ensure that it remains representative of the cryptocurrency market's performance.

The only drawback of the S&P Cryptocurrency Broad Digital Market Index is that its price capture time is 4:00 PM Eastern Time Zone (GMT -5). In contrast, CoinMarketCap's capture time for historical data is 11:59 PM Greenwich Mean Time (GMT +0). This creates an approximate difference of 3 hours (as I have not accounted for daylight saving time) between the price of cryptocurrencies included in the S&P index and CoinMarketCap's historical snapshot. For this thesis, I will assume that this difference is negligible and has no effect on the results.

Index market return (in percents) in time t with the use of the S&P Cryptocurrency Broad Digital Market index returns is computed as follows:

$$Market\ index_t = \frac{CBDMindex_t - CBDMindex_{t-1}}{CBDMindex_{t-1}} \cdot 100. \qquad (4.1)$$

4.3 Additional Data

The yield of the 1-month US Treasury bill is used as the proxy for the risk-free rate, which is the same methodology as in Fama & French (1992). This data is retrieved from Board of Governors of the Federal Reserve System (2023)[Assessed on 2023-03-07]. The reason why we are not using some proxy from a cryptocurrency market is that there does not exist any completely risk-free rate in the cryptocurrency market.

4.4 Dataset Construction

We downloaded the first 200 cryptocurrencies on the last day of each month in a time span ranging from 31.03.2017 to 28.02.2023. Then, we removed all dead cryptocurrencies. Each of these last-day-in-month portfolios represents a cryptocurrency portfolio for the following month; this means we do not have a stable portfolio of cryptocurrencies as Barberis *et al.* (2016); Thoma (2020); Chen *et al.* (2022) had. The main reason is that we want to prevent the influence of small-cap cryptocurrencies. Another reason why we do portfolio sorting before the start of the next month is to prevent survivorship bias and hindsight bias. Hindsight bias occurs when the analyst has access to information that was unavailable at the time of portfolio formation (Roese & Vohs 2012). Survivorship bias occurs when only the surviving portfolios are included in the sample, which can lead to overestimating the performance of portfolios (Garcia & Gould 1993).

Next, we made a large cryptocurrency dataset containing all unique cryptocurrencies that appeared in the monthly portfolios at least once. In this dataset is together 847 unique cryptocurrencies. We downloaded the whole history from 01.12.2016 to 07.03.2023 for each cryptocurrency in that set if the cryptocurrency had data for the whole time span; otherwise, the longest possible time period was downloaded. Then, we removed data for cryptocurrencies with a market capitalisation of less than \$50 000, cryptocurrencies with a close price of less than \$0.01, cryptocurrencies with a volume less than \$1, or cryptocurrencies with daily returns bigger than \$1500. Thus, if the cryptocurrency does not meet any of these conditions, it is automatically removed from the sample. Then, we performed basic data cleanup and computed inputs to the models, including computation of PT value, momentum, maximum, and minimum value. After all of this was done, we filtered the final monthly rolling portfolio from this large cryptocurrency dataset, i.e. we assigned to each cryptocurrency for a given day in the monthly portfolio all its values in the large cryptocurrency portfolio. From now on, the only dataset which will be used is this monthly rolling portfolio dataset. The risk-free rate is the daily yield of the one-month US Treasury Bill.

4.5 Variables Construction

This section defines the variables necessary for our analysis and presents summary statistics for these variables.

4.5.1 Variables Definition

Firstly, we define all return variables. Let us denote $P_{i,t}$ to the closing price of cryptocurrency i at time t. Then, the cryptocurrency i's return at time t is defined as

$$Ret_{i,t} = \frac{P_{i,t} - P_{i,t-1}}{P_{i,t-1}} \cdot 100. \tag{4.2}$$

However, we will also use return in a decimal form. The decimal form of cryptocurrency i's return at time t is defined as

$$Dec\_ret_{i,t} = \frac{P_{i,t} - P_{i,t-1}}{P_{i,t-1}}. \tag{4.3}$$

The definition of the logarithmic return in percentage form of cryptocurrency i at time t is

$$\text{Log return in percentage form}_i = \log\left(\frac{P_{i,t}}{P_{i,t-1}}\right) \cdot 100. \tag{4.4}$$

However, we will also use logarithmic return in a decimal form. The decimal form of cryptocurrency i's logarithmic return at time t is defined as

$$\text{Log return in decimal form}_i = \log\left(\frac{P_{i,t}}{P_{i,t-1}}\right). \tag{4.5}$$

Next, the market return is defined as follows. First, the number of cryptocurrencies in the portfolio is calculated for each time period, i.e. for each day in a dataset. Next, the weight of each cryptocurrency in the portfolio is calculated as the reciprocal of the number of cryptocurrencies in the portfolio. Then, the contribution of each cryptocurrency to the portfolio return is calculated as the product of its weight and its return for that time period. Finally, the portfolio return is calculated as the sum of the contributions of each cryptocurrency in the portfolio.

$$MKT_t = \frac{\sum_{i=1}^{n_t} Ret_{i,t}}{n_t}, \tag{4.6}$$

where n_t is the number of cryptocurrencies in the sample in time t.

Now, we will define the values which will be used in the regression analysis part. The values will be different as we have PT values from 7-day past returns and 14-day part returns. For a definition, we will use 7-day values for the percentage form of return.

Mom is represented by taking the moving average of the past 7 days' cryptocurrency returns, i.e. momentum of cryptocurrency i in time t is defined as $Mom_{i,t} = \sum_{j=t-1}^{t-8} Ret_{i,j}$. For example, this approach can be found in Bhatti & Khan (2022). The reason why we chose moving average instead of cumulative return is that we have simple returns; thus, we can easily average them and, moreover, to mitigate the potential reasoning that PT is only an average of past returns. Furthermore, according to Marshall *et al.* (2016), returns generated by moving average and cumulative return method frequently have correlations that are in excess of 0.8.

The next variable is *Size*, defined as a logarithm of the market capitalisation of a given cryptocurrency on a given day. Size of cryptocurrency i at time t is defined as $Size_{i,t} = \log(market\ capitalisation_{i,t-1})$. Both Elendner *et al.* (2018) and Liu *et al.* (2022) showed that cryptocurrencies exhibit a size effect like stocks.

Vol is defined as an average of the logarithmic volume of a cryptocurrency i at time t over the past 7 days, i.e. $Vol_{i,t} = \frac{1}{7}\sum_{j=t-1}^{t-8} \log(volume_{i,j})$. *SdVol* is defined as a standard deviation of *Vol*.Liu *et al.* (2022) found empirical support for both *Vol*, *SdVol* as predictors for cryptocurrencies' returns.

As Barberis *et al.* (2016) found that there is a relationship between a probability weighting component of PT value captures and fat tails and extremes of cryptocurrency's return distribution, we will include in the analysis two skewness controls: *Skew* and *Kurt*. *Skew* is defined as skewness of the daily return of cryptocurrency of the past 7 days, i.e. skewness of *Ret* for time $t-1$ to $t-8$. *Kurt* is defined as kurtosis of the daily return of the risk-adjusted return of cryptocurrency in excess of the market return for the past 7 days, i.e. kurtosis of *Ret* for time $t-1$ to $t-8$.

Similar to Bali *et al.* (2011), we include variables *Min* and *Max*. *Min* is defined as a negative of the minimum of *Ret* for time $t-1$ to $t-8$. *Max* is defined as maximum of *Ret* for time $t-1$ to $t-8$. In addition, Grobys & Junttila (2021) found support for the predictive power of *Min* and *Max*.

Based on the work of Jia *et al.* (2020), we also include *Sd*. *Sd* is defined as a standard deviation of *Ret* for time $t-1$ to $t-8$. The last variable included in the analysis is *Beta*, which is the slope from the regression of cryptocurrency i's daily excess return on the cryptocurrency market index return (defined in Equation 4.1) from day $t-1$ to day $t-31$. These variables are shown for 7 days values but are easily convertible to 14 days. Table 4.1 presents summary statistics for variables that we use in the analysis.

For regression analysis with PT value made from 14-day historical daily return distribution, variables $Beta$ and $Size$ are the same, but variables: Mom, *Sd*, Vol, *SdVol*, *Skew*, $Kurt$, Min, and Max are made from cryptocurrency i's returns from day $t-1$ to day $t-15$. For regression with PT value made from returns in decimal form, variables: $Beta$, $Size$, Vol, and $SdVol$ are the same, variables: Mom, Sd, Min, and Max are scaled by $\frac{1}{100}$, and variables $Skew$, $Kurt$ must be recalculated with decimal form of return.

4.5.2 Summary Statistics

Summary statistics of variable *Ret*, defined in Equation 4.2, and all variables defined in Table 4.1 with PT value made from a 7-day construction window and inferred parameters are reported in Table 4.2. Panel A presents the means and standard deviations, whereas panel B reports the pairwise correlations.

