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Investor Attitude and Price Paths: The Effect of Trendlines and Crypto Labelling on Risk Perception and Willingness to Invest

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ABSTRACT

Various research has shown that the way economic information is presented influences investor attitude. Previous findings indicate that in a price path setting, multiple (visual) elements have an effect on investor discission making, expectations and judgement. Given the increasing popularity of graphical instruments and cryptocurrencies, this thesis investigates the effect of trendlines and crypto labels on risk perception and willingness to invest to come to a better understanding what the consequences are of the inclusion of these two elements in a price path setting. An experimental survey shows that these elements have a significant impact on investor attitude. This research contributes to a more complete perspective on the way in which trend indicating graphical instruments, like trendlines, and crypto labelling influence investor decision making and perception.

Keywords: price paths, price charts, trendlines, cryptocurrency, labelling, risk perception, willingness to invest, investor attitude, behavioural finance, experimental finance

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1. Introduction

More and more people are investing. It is easier than ever to sign up with an online broker or open an investing account at the bank. As a result, people are trying out more and more innovative investing possibilities, like trading in cryptocurrencies. When trading, investors have access to numerous graphical instruments to help them make investment decisions.[1] Especially on cryptocurrency trading platforms, the available tools are countless. One of the most important instruments that is used to evaluate assets, is past performance information. This past performance information often takes the shape of a price path (Borsboom & Zeisberger, 2020). Price paths are widely employed graphical instruments, and are used to discover patterns and to predict the future direction of the price of an asset (Nolte & Schneider, 2018; Fama, 1995).

The problem that rises with graphical information (in general, but also in price path settings in particular), is that the way in which it is presented, influences the risk perception, beliefs and investment propensity of the people who make use of it (Diacon & Hasseldine, 2007; Borsboom & Zeisberger, 2020). In other words: graphical presentation of economic information in the form of price paths influences the attitude of investors (subjective factors in which evaluating economic information can be measured) towards an investment prospect. This means that relevant visual information about assets can be manipulated in such way that people might perceive less risk or expect a more positive return. This can, undoubtedly, cause problems for private investors, since they might make choices with big consequences based on information that is manipulated in their disadvantage. Some examples of manipulations of visual information that affect investor attitude in favour of the provider of the financial asset are customizing the price scale, time horizon, labels, return bars and performance ratios (Huber & Huber, 2019; Diacon & Hasseldine, 2007; Glaser et al., 2019).

When zooming in on price paths, we see that not only their scale and time horizons, but also their shape can influence investor attitude. More specific, factors like risk perception, investor satisfaction, expected return and willingness to invest are all at least partly determined by the shape of a price path (Borsboom & Zeisberger, 2020; Grosshans & Zeisberger, 2018; Nolte & Schneider, 2018). The shape of a price path, furthermore, is determined by different elements that each influence investor attitude in a specific way. Total return, for example, influences risk perception

[1] See for example: https://dashboard.incryptohub.com/charts/bitcoin-charts/

of investors (Borsboom & Zeisberger, 2020; Choi et al., 2010). Improving and decreasing sequences are found to influence risk perception, preferences and satisfaction (Loewenstein & Prelec, 1993; Huber & Huber, 2019; Grosshans & Zeisberger, 2018). Turning points (or: extrema locations) influence risk perception, satisfaction and also weight given to information (Bhootra & Hur, 2013; Borsboom & Zeisberger, 2020; Grosshans & Zeisberger, 2018). Last, peaks and the length of a price path influence trading decisions and risk perception (Huddart et al., 2009; Huber & Huber, 2019; Raghubir and Das, 2010).

As shown above, there is well established literature on factors that affect risk perception, willingness to invest, satisfaction (and other investor attitudes) in the context of price paths. Not only factors like time horizons, scales and labels are found to be relevant, but also the shape of the price path itself. However, considering a holistic perspective on the subject, there is room and need for more research. Namely, there are other factors that could also influence investor attitude in the context of price paths, one of the most used graphical instruments in the investment sector. In this thesis, we focus on two of these factors on which the literature, to the best of our knowledge, is lacking. Those factors are (i) trendlines and (ii) crypto labels. Trendlines are used to give investors an idea of the direction in which the price of an asset is going (Beattie & Jones, 2000). And in this thesis, a crypto label indicates that the price path that is shown, resembles the price development of a cryptocurrency asset.