Several relationships can be observed from the Table 4.2. Firstly, there is a positive correlation between the size of a cryptocurrency and its PT value, indicating that larger cryptocurrencies have higher PT values. Additionally, cryp-

Table 4.1: Variable descriptions

Variable name	Description	Reference
PT	Prospect theory value of cryptocurrency i's historical daily return distribution from day $t-1$ to day $t-8$	Barberis *et al.* (2016)
$Size$	Natural logarithm of cryptocurrency i's market capitalisation on day $t-1$	Elendner *et al.* (2018) & Li *et al.* (2019)
Mom	Average of cryptocurrency i's daily returns from day $t-1$ to $t-8$	Marshall *et al.* (2016) & Grobys *et al.* (2019)
Vol	Average of the natural logarithm of cryptocurrency i's trading volume from day $t-1$ to day $t-8$	Liu *et al.* (2022)
$VolSd$	Standard deviation of the natural logarithm of cryptocurrency i's trading volume from day $t-1$ to day $t-8$	Liu *et al.* (2022)
$Skew$	Skewness of cryptocurrency i's returns from day $t-1$ to $t-8$	Jia *et al.* (2020)
$Kurt$	Kurtosis of cryptocurrency i's returns from day $t-1$ to $t-8$	Jia *et al.* (2020)
Min	Negative minimum of cryptocurrency i's return from day $t-1$ to $t-8$	Bali *et al.* (2011) & Grobys & Junttila (2021)
Max	Maximum of cryptocurrency i's returns from day $t-1$ to $t-8$	Bali *et al.* (2011) & Grobys & Junttila (2021)
Sd	Standard deviation of cryptocurrency i's returns from day $t-1$ to day $t-8$	Jia *et al.* (2020)
$Beta$	Slope from the regression of cryptocurrency i's daily excess return on the cryptocurrency market index excess return, $Market\ index_t$ from day $t-1$ to day $t-31$	Liu *et al.* (2022)

Note: Table presents a set of variables that have been identified in recent literature as predictors of asset/cryptocurrency returns. In the second column is the definition of each variable. The third column provides supporting literature for each variable. These variables are used in regression analysis in Section 6.2.

tocurrencies with high momentum also demonstrate higher PT values. Moreover, there is a high negative correlation coefficient between momentum and PT, meaning that cryptocurrencies with high minimum values tend to have higher PT values, which also supports both hypotheses.

Of particular interest is the correlation coefficient between PT and *Ret*.

Table 4.2: Means and correlations: 7 days, inferred parameters, percentage rate

A. Means and standard deviations

	PT	Ret	Size	Mom	Vol	SdVol	Skew	Kurt	Min	Max	Sd	Beta
Mean	-1.40	0.10	19.07	0.38	15.71	0.15	0.10	2.46	8.94	11.37	7.07	0.60
Sd	1.74	10.54	2.06	4.18	3.03	0.14	0.73	0.78	7.12	19.90	8.28	2.00

B. Correlations

	PT	Ret	Size	Mom	Vol	SdVol	Skew	Kurt	Min	Max	Sd	Beta
PT	1											
Ret	-0.08	1										
Size	0.13	-0.02	1									
Mom	0.71	-0.005	-0.003	1								
Vol	0.09	-0.02	0.80	-0.04	1							
SdVol	0.01	0.01	-0.18	0.21	-0.21	1						
Skew	0.26	-0.02	-0.03	0.26	-0.03	0.10	1					
Kurt	0.02	0.004	-0.03	0.08	-0.03	0.05	0.17	1				
Min	-0.67	0.09	-0.20	-0.11	-0.17	0.20	-0.20	0.16	1			
Max	0.20	0.06	-0.11	0.78	-0.12	0.27	0.33	0.22	0.36	1		
Sd	-0.02	0.08	-0.15	0.65	-0.15	0.29	0.21	0.19	0.58	0.96	1	
Beta	-0.03	0.002	0.03	0.01	0.04	0.0003	-0.003	-0.003	0.04	0.03	0.04	1

Note: Table shows the time-series averages of daily cross-sectional summary statistics defined in Section 4.5. Panel A displays the mean and standard deviation of each variable. Panel B displays Pearsons's pairwise correlation coefficients.

Table 4.2 reveals a negative relationship, which supports the hypothesis that cryptocurrencies with high PT values are associated with lower subsequent returns. However, it is important to note that correlation does not imply causation and further research is needed to establish the causal relationship between the PT value and subsequent cryptocurrency returns.

Furthermore, there is a relationship between skewness and kurtosis, with higher skewness leading to higher kurtosis. There is also a positive correlation between the size of a cryptocurrency and its trading volume, with larger cryptocurrencies having higher trading volumes.

Moreover, larger cryptocurrencies tend to have higher maximum daily returns and a higher standard deviation of daily returns. Cryptocurrencies with high momentum also have higher maximum daily returns and a higher standard deviation of daily returns.

Finally, the data indicate that cryptocurrencies with higher trading volumes tend to have a higher standard deviation of trading volume. Additionally, there is a negative correlation between Min and Max, which suggests that cryptocurrencies that experience large negative returns also tend to experience large positive returns.

Chapter 5

Methodology

In Section 5.1, we provide a method for analysis of the validity hypothesis #1 and hypothesis #2 through the decile-sorting method. Meaning that we sort cryptocurrencies into ten deciles for each day and then analyse the properties of each decile. The objective is to determine whether a portfolio consisting of the lowest decile minus the highest decile generates abnormal returns. The presence of abnormal returns (gains) generated by the portfolio consisting of the lowest decile minus the highest decile would support the hypothesis's validity.

In Section 5.2, we present an approach to evaluate the validity of hypothesis #1 and hypothesis #2 using linear regression analysis. Our objective is to determine whether the PT value has the ability to predict subsequent cryptocurrency returns in excess of the market even after controlling for other known predictors of cryptocurrency's return. If the linear regression analysis reveals a significant and positive PT coefficient, it would support the hypothesis's validity.

5.1 Decile-sorting

This section represents the first approach for testing hypothesis #1 and hypothesis #2. We will use the decile-sorting approach similar to Barberis *et al.* (2016) and Thoma (2020), and the entire analysis will be conducted solely with equal-weighted returns. Cryptocurrencies are sorted according to PT value made from eight different PT settings defined in Table 3.3. But then, the rest of the analysis is made with percentage forms of return.

For each day from 01.04.2017 to 06.03.2023 in the monthly rolling portfolio, we sort cryptocurrencies into ten deciles according to the PT value of each cryptocurrency in ascending order, i.e. in the first decile is one-tenth of cryptocurrencies with the lowest PT value for each day, and in the tenth decile is one-tenth of cryptocurrencies with the highest PT value for each day.

Then, for each day and for each decile, we compute an equal-weighted decile return which is simply a mean return of a decile for a given day, let's denote it $Decile\_Ret_{i,t}$, where $i = 1, .., 10$ is the decile number, and t is time.

$$Decile\_Ret_{i,t} = \frac{1}{n_{i,t}} \sum_{j=1}^{n_{i,t}} Ret_{i,j,t}, \tag{5.1}$$

where $Decile\_Ret_{i,t}$ is the equal-weighted decile return for decile i at time t, $n_{i,t}$ is the number of assets in decile i at time t, and $Ret_{i,j,t}$ is the return of asset j in decile i at time t and is defined in Equation 4.2.

These decile-sorted portfolios will be used as input for two models to compute the abnormal return: autoregressive model and Capital Asset Pricing Model (CAPM) (Sharpe 1964). Our goal is to estimate the intercepts of each model for each decile because the intercept represents an abnormal return.

5.1.1 Autoregressive Model

To compute the abnormal return using the autoregressive model of the first order, we need to define a new variable: the decile return in excess of the market, which is calculated as the decile return minus the market return. For each decile i, $i = 1, 2, ..., 10$, Decile Return in excess of the Market (DRM) at time t is defined as:

$$DRM_{i,t} = Decile\_Ret_{i,t} - MKT_t, \tag{5.2}$$

where MKT, defined in Equation 4.6, is market return, and $Decile\_Ret_{i,t}$, defined in Equation 5.1, is decile return.

The autoregressive model of the first order is then applied to the decile returns in excess of the market. The model equation is given by:

$$DRM_{i,t} = \alpha_{i,t} + \beta_{i,t} DRM_{i,t-1} + \varepsilon_t, \tag{5.3}$$

where DRM_t is the dependent variable at time t, DRM_{t-1} is the dependent variable at the previous time period, $\alpha_{i,t}$ is the intercept, $\beta_{i,t}$ is the coefficient for the lagged dependent variable, and ε_t is the error term at time t. The lagged dependent variable, $DRM_{i,t-1}$, represents the decile return in excess of the market at the previous time period.

The alpha coefficient is of particular interest as it denotes whether there is an abnormal return for each decile i at time t, abnormal gain when alpha is positive or abnormal loss when alpha is negative. By analysing the alpha coefficients for each decile over time, we can determine which deciles of cryptocurrencies have consistently outperformed or underperformed the market.