The particular relevance of research on the effect of these two components in a price path setting lies in their practical use. As has been noted, there are more and more possibilities for non-professional traders to use graphical tools and to invest in exotic assets like cryptocurrencies. First, the possibility to employ trendlines are numerous. Not only applications like Excel provide the use of this graphical tool, but also countless other platforms like trading websites (especially in the crypto segment) offer the possibility to display trendlines based on a certain period. There are even trading platforms on which you can draw your own trendlines. Second, cryptocurrencies are on the rise. These assets have gaining momentum and dominate the news in the financial world. Almost 20% of the population between the age of 16 and 34 owns at least one cryptocurrency asset, and this number is rising.[2] Since both using trendlines and trading in cryptocurrencies is easier and more accessible than ever, their potential influence on investor behaviour in a price path context

[2] https://eenvandaag.avrotros.nl/item/cryptocurrency-voor-veel-jongeren-nog-abracadabra-6-op-10-begrijpen-het-niet-echt/

should not be disregarded. More specific, this thesis seeks to investigate what the effect of these factors is on risk perception and willingness to invest, two examples of investor attitude. So, in order to contribute to the completeness of the literature on investor attitude in the context of price paths, the following research question is posed:

What effect do trendlines and crypto labelling in price paths have on risk perception and willingness to invest?

This research question was addressed by conducting an online experiment in which the subjects were randomly divided into four categories. In each category, the subjects were shown 4 out of 16 generated price charts and were asked how risky they perceived the asset to be and how willing they were to invest in the asset, based on the price chart that resembled that asset. The shown price charts differed in movement (up-down or down-up) and turning point (late or early), but had the same starting point (100) and end point (110). Furthermore, one of the four shown graphs contained a trendline and a crypto label. The other 3 graphs contained either a trendline, a crypto label or no trendline or crypto label. The trendlines that were used were always positive and rising, but differed in steepness. Half of the trendlines was steep, the other half was flat. These and all other choices that were made concerning the exact execution of the research will be explained and answered for later on in chapter 3.

The results show that trendlines and crypto labels are of significant influence on the investor attitudes risk perception and willingness to invest. The implication of the used models is that trend following behaviour in the context of price paths can be detected in the effects that trendlines cause. Especially steeper trendlines have a profound effect, which is directly in line with the literature. Furthermore, the results also indicate that crypto labels lead to higher perceived risk and lower willingness to invest. This result could possibly reveal a somewhat negative image individuals might have of cryptocurrencies; at least it tells us something about the role the perception of cryptocurrencies plays in assessing risk and making investment choices. The mechanisms that lay behind this result are not evident: it could be negative media coverage, a lack of knowledge of the technical aspect behind crypto trading or a combination of other (unknown) factors. In addition to the main focus of this thesis, we also find, again completely in line with the previous literature, a significant effect of price path movement (up-down or down-up) on risk perception and investment

propensity. However, our results cannot confirm the findings of the previous literature concerning the effect of turning points; such a significant influence was not found in this thesis.

There are multiple interests that research on the effect of trendlines and crypto labelling on investor attitude in the context of price paths can serve. First of all, there is the already discussed holistic view of the subject: this thesis can provide additional information to better understand investor attitude in price path settings, contributing to a more complete image of relevant behavioural aspects within the reach of the subject. Second, the research can be relevant for policymakers that might want to regulate (online) brokers or banks that offer investment possibilities to the public, in which they provide assets like cryptocurrencies or graphical instruments like trendlines. This use would be consistent with the growing amount of legislation that seeks to protect the public from complicated financial products and the providers of those products like banks. Third, the research might enlighten private investors and make the public more aware of elements that can influence their financial decision making. Last, the research can also be of value to suppliers of financial products, enabling them to improve their services by providing them with valuable information on how the minds of their (potential) customers work.

2. Theoretical Framework

This chapter provides an overview of the (for this thesis relevant) literature on investor attitude in the context of price paths. First, the effect of graphical features on different investor attitudes in general and in the specific context of price paths will be discussed. Second, significant literature on the influence of the shape of price paths on investor attitude is reviewed. Last, this chapter will elaborate on the apparent lacking literature on crypto labelling. In addition to the literature overview, the hypotheses based on the theoretical framework are provided.