5.1.2 Capital Asset Pricing Model

This section explains the second method of estimating each decile portfolio's abnormal performance. We do this by fitting the CAPM model (Sharpe 1964), the most common asset pricing model in the finance literature that describes the relationship between expected returns and systematic risk.

In the context of cryptocurrencies' deciles, the CAPM analysis involves calculating the return of each decile of cryptocurrencies in excess of the risk-free rate and regressing it against the market return in excess of the risk-free rate (market return minus the risk-free rate). The equation for the CAPM model is:

$$Decile\_Ret_{i,t} - Rf_t = \alpha_{i,t} + \beta_{i,t} \cdot (MKT_t - Rf_t) + \varepsilon_{i,t}, \tag{5.4}$$

where $Decile\_Ret_{i,t}$,defined in Equation 5.1, is decile return, MKT_t, defined in Equation 4.6, is market return at time t, Rf_t is risk-free return defined in Section 4.3, $\alpha_{i,t}$ is the intercept, $\beta_{i,t}$ can be interpreted as a measure of the way how a cryptocurrency i moves with respect to the market, and ε_t is the error term at time t.

The alpha coefficient is called Jensen's alpha and, similarly as in the autoregressive model in Subsection 5.1.1, denotes whether there is an abnormal gain (when alpha is positive) or abnormal loss (when alpha is negative) for each decile i at time t. By analysing the alpha coefficients for each decile over time, we can determine which deciles of cryptocurrencies have consistently outperformed or underperformed the market.

5.2 Linear Regressions

This section represents the second approach for testing hypothesis #1 and hypothesis #2. To be precise, in this section, we will test whether PT value has predictive power for subsequent cryptocurrency returns in excess of the market even after controlling for other known predictors of cryptocurrency's return. Since we have a rolling data set that changes every month and we want to run regressions over the whole period, we have decided not to do fixed effect analysis as discussed by Chen *et al.* (2022) or panel data analysis as discussed by Thoma (2020). Instead, we use linear regression analysis and treat the data as cross-section data. By doing so, we aim to analyse the relationship between the variables of interest and estimate the coefficients, mainly the PT coefficient, while assuming that the data at each point in time are independent and identically distributed. The dependent variable in all regressions is the daily return of cryptocurrency in excess of the market return, defined as:

$$MRet_{i,t} = Ret_{i,t} - MKT_t, \tag{5.5}$$

in which Ret was defined in Equation 4.2 and MKT was defined in in Equation 4.6. In regressions with PT value made from a decimal form of return, variable $MRet_{i,t}$ is divided by 100.

The analysis using linear regression will proceed according to the following logic. First, simple linear regression is fitted with only PT as an independent variable, without any other controls. This is followed by adding one control variable, as defined in Section 4.5, at a time, to the model in each subsequent column. Those controls are momentum (Mom), market capitalisation ($Size$), the beta ($Beta$), volume (Vol), the standard deviation of volume ($SdVol$), minimum (Min), maximum (Max), skewness ($Skew$), and kurtosis ($Kurt$). Therefore, together we have ten following linear models which we need to fit:

$$
\begin{aligned}
&(1) \quad MRet_{i,t} = \beta_0 + \beta_1 PT_{i,t} + \varepsilon_{i,t}, \\
&(2) \quad MRet_{i,t} = \beta_0 + \beta_1 PT_{i,t} + \beta_2 Mom_{i,t} + \varepsilon_{i,t}, \\
&(3) \quad MRet_{i,t} = \beta_0 + \beta_1 PT_{i,t} + \beta_2 Mom_{i,t} + \beta_3 Size_{i,t} + \varepsilon_{i,t}, \\
&(4) \quad MRet_{i,t} = \beta_0 + \beta_1 PT_{i,t} + \beta_2 Mom_{i,t} + \beta_3 Size_{i,t} + \beta_4 Beta_{i,t} + \varepsilon_{i,t}, \\
&(5) \quad MRet_{i,t} = \beta_0 + \beta_1 PT_{i,t} + \beta_2 Mom_{i,t} + \beta_3 Size_{i,t} + \beta_4 Beta_{i,t} + \beta_5 Vol_{i,t} + \\
&\qquad\qquad + \varepsilon_{i,t}, \\
&(6) \quad MRet_{i,t} = \beta_0 + \beta_1 PT_{i,t} + \beta_2 Mom_{i,t} + \beta_3 Size_{i,t} + \beta_4 Beta_{i,t} + \beta_5 Vol_{i,t} + \\
&\qquad\qquad + \beta_6 SdVol_{i,t} + \varepsilon_{i,t} \\
&(7) \quad MRet_{i,t} = \beta_0 + \beta_1 PT_{i,t} + \beta_2 Mom_{i,t} + \beta_3 Size_{i,t} + \beta_4 Beta_{i,t} + \beta_5 Vol_{i,t} + \\
&\qquad\qquad + \beta_6 SdVol_{i,t} + \beta_7 Min_{i,t} + \varepsilon_{i,t}, \\
&(8) \quad MRet_{i,t} = \beta_0 + \beta_1 PT_{i,t} + \beta_2 Mom_{i,t} + \beta_3 Size_{i,t} + \beta_4 Beta_{i,t} + \beta_5 Vol_{i,t} + \\
&\qquad\qquad + \beta_6 SdVol_{i,t} + \beta_7 Min_{i,t} + \beta_8 Max_{i,t} + \varepsilon_{i,t}, \\
&(9) \quad MRet_{i,t} = \beta_0 + \beta_1 PT_{i,t} + \beta_2 Mom_{i,t} + \beta_3 Size_{i,t} + \beta_4 Beta_{i,t} + \beta_5 Vol_{i,t} + \\
&\qquad\qquad + \beta_6 SdVol_{i,t} + \beta_7 Min_{i,t} + \beta_8 Max_{i,t} + \beta_9 Skew_{i,t} + \varepsilon_{i,t}, \\
&(10) \quad MRet_{i,t} = \beta_0 + \beta_1 PT_{i,t} + \beta_2 Mom_{i,t} + \beta_3 Size_{i,t} + \beta_4 Beta_{i,t} + \beta_5 Vol_{i,t} + \\
&\qquad\qquad + \beta_6 SdVol_{i,t} + \beta_7 Min_{i,t} + \beta_8 Max_{i,t} + \beta_9 Skew_{i,t} + \\
&\qquad\qquad + \beta_{10} Kurt_{i,t} + \varepsilon_{i,t}.
\end{aligned}
$$

This process will also allow us to observe the impact of each control variable on the PT coefficient. We can assess whether the inclusion of each control variable causes the PT coefficient to change and by how much. Moreover, by comparing the coefficient estimates across the different models, we can identify which control variables are significant predictors of cryptocurrency returns and which variables have little to no effect. This can provide insight into the factors that drive cryptocurrency returns and help us better to understand the relationship between PT, control variables and future returns.

Lastly, in Section 6.2 with results, we report t-statistics for each coefficient rather than standard error. The reasoning behind this is that we want to observe the impact of each control variable on the PT coefficient's significance.

Chapter 6

Results

This chapter displays results achieved by applying the decile-sorting and linear regression analyses defined in Chapter 5. Results are provided for all combinations of PT settings defined in Table 3.3.

6.1 Decile-sorting Analysis

This section presents the findings from the first approach employed to test hypothesis #1 and hypothesis #2. We used the decile-sorting method to conduct this analysis, following the procedure outlined by Barberis *et al.* (2016). More information on the methodology and steps followed can be found in Section 5.1.

Table 6.1 reports the results of portfolio analysis using the decile-sorting approach based on the PT value made from inferred parameters and returns in the percentage form of each cryptocurrency. In the right-most column, "low minus high", are reported the differences between the lowest PT value portfolio and the highest PT portfolio – zero investment portfolio that buys the cryptocurrencies in the lowest PT decile and shorts the cryptocurrencies in the highest PT decile.

The results show that the low-PT portfolio consistently outperforms the high-PT portfolio. For example, for the Autoregressive Model (AR) approach and a holding period of seven days, the low-PT portfolio has an average AR abnormal return of 0.719%, while the high-PT portfolio has an average AR abnormal return of 0.083%, resulting in a difference of 0.636%, which is the abnormal return of low minus high PT portfolio.

Table 6.2 reports the results of portfolio analysis using the decile-sorting approach based on the PT value made from inferred parameters and returns in decimal form, as in Table 6.1, the results show that the low-PT portfolio consistently outperforms the high-PT portfolio across all holding periods. For example, for the AR approach and a holding period of seven days, the low-PT portfolio has an average AR return of 0.561%, while the high-PT portfolio has an average AR return of 0.082%, resulting in a difference of 0.479%. Even though low minus high portfolios are still significant and positive, as in Table 6.1, each return is less, at least about 0.01%, than in Table 6.1. This suggests that a percentage form of returns is more suitable for the PT construction period of 7 days.

Results from Table 6.1 and Table 6.2 are visualised in Figure 6.1. The horizontal axis shows deciles in ascending order, and the vertical axis is the daily abnormal returns, in other words, alpha, in %. All these alphas follow a U-shape when moving from decile 1 up to decile 10. Alphas are mostly decreasing from decile 1 to decile 8 but then increase again. Interestingly, for decile 1, alpha for a decimal form of return is always smaller than for a percentage form of return.

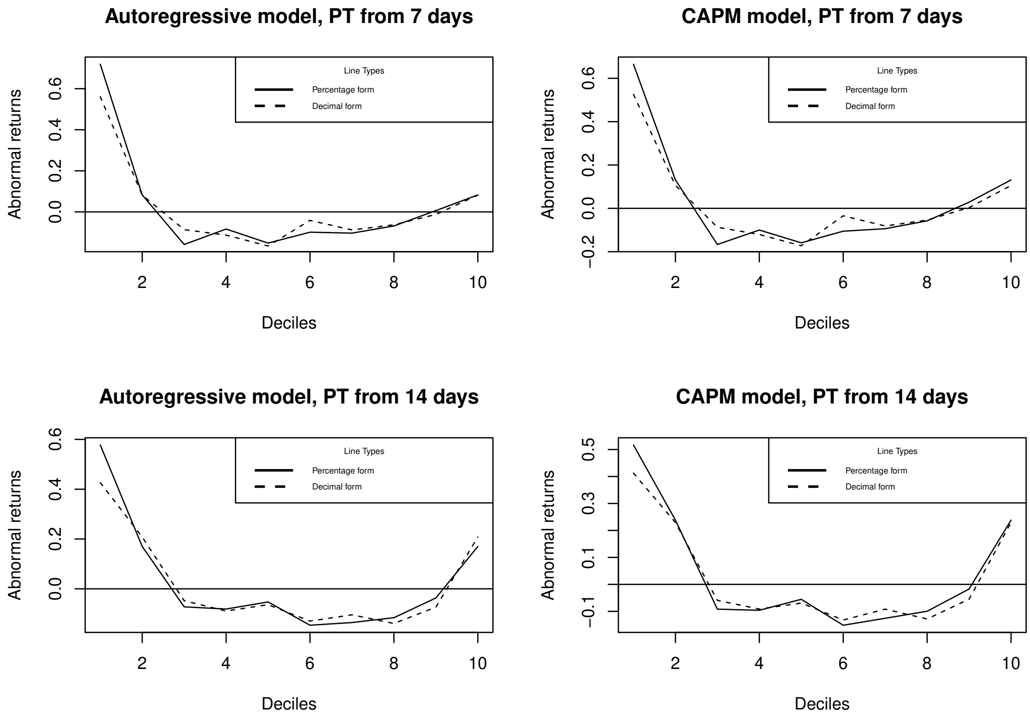
These results support not only hypothesis #1 but also hypothesis #2 that the PT value of cryptocurrency historical returns predicts future cryptocurrency returns (in a percentage form) with a negative sign. This evidence is striking as this supports the hypothesis that not only PT value from a decimal form which was shown in (Thoma 2020; Chen *et al.* 2022) of cryptocurrency return, can be used to yield similar results.

Finally, to have a comparison with empirical parameters, Table 6.3 reports the results for empirical parameters in percentage form. The decimal form is not reported because the results for the percentage form and the decimal form are exactly the same. The results show that the low-PT portfolio consistently outperforms the high-PT portfolio across all holding periods; all low minus high portfolios are significant and positive.

Overall, the results show that the low-PT portfolio consistently outperforms the high-PT portfolio across all returns (i.e. decile form of return and percentage form of return), all holding periods (i.e. 7-day and 14-day holding period), and all parameters (i.e. empirical and inferred parameters).

These findings are intriguing as they indicate that the method used to construct the PT value, whether PT value is constructed by plugging the decimal form of cryptocurrency's returns into the value function or by plugging the percentage form of cryptocurrency's returns into the value function, which changes the shape of the function, does not seem to have a significant impact as the

Figure 6.1: Abnormal returns



Note: The figure represents results from Tables 6.1 and 6.2, and plot the results in ascending order from decile 1 to decile 10. The abnormal returns are made using inferred parameters in the value function. Line $f(x) = 0$ represents zero abnormal return. Low minus high portfolio is not included.

low-PT portfolio consistently outperforms the high-PT portfolio; these two different shapes are depicted in Figure 6.2 for inferred parameters, where the range of value is the interquartile range which was showed in Section 3.2. It is clear from the figure that the value function for gains is overweighting these gains up until 1, which is 100%, but in contrast value function for gains in percentage from overweights gains only to 1% and then starts underweighting gains. This also suggests that the value function component of the prospect theory does not play that important role in PT value's predictive power and that a substantial portion of the PT value's predictive power for returns originates from the probability weighting component of prospect theory; this is in line with Barberis *et al.* (2016) findings. Probability weighting induces individuals to place greater importance on the extreme ends of the return distribution, reflecting a preference for high-risk, high-reward gambles, such as lotteries. However, it is not in line with Chen *et al.* (2022) found that the value function has the largest effect among all components of the prospect theory function.

Table 6.1: Portfolio analysis: inferred parameters, percentage form

		P1 Low PV	P2	P3	P4	P5	P6	P7	P8	P9	P10 High PV	PV Low-high Portfolio
7 days	AR	**0.719***	**0.083***	**-0.159***	**-0.083***	**-0.152***	**-0.099***	**-0.103***	**-0.069**	0.006	0.083	**0.636***
		(0.093)	(0.043)	(0.039)	(0.036)	(0.035)	(0.036)	(0.035)	(0.041)	(0.054)	(0.080)	(0.121)
	Alpha	**0.665***	**0.131***	**-0.167***	**-0.100***	**-0.159***	**-0.105***	**-0.094***	-0.058	0.029	**0.131***	**0.534***
		(0.091)	(0.043)	(0.039)	(0.036)	(0.035)	(0.036)	(0.034)	(0.041)	(0.053)	(0.079)	(0.119)
14 days	AR	**0.578***	**0.170**	**-0.072**	**-0.081**	**-0.053***	**-0.146***	**-0.135***	**-0.116**	-0.037	**0.170**	**0.407***
		(0.087)	(0.045)	(0.036)	(0.036)	(0.034)	(0.036)	(0.034)	(0.049)	(0.053)	(0.077)	(0.115)
	Alpha	**0.517***	**0.238***	**-0.092***	**-0.096***	**-0.055***	**-0.151***	**-0.126***	**-0.100***	-0.017	**0.238***	**0.279***
		(0.020)	(0.011)	(0.009)	(0.009)	(0.008)	(0.009)	(0.008)	(0.012)	(0.013)	(0.018)	(0.112)

Note: Table reports the average daily abnormal returns, which are represented by the intercepts of the autoregressive model of first order (AR) and the CAPM model (alpha) on an equal-weighted (EW) basis of cryptocurrencies' portfolios sorted on PT value in which the value function was made with inferred parameters and returns in the percentage form. Each day, all cryptocurrencies are sorted into deciles based on PT value. We report the average abnormal return for each decile portfolio, P1 (the lowest PT) through P10 (the highest PT). AR means that the excess return was obtained from the autoregressive model of first order. In parentheses are reported standard errors. Significance levels: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table 6.2: Portfolio analysis: inferred parameters, decimal form

		P1 Low PV	P2	P3	P4	P5	P6	P7	P8	P9	P10 High PV	PV Low-high Portfolio
7 days	AR	**0.561*****	**0.082****	**-0.087****	**-0.113*****	**-0.166*****	-0.041	**-0.088****	-0.063	-0.012	0.082	**0.479*****
		(0.082)	(0.040)	(0.035)	(0.034)	(0.033)	(0.037)	(0.036)	(0.040)	(0.054)	(0.091)	(0.122)
	Alpha	**0.526****	**0.105****	**-0.087*****	**-0.121*****	-0.173	**-0.034****	-0.081	-0.054	0.004	0.105	**0.421*****
		(0.080)	(0.040)	(0.035)	(0.034)	(0.033)	(0.037)	(0.036)	(0.040)	(0.054)	(0.091)	(0.120)
14 days	AR	**0.426*****	0.208	-0.048	**-0.089*****	**-0.064****	**-0.130*****	**-0.104*****	**-0.139*****	**-0.074***	**0.208****	**0.218***
		(0.073)	(0.052)	(0.037)	(0.034)	(0.038)	(0.035)	(0.035)	(0.051)	(0.045)	(0.091)	(0.117)
	Alpha	**0.412*****	**0.229***	**-0.059*****	**-0.091*****	**-0.069*****	**-0.132*****	**-0.092*****	**-0.128*****	**-0.055*****	**0.229*****	**0.183***
		(0.017)	(0.013)	(0.009)	(0.008)	(0.009)	(0.008)	(0.008)	(0.012)	(0.011)	(0.022)	(0.115)