2.1 Graphical Instruments, Price Paths and Investor Attitude

Information in the form of a visual representation is attractive to investors when evaluating possible investments (Lurie & Mason, 2007). That is why listed companies make frequent use of graphical instruments in their communication to (potential) clients, such as price and return charts (Breu et al., 2015; Glaser et al., 2019). One of the most popular visual instruments in an investment setting is the price path, which is used to find patterns and predict future developments of the prices of assets (Fama, 1995).

Behavioural economics has shown, in recent but also in less recent research, that investor attitudes depend on multiple factors; visual representation being one of those factors. For instance, it was long thought that standard deviation of returns was the main measure of risk in investment settings (Borsboom & Zeisberger, 2020). However, since Markowitz (1952), numerous experiments have been conducted which showed different results. Holzmeister et al. (2019) found that loss probability was a stronger indicator of risk perception than standard deviation of returns, by conducting an experiment in which they showed their subjects return bar charts of annual asset returns and subsequently asked them about their risk perception. Zeisberger (2022) presented similar results and also concluded that loss probability plays a bigger role than volatility when predicting risk perception, also using return bar chars of annual returns. Duxbury and Summers (2004) came to the same conclusion, and additionally found that maximum loss also shows a more significant relationship with perceived risk than standard deviation. Diacon & Hasseldine (2007) furthermore, showed that presenting subjects with return bar charts compared to price charts yields different levels of risk perception, pointing out yet another factor of importance. Huber & Huber (2019), finally, found that narrowing the scale of return charts and price charts strongly affects risk

perception. When taking all this research into account, it can be concluded that risk perception depends on multiple (visual) factors, like loss probability, maximum loss, framing and scale.

But not only risk perception, also other examples of investor attitude are influenced by different (graphical and visual) elements. Glaser et al. (2019) for instance, showed that expectations of individuals are highly dependent on the visual format in which information is presented. Namely, their research indicated that the expectations of subjects were higher when asked to forecast the future in returns compared to prices. On the other hand, the expectations were lower when the subjects were asked to base their forecast on return charts versus price charts. Borsboom et al. (2022) analysed the effect of time frames of price charts on investor behaviour (more specific: risk-taking and trading activity). They concluded that the display horizons of price charts affect trading volume and frequency: when time frames are shorter, there is more trading activity, meaning that transaction fees and losses are higher for investors. Spiller et al. (2020) concluded that a positive or negative judgement can be dependent on the different ways quantity is depicted. They found that if time series data is presented in quantity at each point of time (stocks) or in change of quantity from one point in time to another (flows) can lead to different assessments and varying degrees of optimism. These and the findings noted in the previous paragraph, thus indicate that multiple (visual) salient elements can be of important influence when investors evaluate economic information (Shaton, 2017). Investors seem to frequently use 'heuristics' to gather information that they deem relevant (Gigerenzer & Gaissmaier, 2011; Li & Yu, 2012). And so, multiple (visual or graphical) factors can influence investor attitudes like risk perception, trading activity, and expectations.

The last few years investment attitude within the specific context of price paths has been explicitly researched. These studies focused on the effect of certain characteristics of the price path itself (instead of the influence of more general visual factors) on elements like risk perception, satisfaction and willingness to invest. Nolte & Schneider (2018), to name one of the more cited papers, found that price paths themselves have an impact on investment decisions. More specific, they found that the particular shape of a price path can influence the willingness to invest in a certain asset, even if the shape does not contain any relevant information. Furthermore, they concluded that risk perception depends on the range of prices displayed in a price path, or the amount of amplitude. Grosshans & Zeisberger (2018) also looked at the effect of price paths and observed that price paths systematically influence investor attitudes like return beliefs, trading

behaviour, investor satisfaction and risk perception. They also came to the conclusion that risk perception is influenced by longer runs of up- or downward trends, indicating that individuals believe in (short-term) trend continuation. Their experimental set-up consisted, first, of constructing different price paths with different properties like a down-up or up-down movement and a positive or negative end price. After that they created a survey in which they asked subjects to evaluate the shown price charts by stating how satisfied they were with an asset based on that shown price chart. Furthermore, subjects were asked how likely it was for them to sell the asset. For both these evaluations, a Likert scale was used. Borsboom & Zeisberger (2020) concluded that price paths that have the same underlying returns and standard deviations are perceived different in terms of risk due to their different pattern and shape. They also found that salient features like maximum prices, minimum prices and total returns are of significant influence on risk perception. In that study also different price paths with different properties in salient features were created. The price paths had different maximum prices, minimum prices, maximum crashes (maximum price decrease in 30 days) and maximum price recovery. Again, the subjects in the experiment were asked to evaluate the price charts and to express how risky they perceived the asset to be, how they viewed the return potential of the asset and how willing they were to invest in the asset based on the shown price chart. For these questions, Likert scales with different ranges were used. To elaborate further on salient elements within the context of price paths, Bose et al. (2022) created an algorithm to predict visual salient elements in price paths. The algorithm assigned decision weights to past returns based on how visually noticeable parts of the price path were. It turned out that this model was able to explain actual investment decisions made by investors based on the identified salient features. An example of a less recent study on this subject is Mussweiler & Schneller (2003). They found that highs and lows in a price path influence beliefs and decisions of investors. Taking all these findings into account, there is clear evidence that the shape of price paths is of influence on investor attitude.