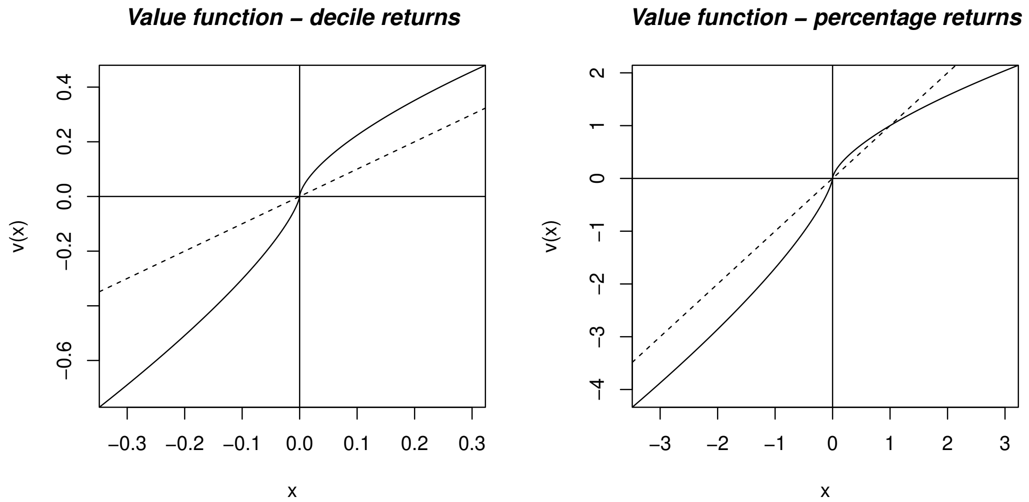
Note: Table reports the average daily abnormal returns, which are represented by the intercepts of the autoregressive model of first order (AR) and the CAPM model (alpha) on an equal-weighted (EW) basis of cryptocurrencies' portfolios sorted on PT value in which the value function was made with inferred parameters and returns in the decimal form. Each day, all cryptocurrencies are sorted into deciles based on PT value. We report the average abnormal return for each decile portfolio, P1 (the lowest PT) through P10 (the highest PT). AR means that the excess return was obtained from the autoregressive model of first order. In parentheses are reported standard errors. Significance levels: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table 6.3: Portfolio analysis: empirical parameters, percentage form

		P1 Low PV	P2	P3	P4	P5	P6	P7	P8	P9	P10 High PV	PV Low-high Portfolio
7 days	AR	**0.634*****	**0.089*****	**-0.113*****	**-0.079****	**-0.129*****	**-0.135*****	-0.052	**-0.078****	0.008	0.089	**0.545*****
		(0.083)	(0.042)	(0.037)	(0.034)	(0.034)	(0.034)	(0.039)	(0.038)	(0.055)	(0.090)	(0.121)
	Alpha	**0.581*****	**0.127*****	**-0.120*****	**-0.091*****	**-0.138*****	**-0.129*****	-0.045	**-0.058***	0.029	0.127	**0.454*****
		(0.080)	(0.042)	(0.037)	(0.034)	(0.034)	(0.034)	(0.039)	(0.037)	(0.055)	(0.089)	(0.119)
14 days	AR	**0.519*****	**0.208****	**-0.065***	**-0.106*****	**-0.078***	**-0.096*****	**-0.103*****	**-0.120*****	-0.054	**0.208****	**0.312*****
		(0.076)	(0.043)	(0.036)	(0.034)	(0.046)	(0.035)	(0.035)	(0.049)	(0.043)	(0.090)	(0.117)
	Alpha	**0.482*****	**0.249*****	**-0.080*****	**-0.112**	**-0.097*****	**-0.096*****	**-0.093*****	**-0.112*****	**-0.025****	**0.249*****	**0.234****
		(0.018)	(0.010)	(0.009)	(0.008)	(0.011)	(0.008)	(0.008)	(0.012)	(0.010)	(0.022)	(0.115)

Note: Table reports the average daily abnormal returns, which are represented by the intercepts of the autoregressive model of first order (AR) and the CAPM model (Alpha) on an equal-weighted basis of cryptocurrencies' portfolios sorted on PT value in which the value function was made with empirical parameters and returns in the percentage form (however, returns in decimal form yields similar results). Each day, all cryptocurrencies are sorted into deciles based on PT value. We report the average abnormal return for each decile portfolio, P1 (the lowest PT) through P10 (the highest PT). AR means that the excess return was obtained from the autoregressive model of first order. In parentheses are reported standard errors. Significance levels: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Figure 6.2: Value function for decimal and percentage form



Note: Figure compares the two different shapes of the value function. The left plot is a shape of the value function when a decimal form of returns is used as input, whereas the right plot is a shape of the value function when a percentage form of return is used as an input. Therefore, 0.3 on the left plot is equal to 3 on the right plot, -0.3 on the left plot is equal to -3 on the right plot, etc.

6.2 Regression Analysis

This section presents the findings from the second approach employed to test hypothesis #1 and hypothesis #2. We used the linear regression method to conduct this analysis, following the procedure outlined in Section 5.2.

Tables in this section report those empirical findings in the following logic: it shows ten columns, numbered from (1) to (10), with each column displaying the results of a single regression analysis. In column (1), a simple linear regression without controls is performed with only PT as the predictor variable. This is followed by adding one control variable, as defined in Section 4.5, at a time, to the model in each subsequent column. Those controls are momentum (Mom), market capitalisation ($Size$), the beta ($Beta$), volume (Vol), the standard deviation of volume ($SdVol$), minimum (Min), maximum (Max), skewness ($Skew$), and kurtosis ($Kurt$).

Results from Table 6.4 show that the data support hypothesis #2 even with all controls, i.e. PT value predicts subsequent returns with a negative sign. Moreover, PT value retains its significant predictive power from column (1) through column (10), i.e. adding control variables to the regression analyses does not substantially affect the PT coefficient's magnitude or significance, indicating that the predictive power of PT value for future returns is robust to the inclusion of other predictors. The PT coefficient estimates are -0.109

in the simple regression (column 1) and -0.085 in the full model (column 10), attaining a maximum of -0.450 in column 6, indicating a consistent negative effect of PT value on subsequent returns.

T-statistics of the PT coefficient are high in all models in Table 6.4, -11.92 in the simple regression (column 1) and -2.69 in the full model (column 10); in five columns, t-statistics are above 30. These high t-statistics indicate that the PT coefficient is highly significant and unlikely to be due to chance. Column 7 (Table 6.4) shows that including Min in the regression substantially reduces the t statistics of the PT coefficient. However, the largest PT coefficient reduction is when the Max is added to the regression. Notable are also effects on the PT coefficient when $Skew$ and $Kurt$ are added, each reducing the PT coefficient by approximately 0.05, suggesting that these variables are also important predictors of cryptocurrency returns. Although these results are really appealing, it is important to take them with a degree of scepticism, specifically the use of linear regression and simple returns rather than log returns, which implies right-skewness of the data caused the errors to exhibit a right tail. Moreover, there is a high chance of not including some significant variable which would decrease the t-statistics of the PT coefficient.

Additionally, Table 6.4 provides several interesting insights regarding the relationships between various control variables and subsequent returns of cryptocurrencies. Firstly, apart from the tenth column, Mom exhibits a positive relationship with subsequent returns. This suggests that cryptocurrencies with high momentum tend to earn high subsequent returns on average in the sample. Similarly, the market capitalisation variable $Size$ has a positive significant relationship with subsequent returns. Cryptocurrencies with larger market capitalisation tend to earn higher subsequent returns on average in the sample.

On the other hand, an increase in $Beta$ has a negative effect on subsequent returns. This implies that cryptocurrencies with high $Beta$ tend to earn low subsequent returns on average in the sample. Likewise, the volume variable, Vol, and standard deviation of the volume variable, $SdVol$, also exhibit negative relationships with subsequent returns. Cryptocurrencies with high volume or standard deviation of volume tend to earn low subsequent returns on average in the sample.

Furthermore, an increase in weekly maximum return, Min, positively impacts subsequent returns. Cryptocurrencies with higher maximum value tend to earn high subsequent returns on average in the sample. Lastly, both the $Skew$ and the $Kurt$ exhibit negative relationships with subsequent returns.