2.2 Price Path Characteristics and Their Impact

We now have established that investor attitudes like risk perception, expectations, risk-taking and trading activity are influenced by multiple visual and graphical elements that individuals are confronted with when making investment decisions. Subsequently, we showed that the shape of

price paths also has a relevant and significant effect on investor attitude. In this section we zoom in on the specific characteristics of price paths that cause these effects.

2.2.1 Positive and Negative Returns

The first salient characteristic of importance in price paths that grabs the attention of investors is overall return. Borsboom & Zeisberger (2020) found that the total return of a price path ('the return achieved during the entire displayed period') has a negative effect on risk perception. Meaning that, the higher the total return, the less risky the underlying asset of a price path is perceived. Moreover, Grosshans & Zeisberger (2018) concluded that stocks with a higher overall return (winner stocks) yield higher satisfaction with investors than stocks with a lower overall return (loser stocks). These findings clearly point out investor attitudes like risk perception and satisfaction depend on overall return.

2.2.2 Turning Points

Extreme locations, or turning points, are also found to be of significant influence on investor attitude. Murdock (1962) found that these turning points are weighted heavier when they are closer to the current price. This phenomenon can be explained by the recency bias; the tendency to overweigh information close to the present when compared to more distant information (in this setting: more distant prices). Such a recency bias was found for the maximum price near the current price by Bhootra & Hur (2013). Lin (2018) found that recommendations of stock analysts rise in number when the stock price reaches its high or low. Baily et al. (2011) concluded that investors prefer assets with more recent positive or high returns. Glaser et al. (2019) showed that more recent returns are taken more in account than distant returns when investors forecast the future. All of these findings indicate that investors should have a preference for recent turning points (that would mean a late turning point in a price path setting) that have a down-up movement. However, in contrast to this expectation, Grosshans & Zeisberger (2018) found that individuals have a preference for an early turning point when shown a down-up movement, and a late turning point when shown an up-down movement (as has been noted earlier in section 2.1: risk perception is influenced by longer runs of up- or downward trends).

2.2.3 Improving Sequences

Individuals have a preference for postponed favourable returns; they rather encounter less favourable results first and wait for more positive outcomes in the future (Loewenstein & Prelec, 1993; Read & Powell, 2002). This bias for improving sequences means that people do not like be confronted with decreasing returns when they compare them to earlier returns. In Dutch there is a saying: "*Eerst het zuur, dan het zoet*," which exactly addresses this bias. The preference for improving sequences results in the finding that price path trends that rise are perceived as less risky than price paths trends that fall (Huber & Huber, 2019). Additionally, Grosshans & Zeisberger (2018) found that investors are more satisfied with price paths with a down-up than with an up-down movement. Nolte & Schneider (2018) furthermore, concluded that individuals are more willing to invest in assets with price paths that have a down-up movement than an up-down movement. Other research showed that individuals not only seem to have a preference for improving sequences, but that they also show trend-following behaviour (Anufriev & Hommes, 2012). That means that investors base trading decisions on recent trends, possibly resulting even in (almost-)self-fulfilling equilibria (Hommes, 2021). Trading behaviour based on trends, past and future performance indicators furthermore, is so strong, that prediction models that are constructed around this principle are able to match and explain empirical financial data and phenomena like bubbles and crashes (Schmitt & Westerhoff, 2021).