Table 6.4: Regression analysis: inferred parameters, percentage form, 7 days

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
PT	**-0.109**	**-0.440**	**-0.439**	**-0.439**	**-0.437**	**-0.450**	**-0.420**	**-0.236**	**-0.155**	**-0.085**
	(-11.92)	(-33.89)	(-33.25)	(-33.21)	(-33.05)	(-33.50)	(-16.70)	(-8.05)	(-5.16)	(-2.69)
Mom		**0.193**	**0.193**	**0.193**	**0.191**	**0.199**	**0.192**	**0.043**	-0.024	**-0.059**
		(35.84)	(35.47)	(35.44)	(35.01)	(35.21)	(24.54)	(2.98)	(-1.53)	(-3.59)
Size			-0.003	-0.003	**0.073**	**0.073**	**0.073**	**0.072**	**0.065**	**0.066**
			(-0.41)	(-0.40)	(5.66)	(5.61)	(5.67)	(5.57)	(5.03)	(5.07)
Beta				**-0.018**	**-0.018**	**-0.018**	**-0.018**	**-0.018**	**-0.017**	**-0.017**
				(-2.11)	(-2.03)	(-2.04)	(-2.04)	(-2.03)	(-2.01)	(-2.02)
Vol					**-0.065**	**-0.070**	**-0.070**	**-0.067**	**-0.065**	**-0.065**
					(-7.42)	(-7.95)	(-7.94)	(-7.63)	(-7.41)	(-7.40)
SdVol						**-0.642**	**-0.660**	**-0.698**	**-0.580**	**-0.594**
						(-5.46)	(-5.58)	(-5.90)	(-4.89)	(-5.01)
Min							0.006	0.002	**-0.011**	-0.004
							(1.41)	(0.43)	(-2.44)	(-0.77)
Max								**0.025**	**0.040**	**0.045**
								(12.26)	(16.50)	(17.79)
Skew									**-0.314**	**-0.306**
									(-11.57)	(-11.28)
Kurt										**-0.157**
										(-7.04)

Note: Table presents the results of linear regression analysis where all data are treated as cross-sectional. The dependent variable in all regressions is cryptocurrency return in excess of the market in percentage form. All independent variables were defined in Section 4.5. We excluded the Sd variable as after adding it to the regression variance inflation factor (VIF) of Sd, and Max escalates to almost 170, which means a problem with multicollinearity and violates the assumption of linear regression. Without the Sd, regression in column (10) does not have any variable with VIF higher than 10 and meets all the assumptions. The highest VIF has Mom and Max. T-statistics are shown in parentheses. The coefficient significant at the 10% level is denoted by bold typeface.

Cryptocurrencies with high skewness or high kurtosis tend to earn low subsequent returns on average in the sample.

In addition, Table 6.5 presents the regression analysis for returns in decimal form with a 7-day construction window for PT. The regression equations are still the same for the decimal rate, but the variables are scaled according to Section 4.5. PT coefficient is still highly significant; the t-statistics for the PT coefficient are approximately similar in both tables, which suggests that the relationship between PT and returns is robust and stable across different variations of returns. However, the value of the PT coefficient is higher for all regressions in Table 6.4, which indicates that the percentage form of returns is more profitable.

Finally, the linear regression analysis for the rest of the combinations analysed, defined in Table 3.3, is provided in appendix Tables A.1, A.2, A.3, and A.4. All of these tables exhibit similar properties as Tables 6.4 and 6.5. Not only the PT coefficient but also the rest of the coefficients display similar properties as in Tables 6.4 and 6.5. Most importantly, PT coefficients are still negative and highly significant. Additionally, the t-statistics in all tables also exhibit similar properties. Therefore, the results presented in Tables 6.4 and 6.5 are not limited to a specific PT construction widow but are rather generalisable to other combinations of time windows and parameters as well. This gave further evidence in favour of hypothesis #1 and hypothesis #2.

Table 6.5: Regression analysis: inferred parameters, decimal form, 7 days

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
PT	**-0.013**	**-0.166**	**-0.165**	**-0.165**	**-0.164**	**-0.166**	**-0.140**	**-0.104**	**-0.077**	**-0.065**
	(-5.20)	(-35.85)	(-35.27)	(-35.23)	(-35.02)	(-35.21)	(-20.55)	(-13.82)	(-9.45)	(-7.73)
Mom		**0.276**	**0.275**	**0.275**	**0.272**	**0.278**	**0.249**	**0.116**	**0.047**	0.021
		(39.20)	(38.72)	(38.69)	(38.26)	(38.21)	(27.19)	(7.94)	(2.77)	(1.21)
Size			-0.0001	-0.0001	**0.001**	**0.001**	**0.001**	**0.001**	**0.001**	**0.001**
			(-1.58)	(-1.57)	(4.72)	(4.65)	(5.08)	(5.17)	(4.86)	(4.95)
Beta				**-0.0002**	**-0.0002**	**-0.0002**	**-0.0002**	**-0.0002**	**-0.0002**	**-0.0002**
				(-2.04)	(-1.96)	(-1.96)	(-2.02)	(-2.07)	(-2.05)	(-2.08)
Vol					**-0.001**	**-0.001**	**-0.001**	**-0.001**	**-0.001**	**-0.001**
					(-7.10)	(-7.45)	(-7.51)	(-7.35)	(-7.26)	(-7.29)
SdVol						**-0.004**	**-0.005**	**-0.006**	**-0.005**	**-0.006**
						(-3.68)	(-4.55)	(-5.09)	(-4.53)	(-4.69)
Min							**0.018**	0.003	**-0.007**	-0.005
							(5.29)	(0.81)	(-1.92)	(-1.20)
Max								**0.023**	**0.034**	**0.038**
								(11.55)	(14.27)	(15.30)
Skew									**-0.002**	**-0.002**
									(-8.38)	(-8.29)
Kurt										**-0.001**
										(-6.29)

Note: Table presents the results of linear regression analysis where all data are treated as cross-sectional. The dependent variable in all regressions is cryptocurrency return in excess of the market in the decimal form. All independent variables were defined in Section 4.5. We excluded the Sd variable as after adding it to the regression variance inflation factor (VIF) of Sd, and Max escalates to almost 170, which means a problem with multicollinearity and violates the assumption of linear regression. Without the Sd, regression in column (10) does not have any variable with VIF higher than 10 and meets all the assumptions. The highest VIF has Mom and Max. T-statistics are shown in parentheses. The coefficient significant at the 10% level is denoted by bold typeface.

Chapter 7

Further Analyses and Robustness Tests

7.1 Robustness of Decile-sorting

In order to assess the validity of the results obtained in Chapter 6, we conducted a robustness check to test whether the findings that high (low) cumulative prospect theory value earn low (high) subsequent returns hold for different variations in PT settings. Specifically, we tested different periods of the PT construction window and different methods of calculating returns. In addition, we tested the situation when the reference point for PT value is not zero but the risk-free rate, i.e. when the PT value is constructed from cryptocurrencies' simple returns in excess of the risk-free rate, in Table 7.1 denoted as Simple-RF.

Table 7.1 presents the results of the robustness check of the decile-sorting analysis done with an autoregressive model of the first order. The construction window refers to the period of PT construction. The study tested three different periods: 7 days, 14 days, and 30 days. The transformation of returns refers to the method used to calculate returns: simple returns and logarithmic returns defined in Equation 4.4 and Equation 4.5. The form of returns refers to the unit in which returns are expressed. The most important is the second most right column, which shows the low minus high portfolio return, i.e. the differences between the lowest PT value portfolio and the highest PT portfolio - zero investment portfolio that buys the cryptocurrencies in the lowest PT decile and shorts the cryptocurrencies in the highest PT decile. The findings indicate that hypotheses #1 and hypothesis #2 hold for all of the tested variations; the low-high portfolio returns are positive and statistically significant for most of

Table 7.1: Robustness check

Construction window	Transformation of returns	Form of returns	Parameters	Low-High Portfolio	Standard error
7 days	Log	Percentage	Empirical	**0.669*****	(0.127)
7 days	Log	Percentage	Inferred	**0.685*****	(0.122)
7 days	Log	Decimal	Empirical	**0.629*****	(0.125)
7 days	Log	Decimal	Inferred	**0.678*****	(0.124)
7 days	Simple-RF	Percentage	Empirical	**0.498*****	(0.123)
7 days	Simple-RF	Percentage	Inferred	**0.598*****	(0.124)
14 days	Log	Percentage	Empirical	**0.573*****	(0.123)
14 days	Log	Percentage	Inferred	**0.546*****	(0.122)
14 days	Log	Decimal	Empirical	**0.573*****	(0.123)
14 days	Log	Decimal	Inferred	**0.511*****	(0.120)
14 days	Simple-RF	Percentage	Empirical	**0.226****	(0.118)
14 days	Simple-RF	Percentage	Inferred	**0.336*****	(0.117)
30 days	Simple	Percentage	Empirical	0.037	(0.123)
30 days	Simple	Percentage	Inferred	0.132	(0.118)

Note: Table reports the average daily abnormal returns of low-high portfolios, which are represented by the intercept of the autoregressive model of first order (AR) for decile 1 minus the intercept of the autoregressive model of first order (AR) for decile 10. In parentheses are reported standard errors. Significance levels:*p<0.1; **p<0.05; ***p<0.01.

the specifications tested; the only non-significant returns are of the 30-day PT construction window.