Although there is, to the best of our knowledge, no literature available on the specific effect of trendlines on investor attitude in the context of price paths, the same arguments and line of thoughts that result from the research above can be exerted to constitute a well-grounded hypothesis that poses a presumed effect of a trendline in a price path context. Namely, given the fact that individuals appear to have a strong preference for improving sequences (as Loewenstein & Prelec (1993) and Read & Powell (2002) indicate), we would expect that a rising trendline will positively affect the preference of the subjects for the price path that is shown to them. This argumentation in combination with the findings of Borsboom & Zeisberger (2020) and Grosshans & Zeisberger (2018) that a positive return yields more satisfaction and less perceived risk (that also indicate that the subjects would deem a price path with a positive trendline less risky because a positive trendline indicates a down-up movement) is the foundation of the following hypothesis:

Hypothesis 1: Price paths that contain a positive trendline will be perceived as less risky.

Considering the strong preference of individuals for improving sequences, positive returns and trend-following behaviour, we would expect that a positive trendline would not only have a negative effect on perceived risk (a positive trendline causes less risk to be perceived) but also a positive effect on subjects' willingness to invest. Nolte & Schneider (2018) even explicitly investigated willingness to invest as a specific investor attitude and found that it increases when a down-up movement in a price path occurs. This fact also indicates that a positive trendline would positively affect willingness to invest, since a positive trendline also makes a down-up movement, although it being a linear line. This consideration leads to the following hypothesis:

Hypothesis 2: Price paths that contain a positive trendline will lead to a higher willingness to invest.

As has been noted, the trendline is one of the most popular, easy to use graphical tools, and, moreover, quite understandable for a lot of people. Its use is to show the investor in which direction the investment moves and where it might move in the future. Furthermore, it is known that, in business settings, the axes of a price path are often manipulated to influence the trendline to give investors a better (but sometimes false) feeling about the direction of the price path (Beattie & Jones, 2000; Huber & Huber, 2019). Using the literature that is available and (at least partly) relevant, we expect a positive trendline to have a negative effect on risk perception and a positive effect on willingness to invest.

2.3 Investor Attitude, Price Paths and Cryptocurrencies

Cryptocurrencies are on the rise. They have gaining popularity and are more and more traded and owned by a growing number of people. Since the literature on the effect of price paths on investor attitude is quite new (more or less starting from 2018), the effect that a cryptocurrency frame or label might have in this context has, to the best of our knowledge, not been researched yet. Still, considering the rising popularity of digital currencies, the addition of a crypto element to the research on price paths could be highly relevant and provide useful insights. People are reminded

everyday by popular news sources that cryptocurrencies are risky.[3] That is why we would expect that the public perceives cryptocurrencies as riskier than 'normal' assets, but there is no evidence for that to the best of our knowledge. What is established by Roppelt (2019), however, is that owners of cryptocurrencies perceive them as less risky and that they have more trust in them.[4] Moreover, the risk-return trade-off of cryptocurrencies differs significantly from that of regular assets (Liu et al., 2018). That is, because cryptocurrencies like Bitcoin, Ripple and Ethereum are not exposed to usual market and macroeconomic factors. Furthermore, cryptocurrencies are not coherent with or dependent of returns of other (non-crypto) currencies, assets or commodities. Instead, price developments of cryptocurrencies can be (at least partly) explained by factors that are explicitly related to the markets on which they are traded, resulting in the observation of a strong time-series momentum effect (Liu et al., 2018). However, since the cryptocurrency market is still unclear and very abstract to most of the population, it cannot be expected that numerous people take advantage of these findings. The cryptocurrency market caused division between people, because a small part of the population took the effort to explore, discover and understand the mechanisms behind it, while others completely rejected it. For this thesis, that can mean that experienced crypto traders, who are more familiar with this special kind of asset, would perceive crypto assets as less risky, while they are more willing to invest in them. On the other hand, it could be possible that experienced crypto users are well aware of the risks and thus also perceive crypto assets to be more risky than more common assets. The most important variables that can predict the adaptation of cryptocurrencies are performance and effort expectancy. This is because users want to understand what concrete advantages cryptocurrencies can provide them when they feel incapable of using the technology themselves (McMorrow & Seyed Esfahani, 2021). Research on the behavioural aspects of bitcoin trading, moreover, reveals biases as herding, optimism, overconfidence, confirmation biases and gamblers' fallacy (Hidajat, 2019). These biases are of course also empirically found when investigating traders that engage in transactions of more common assets. However, these results do not suggest something about the effect of a cryptocurrency frame or label in a price path context. We only can combine the fact that still many people are unfamiliar with trading cryptocurrencies and the mechanism that lays behind it and the

[3] Just some examples: https://www.fool.com/investing/stock-market/market-sectors/financials/cryptocurrency-stocks/is-cryptocurrency-good-investment/,https://www.cmcmarkets.com/en-sg/learn-cryptocurrencies/what-are-the-risks,https://www.thetimes.co.uk/money-mentor/article/invest-bitcoin-cryptocurrencies/

[4] Roppelt (2019) is a master thesis by a student of the University of Twente. Nevertheless, I found the result interesting enough to add to this thesis.

fact that people might associate cryptocurrencies with enormous risk to pose a hypothesis that fits the purpose of this thesis. That results in the following hypothesis:

Hypothesis 3: Price paths that contain a crypto label will be perceived as riskier.

We could add to the considerations above the concept of loss aversion (established by Kahneman and Tversky (1979)). This bias could also play a significant role in this case because individuals might be reluctant to invest in cryptocurrencies because of lacking knowledge and high perceived riskiness: subjects could be scared to lose a great part of their invested amount if they buy cryptocurrencies. This results in the following hypothesis:

Hypothesis 4: Price paths that contain a crypto label will lead to a lower willingness to invest.

The most important properties of cryptocurrencies that have led to these two hypotheses thus are that a great part of the population lacks knowledge about these assets, that they are often very volatile and that they are most likely perceived as very risky because of their media coverage.

3. Methodology

This thesis seeks to investigate the effect of trendlines and crypto labelling on risk perception and willingness to invest in a price path setting. In doing so, an experiment was created in which subjects were asked to evaluate four different price charts that were shown to them. The experiment was conducted via Qualtrics. The purpose of this chapter is to provide an extensive illustration on how the experiment that was used to investigate the main research question, was created and conducted. First, 16 different price charts were created with different properties and manipulations (APPENDIX A). Section 3.1 elaborates on the creation and design of these price charts. The price charts were then incorporated in a survey, in which the participants were asked to evaluate how risky they perceived the asset to be, as well as how willing they were to invest in the asset, based on the shown price chart (APPENDIX B). After that, participants were asked some questions concerning demographics and personal circumstances (APPENDIX C). The survey was completely conducted in Dutch. Section 3.2 elaborates on the design and creation of the questionnaire, as well as the different treatments.

3.1 Price Chart Characteristics

In the experiment, participants were asked with every graph they were shown, to indicate how risky they perceived the asset to be and how willing they were to invest in the asset, based on the shown price chart. The four shown price charts all contained a price path, and three of them contained a crypto label, a trendline or both. In this section, first the construction and design of the price paths (3.1.1) is discussed, after which the different manipulations (3.1.2) will be explained.

3.1.1 Construction and Design of Price Paths

Based on the work of Nolte & Schneider (2018) and Grosshans & Zeisberger (2018), four different price paths were created. Each price path was created by simulating a total of 1000 ticks. Using a time frame of 1 year, that would come down to 2,74 ticks per day. That is less than for example Grosshans & Zeisberger (2018) use (they use 10 ticks per day). However, taking into account the eventual realistic looks of the paths and the simpler amount of 1000 ticks, there was no reason to add more ticks per day. The time frame of 1 year was chosen on purpose, because that time frame is widely used by investors when evaluating assets based on price paths, most of the times even being the default time frame. Furthermore, a time frame of 12 months is also in line with the

relevant findings concerning myopic loss aversion: namely, investors use a personal evaluation period of 1 year (Benartzi & Thaler, 1995). The random ticks were generated around fixed points which took the price values of 100, 85 or 135 and 110, in which the process of Geometric Brownian Motion was used to create random stock prices. However, the mean and the standard deviation of this process were controlled, in order to steer the price development in the desired direction. Two elements were used to mimic a realistic looking price development: (i) drift and (ii) uncertainty. The uncertainty was controlled by the given mean and standard deviation (which deviated between the price paths), and the drift was dependent on every previous data point and the chosen drift rate (which was 0,0005 for all price paths).