Notably, the results show that hypotheses #1 and hypothesis #2 hold for the logarithmic forms of returns, both in percentage and decimal form and for the simple returns in excess of the risk-free rate. However, the results are less robust when the construction window of the PT value is longer (30 days) and when the logarithmic returns are expressed in percentage form. This is interesting as it means that potentially Thoma (2020); Chen *et al.* (2022) could have achieved higher low-high abnormal returns if they plugged percentage form or returns into the prospect theory value function. Compared to Thoma (2020); Chen *et al.* (2022), we used a smaller PT construction window, which does not prove anything. Instead, more research is needed to explore this topic further.

Overall, the results suggest that the decile-sorting analysis is robust to variations in the data and variables, which indicates that the results are not driven by any particular specification of the data, meaning that hypothesis #1 and hypothesis#2 are less sensitive to variations in PT settings. Therefore, a deeper analysis of the variation of PT settings and also PT parameters can be a potential topic for further research.

7.2 Prospect Theory Drivers

Finally, we analysed decile portfolios to determine the potential cryptocurrency characteristics that can provide insights into prospect theory value and help identify whether each decile has unique features. Table 7.2 presents characteristic statistics of decile portfolios based on factors defined in Section 4.5 over a period of 7 days using the inferred parameters and variable $MRet$, which is the dependent variable in regression analysis in Section 6.2 and means the daily return of cryptocurrency in excess of the market. Deciles are sorted from 1 to 10, with 1 being the lowest and 10 being the highest.

By analysing the data presented in Table 7.2, it becomes apparent that there is a clear upward trend in the mean values of Mom and $Skew$ as we progress from decile 1 to decile 10. This indicates that higher deciles are associated with higher values of these parameters. This is in line with Barberis *et al.* (2016) who argued that high PT assets should have high past skewness; High skewness makes the assets more attractive, which is captured by the probability-weighting component of the prospect theory function. This smooth increase of skewness over the deciles was also captured by Thoma (2020). Barberis *et al.* (2016) also argued that high PT assets should have low volatility, which means in this study that Min, Max, and Sd should have decreasing tend. While Min decreases monotonically over all deciles, Max and Sd do not have a clear trend. Max seems to have a U-shape trend, and Sd is decreasing from decile 1 to decile 7, but then it increases.

Moreover, $Beta$ has a decreasing trend, indicating that low PT value cryptocurrencies tend to react more similarly as a market. Additionally, except for decile 10, $Size$ has a strictly increasing trend, which means that high PT cryptocurrencies tend to have large market capitalisation. Lastly, $MRet$ again confirms hypothesis #2 as it shows that decile 1 has the highest value of $Mret$.

In summary, this section's findings provide insights into the factors that influence PT value. Most importantly, we found that low PT cryptocurrencies have low skewness and high PT cryptocurrencies have high skewness, which is consistent with findings of Barberis *et al.* (2016); Thoma (2020); Chen *et al.* (2022).

Table 7.2: Characteristic of decile portfolios: inferred parameters, 7 days

Decile	PT	Beta	Size	Mom	Vol	SdVol	Max	Min	Skew	Kurt	Sd	MRet
1	-3.595	0.616	18.418	-2.569	14.823	0.181	11.600	15.997	-0.038	2.498	9.502	0.717
2	-2.387	0.639	18.714	-1.187	15.396	0.155	9.280	11.172	-0.023	2.415	7.107	-0.125
3	-1.984	0.632	18.899	-0.698	15.680	0.147	8.996	9.962	-0.014	2.397	6.601	-0.156
4	-1.710	0.629	19.027	-0.354	15.850	0.142	8.949	9.144	0.001	2.397	6.305	-0.090
5	-1.481	0.624	19.143	-0.036	15.918	0.140	9.128	8.554	0.021	2.398	6.156	-0.154
6	-1.261	0.617	19.222	0.286	15.987	0.139	9.444	8.013	0.049	2.417	6.077	-0.101
7	-1.025	0.595	19.313	0.653	15.980	0.141	9.933	7.462	0.094	2.426	6.055	-0.109
8	-0.752	0.590	19.360	1.140	15.948	0.145	10.847	6.939	0.147	2.447	6.189	-0.081
9	-0.365	0.567	19.367	1.902	15.866	0.155	12.615	6.326	0.255	2.509	6.573	0.007
10	0.681	0.529	19.284	4.973	15.704	0.195	23.263	5.468	0.509	2.676	10.115	0.079

Note: Table reports time-series averages of values used in regression analysis. These values are calculated for each PT decile separately.

Chapter 8

Conclusion

The aim of this study was to investigate two hypotheses. The first hypothesis posits that certain investors in the cryptocurrency market base their investment decisions on prospect theory. These investors evaluate cryptocurrencies based on cryptocurrencies' price charts and invest in attractive cryptocurrencies (with high prospect theory value) while disinvesting in unattractive ones (with low prospect theory value). This results in overbought high prospect theory value cryptocurrencies and underbought low prospect theory value cryptocurrencies. In essence, the prospect theory value can predict future cryptocurrency returns in excess of the market with a negative sign. The second hypothesis extends the first by suggesting that hypothesis #1 is true not only for the decimal form of cryptocurrencies' returns but also for the percentage form.

By three main approaches: autoregressive model, CAPM model, and loading linear regressions, this study confirmed the validity of these two hypotheses. Most importantly, the study showed that the hypothesis that prospect theory value predicts future cryptocurrency returns in excess of the market with a negative sign is true for the decimal rate of cryptocurrencies' return and the percentage form or return. Moreover, in robustness analysis, we found that even if we have simple or logarithmic returns in either percentage or decimal form, the prospect theory value function yields approximately similar low minus high abnormal portfolio returns. Furthermore, these results are robust on the choice of a reference point (either zero or risk-free rate) of the prospect theory function.

The study found that the weighting function component of the prospect theory function is a significant contributor to abnormal returns, suggesting that the value function component does not play as important a role in PT value's predictive power. This finding is consistent with Barberis *et al.* (2016), who found that probability weighting plays a crucial role in inducing individuals to take high-risk, high-reward gambles, while it contradicts Chen *et al.* (2022) findings that the value function has the most significant effect among all components of the prospect theory function.

However, the results of this study are limited as only one variation of parameters of value function was used, and no variation of the probability-weighting function, and the PT construction windows examined were only 7 days, 14 days, and 30 days.

These findings contribute to a better understanding of investment behaviour in the cryptocurrency market. However, this study, along with Barberis *et al.* (2016); Thoma (2020); Chen *et al.* (2022) uses the CAPM model based on expected utility to explain that some investors do not behave as what is predicted by the expected utility. Therefore, one possible extension could be constructing a model for predicting cryptocurrencies' returns fully dependent on prospect theory instead of expected utility theory. Moreover, there is still a lack of studies on prospect theory in the cryptocurrency market; further research would be appropriate.

Finally, our results could serve as a foundation for investment strategies based on prospect theory. Specifically, we discovered that investors could potentially earn profits by buying cryptocurrencies in the lowest PT decile (i.e., cryptocurrencies with the lowest PT value) one day before portfolio creation. Therefore, further investigation is necessary to examine the efficiency of this approach, such as determining the prospect theory function parameters that produce the highest returns.

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Appendix A

Additional Tables

This appendix includes supplementary tables for Chapter 6.

Table A.1: Regression analysis: inferred parameters, percentage rate, 14 days

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
PT	**-0.112**	**-0.464**	**-0.465**	**-0.465**	**-0.463**	**-0.488**	**-0.542**	**-0.362**	**-0.279**	**-0.142**
	(-9.30)	(-28.70)	(-27.99)	(-27.94)	(-27.80)	(-28.78)	(-16.54)	(-10.17)	(-7.67)	(-3.44)
Mom		**0.222**	**0.222**	**0.222**	**0.218**	**0.236**	**0.251**	**0.101**	**0.054**	-0.006
		(32.63)	(32.20)	(32.17)	(31.53)	(32.41)	(22.96)	(6.32)	(3.28)	(-0.33)
Size			0.001	0.001	**0.065**	**0.064**	**0.064**	**0.063**	**0.056**	**0.055**
			(0.08)	(0.09)	(4.98)	(4.93)	(4.89)	(4.81)	(4.25)	(4.18)
Beta				**-0.020**	**-0.019**	**-0.019**	**-0.020**	**-0.020**	**-0.019**	**-0.019**
				(-2.15)	(-2.03)	(-2.09)	(-1.94)	(-2.01)	(-2.12)	(-2.06)
Vol					**-0.055**	**-0.061**	**-0.061**	**-0.058**	**-0.058**	**-0.057**
					(-6.18)	(-6.85)	(-6.88)	(-6.55)	(-6.48)	(-6.36)
SdVol						**-0.885**	**-0.868**	**-0.915**	**-0.775**	**-0.782**
						(-7.79)	(-7.62)	(-8.02)	(-6.76)	(-6.82)
Min							**-0.008**	**-0.009**	**-0.016**	-0.002
							(-1.92)	(-2.36)	(-3.94)	(-0.55)
Max								**0.016**	**0.024**	**0.028**
								(13.02)	(16.78)	(18.20)
Skew									**-0.257**	**-0.230**
									(-11.13)	(-9.83)
Kurt										**-0.092**
										(-7.04)

Note: Table presents the results of linear regression analysis where all data are treated as cross-sectional. The dependent variable in all regressions is cryptocurrency return in excess of the market in percentage form. All independent variables were defined in Section 4.5. We excluded the Sd variable as after adding it to the regression variance inflation factor (VIF) of Sd, and Max escalates to almost 170, which means a problem with multicollinearity and violates the assumption of linear regression. Without the Sd, regression in column (10) does not have any variable with VIF higher than 10 and meets all the assumptions. The highest VIF has Mom and Max. T-statistics are shown in parentheses. The coefficient significant at the 10% level is denoted by bold typeface.