The start price for all price paths was 100, the end price for all price paths was 110. That means that all the price paths were winners (+10%). We made this choice because of the use of the trendline. Namely, using a positive return for all price path helps to ensure that the trendline will be positive in all cases, which makes the research of its effects more uncluttered. The specifics concerning this point will be discussed later in this chapter. The maximum price was either 110 (for the down-up price paths) or 135 (for the up-down price paths). The minimum price was either 85 (for the down-up price paths) or 100 (for the up-down price paths) That means that the maximum and minimum prices had a maximum deviation of +25 points or -25 points from the end price, coming down to 135 and 85. We chose to deviate in points rather than percentages, because then we would establish a round deviation as well as a round deviation price, since the end price is 110. Furthermore, the deviation itself of 25 points was chosen in order to maximize the visibility of the price paths movements. Of course, this visibility also depends on the framing of the axis. However, a balanced deviation is also necessary to create clear movements. We chose to deviate from the end price and not from the start price (as Grosshans & Zeisberger (2018) do) because of the recency bias. Namely, the movement from an extrema location to the end price is weighted heavier than prior movements of the price path (Bhootra & Hur, 2013; Glaser et al., 2019). In this way, the slopes of the price paths from the turning point to the end price are more equal across all price graphs, preventing potential influential framing effects (turning points are discussed later this section).

The movement of the price paths that were generated was either up-down or down-up. Just as Grosshans & Zeisberger (2018) and Nolte & Schneider (2018), the up-down price path first rises towards the maximum (in this thesis about 135 or ±135) after which it falls to the end price (110).

The down-up price path on the other hand first falls to the minimum (about 85 or ±85) after which it rises to the end price (110). The up-down and down-up price paths differ then again, in turning point. The turning point indicates when an up-down price paths stops rising and starts falling and when a down-up price path stops falling and starts rising. There are 2 different turning points: one at 30% of the price path, so after 15,6 weeks or 3,6 months (at tick 300), and one at 70% of the price path, so after 36,4 weeks or 8,4 months (at tick 700). Just as Grosshans & Zeisberger (2018), we chose not to add a turning point at exactly 50% of the price path, because this might look too artificial. With the turning points at 30% and 70%, the distinctive features of the different price paths become more visible.

***Table 1**: Basic Characteristics of Price Paths (that are to be found in APPENDIX A)*

	Start Price	End Price	Maximum	Minimum	Turning point	Y-Axis
Up-Down Early	100	110	±135	100	At 3,6 months	90-145
Up-Down Late	100	110	±135	100	At 8,4 months	90-145
Down-Up Early	100	110	110	±85	At 3,6 months	75-120
Down-Up Late	100	110	110	±85	At 8,4 months	75-120

The axes of the price path graphs were designed as follows. The x-axis is the same for all price paths: it has the same length (1 year), the same number of markers (10, 1 per 100 ticks), and the same label: namely on the left side it says “Begin van de periode” (beginning of the period) and on the right side it says “Eind van de periode” (end of the period). The y-axes on the other hand, differ between the up-down and down-up price paths. This choice was made to prevent possible influential framing effects (Diacon & Hasseldine, 2007; Huber & Huber, 2019). The axes were chosen in a way that there would always be a threshold of 10 (or 2 markers/squares) above (beneath) the maximum (minimum) price. That means that for the up-down price paths the y-axis went from 90 to 145 and for the down-up price paths the y-axis went from 75 to 120.

The labels of the y-axes depended on the manipulations, which are explained in the next section. If the price chart that was shown had no manipulation or only the trendline manipulation, the description of the y-axis was “Prijs AANDEEL X” or “Prijs AANDEEL Y”. If the price chart that was shown had the crypto label manipulation, the description of the y-axis was “Prijs CRYPTO

COIN A" or "Prijs CRYPTO COIN B". Which exact label was shown, depended on which treatment was (randomly) selected for a participant. These treatments are discussed in section 3.2.

Of course, other choices concerning the construction and design of the price paths could have been made. However, all decisions were made in order to minimize framing effects and maximize harmonization between the price paths, maintaining at the same time a clear division between the special characteristics of the different price paths. Large, clearly visible differences between the price paths namely would disturb the coherence of the variables risk perception and willingness to invest because a visual coherence would be absent and thus subjects could perceive the price paths totally different. This line of thought in particular applies to the choice of the design of the y-axes. Furthermore, the price paths differ in 2 aspects: up-down movement and turning point. We could have chosen for other differences, for example: in start and end price, multiple peaks, or less (or more) salient features by adjusting the y-axes or decreasing or increasing extrema locations. However, the literature distinctively describes the effect of turning points and up-down/down-up movements in price paths (Grosshans & Zeisberger, 2018; Nolte & Schneider, 2018; Borsboom & Zeisberger, 2020; Glaser et al., 2019). Testing the effect of trendlines and crypto labels in a price path context that deviates in these multiple dimensions would make the research more robust and applicable.