Table A.2: Regression analysis: inferred parameters, decimal rate, 14 days

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
PT	-0.004	**-0.201**	**-0.200**	**-0.200**	**-0.199**	**-0.204**	**-0.200**	**-0.165**	**-0.133**	**-0.108**
	(-1.16)	(-31.78)	(-31.15)	(-31.11)	(-30.95)	(-31.47)	(-20.77)	(-16.50)	(-11.98)	(-9.01)
Mom		**0.355**	**0.353**	**0.354**	**0.349**	**0.364**	**0.359**	**0.215**	**0.158**	**0.112**
		(36.56)	(35.97)	(35.93)	(35.41)	(35.88)	(25.90)	(12.32)	(8.04)	(5.26)
Size			-0.001	-0.001	**0.001**	**0.001**	**0.001**	**0.001**	**0.001**	**0.001**
			(-0.82)	(-0.80)	(4.30)	(4.18)	(4.21)	(4.36)	(4.08)	(4.13)
Beta				**-0.0004**	**-0.0002**	**-0.0002**	**-0.0002**	**-0.0004**	**-0.0003**	**-0.0003**
				(-1.97)	(-1.91)	(-1.80)	(-1.92)	(-1.95)	(-1.98)	(-1.99)
Vol					**-0.001**	**-0.001**	**-0.001**	**-0.001**	**-0.001**	**-0.001**
					(-5.98)	(-6.50)	(-6.50)	(-6.28)	(-6.27)	(-6.26)
SdVol						**-0.007**	**-0.007**	**-0.008**	**-0.007**	**-0.007**
						(-6.13)	(-6.13)	(-6.87)	(-6.30)	(-6.49)
Min							0.002	**-0.010**	**-0.013**	**-0.007**
							(0.51)	(-3.23)	(-3.94)	(-2.10)
Max								**0.016**	**0.021**	**0.024**
								(13.43)	(14.67)	(15.78)
Skew									**-0.002**	**-0.001**
									(-6.31)	(-5.92)
Kurt										**-0.001**
										(-5.86)

Note: Table presents the results of linear regression analysis where all data are treated as cross-sectional. The dependent variable in all regressions is cryptocurrency return in excess of the market in percentage form. All independent variables were defined in Section 4.5. We excluded the Sd variable as after adding it to the regression variance inflation factor (VIF) of Sd, and Max escalates to almost 170, which means a problem with multicollinearity and violates the assumption of linear regression. Without the Sd, regression in column (10) does not have any variable with VIF higher than 10 and meets all the assumptions. The highest VIF has Mom and Max. T-statistics are shown in parentheses. The coefficient significant at the 10% level is denoted by bold typeface.

Table A.3: Regression analysis: empirical parameters, percentage rate, 7 days

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
PT	**-0.012**	**-0.270**	**-0.270**	**-0.270**	**-0.269**	**-0.279**	**-0.324**	**-0.315**	**-0.278**	**-0.240**
	(-2.77)	(-32.51)	(-31.83)	(-31.79)	(-31.68)	(-32.23)	(-14.07)	(-13.69)	(-11.97)	(-9.37)
Mom		**0.264**	**0.264**	**0.264**	**0.262**	**0.274**	**0.305**	**0.168**	**0.110**	**0.079**
		(36.44)	(35.87)	(35.83)	(35.50)	(35.79)	(18.44)	(9.32)	(5.84)	(3.86)
Size			-0.002	-0.002	**0.077**	**0.077**	**0.076**	**0.076**	**0.069**	**0.069**
			(-0.21)	(-0.20)	(5.95)	(5.92)	(5.90)	(5.88)	(5.35)	(5.34)
Beta				**-0.016**	**-0.016**	**-0.016**	**-0.015**	**-0.015**	**-0.016**	**-0.016**
				(-1.99)	(-2.00)	(-1.98)	(-1.94)	(-1.99)	(-2.01)	(-2.02)
Vol					**-0.067**	**-0.072**	**-0.073**	**-0.069**	**-0.068**	**-0.067**
					(-7.63)	(-8.22)	(-8.27)	(-7.87)	(-7.66)	(-7.63)
SdVol						**-0.696**	**-0.680**	**-0.726**	**-0.607**	**-0.611**
						(-5.90)	(-5.74)	(-6.14)	(-5.11)	(-5.15)
Min							**-0.013**	**-0.052**	**-0.063**	**-0.054**
							(-2.12)	(-7.98)	(-9.57)	(-7.47)
Max								**0.033**	**0.045**	**0.046**
								(18.82)	(21.95)	(22.25)
Skew									-0.302	-0.296
									(-11.31)	(-11.07)
Kurt										**-0.085**
										(-3.66)

Note: Table presents the results of linear regression analysis where all data are treated as cross-sectional. The dependent variable in all regressions is cryptocurrency return in excess of the market in percentage form. All independent variables were defined in Section 4.5. We excluded the Sd variable as after adding it to the regression variance inflation factor (VIF) of Sd, and Max escalates to almost 170, which means a problem with multicollinearity and violates the assumption of linear regression. Without the Sd, regression in column (10) does not have any variable with VIF higher than 10 and meets all the assumptions. The highest VIF has Mom and Max. T-statistics are shown in parentheses. The coefficient significant at the 10% level is denoted by bold typeface.

Table A.4: Regression analysis: empirical parameters, percentage rate, 14 days

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
PT	**0.013**	**-0.231**	**-0.229**	**-0.228**	**-0.227**	**-0.241**	**-0.110**	**-0.313**	**-0.280**	**-0.209**
	(2.39)	(-23.35)	(-22.51)	(-22.45)	(-22.35)	(-23.24)	(-4.79)	(-12.64)	(-11.25)	(-6.92)
Mom		**0.273**	**0.271**	**0.271**	**0.267**	**0.286**	**0.181**	**0.182**	**0.143**	**0.088**
		(29.45)	(28.64)	(28.58)	(28.11)	(28.87)	(9.41)	(9.45)	(7.33)	(3.75)
Size			-0.010	-0.010	**0.057**	**0.057**	**0.058**	**0.066**	**0.059**	**0.058**
			(-1.22)	(-1.23)	(4.38)	(4.35)	(4.41)	(5.06)	(4.51)	(4.42)
Beta				**-0.019**	**-0.019**	**-0.018**	**-0.019**	**-0.019**	**-0.019**	**-0.019**
				(-2.01)	(-1.95)	(-1.92)	(-2.02)	(-2.03)	(-2.04)	(-2.11)
Vol					**-0.057**	**-0.063**	**-0.061**	**-0.059**	**-0.059**	**-0.058**
					(-6.44)	(-7.02)	(-6.80)	(-6.66)	(-6.60)	(-6.50)
SdVol						**-0.772**	**-0.822**	**-0.962**	**-0.816**	**-0.812**
						(-6.79)	(-7.21)	(-8.43)	(-7.11)	(-7.07)
Min							**0.029**	**-0.041**	**-0.048**	**-0.033**
							(6.40)	(-7.34)	(-8.63)	(-4.88)
Max								**0.027**	**0.033**	**0.033**
								(21.83)	(24.64)	(24.68)
Skew									**-0.265**	**-0.243**
									(-11.63)	(-10.43)
Kurt										**-0.059**
										(-4.25)

Note: Table presents the results of linear regression analysis where all data are treated as cross-sectional. The dependent variable in all regressions is cryptocurrency return in excess of the market in percentage form. All independent variables were defined in Section 4.5. We excluded the Sd variable as after adding it to the regression variance inflation factor (VIF) of Sd, and Max escalates to almost 170, which means a problem with multicollinearity and violates the assumption of linear regression. Without the Sd, regression in column (10) does not have any variable with VIF higher than 10 and meets all the assumptions. The highest VIF has Mom and Max. T-statistics are shown in parentheses. The coefficient significant at the 10% level is denoted by bold typeface.

Appendix B

Content of Enclosed ZIP file

A ZIP file containing data and R source codes is enclosed in this thesis. The structure of the ZIP file is following:

- File “ReadMe.pdf”: This file contains a detailed description of the folder “Data”.
- Folder “Data”: This folder contains all R source codes together with all datasets used in this thesis.