3.1.2 Manipulations

Now that we showed how the four different price paths were created, the manipulations can be introduced. First, a trendline was added to each of the price paths. That was done by letting Excel draw a linear trendline through the price path, based on the 1000 data points that were generated with Geometric Brownian Motion, as has been explained in the previous section. That resulted in two different kinds of trendlines. The first one was slightly positive and was to be found in the up-down early and down-up late price path. The second one was strongly positive and was to be found in the up-down late and down-up early price paths. The fact that all four of the trendlines were positive, was partly due to the choice of start and end price and the way the y-axes were designed. Since the start price was 100 and the end price 110 (so there was always a positive return of +10%) combined with the up-down and down up movements and choice of the timing of the turning points, we ensured that the trendline was positive in all cases. When we would have chosen 100 as end price (so then the total return would be 0%) for example, and Excel would have generated a linear

trendline, we would end up with a strongly positive, a slightly positive and negative trendlines. In that case, the research would not have been limited enough to test for the effect of the trendline; it would not have been harmonized and demarcated well enough and the results would have been too divergent. Using 2 strongly positive and 2 slightly positive trendlines makes for a more structured and delineated experiment. To minimize framing effects, the trendlines had the same width as the price paths, but were coloured black instead of blue. In that way the differences between the price paths and the trendlines were clear, but the contrast (in colouring and width) was not too big. Second, a crypto label was added as additional manipulation of the price paths. This was simply done by stating that the price path that was shown was that of "crypto munt" "**CRYPTO COIN A**" or "**CRYPTO COIN B**" instead of "**AANDEEL X**" or "**AANDEEL Y**".

Table 2*: All created price charts with their properties (see also APPENDIX A)*

Price Chart	Up-Down	Down-Up	Early	Late	Trendline	Crypto label
1	1	0	1	0	0	0
2	1	0	1	0	1	0
3	1	0	1	0	0	1
4	1	0	1	0	1	1
5	1	0	0	1	0	0
6	1	0	0	1	1	0
7	1	0	0	1	0	1
8	1	0	0	1	1	1
9	0	1	1	0	0	0
10	0	1	1	0	1	0
11	0	1	1	0	0	1
12	0	1	1	0	1	1
13	0	1	0	1	0	0
14	0	1	0	1	1	0
15	0	1	0	1	0	1
16	0	1	0	1	1	1

Note: 1 implies that the concerning price chart possesses properties as a down-up or up-down movement, an early or late turning point, a trendline or a crypto label. 0 on the other hand implies that the given price chart does not possess such characteristics.

The creation of the manipulations that is described above, resulted in four different manipulations: “manipulation 0” (no trendline and no crypto label), “manipulation 1” (trendline), “manipulation 2” (crypto label) and “manipulation 3” (trendline and crypto label). The creation and design of the questions that were asked to the subjects is explained in the next section, as well as the treatment on which the shown labels were based. Table 2 provides an overview of all price charts that were eventually created, with their corresponding characteristics and manipulations.

3.2 Questionnaire & Data Collection

In order to investigate the effect of trendlines and crypto labels on risk perception and willingness to invest, a questionnaire was used to create a unique data set. The subjects that participated in the experiment existed of inner circle contacts. That means: friends, family, co-workers, and fellow students. The survey was spread through direct messages via WhatsApp and via announcements on various social media, like Instagram, LinkedIn and Facebook in order to maximize the number of respondents. Furthermore, when approached via direct messaging, participants were asked to share the research with their contacts. In the experiment, no incentives of any kind were used.

To evaluate perceived risk and willingness to invest with every price chart that was shown to the subjects (four in total), the same approach as Borsboom & Zeisberger (2020) was used. The participants indicated their perceived risk by using a Likert scale from 1 to 7. 1 being ‘zeer laag risico’ (very low risk) and 7 being ‘zeer hoog risico’ (very high risk). Willingness to invest was indicated using a slider bar on a scale from 0 to 100%, with markers every 10%; subjects were asked what percentage they would invest if they had €10.000. Despite the markers every 10%, subjects were able to choose any number between 0 and 100, so e.g., 47% was a possibility. The slider bar method is also used by for example Duxbury & Summers (2018) and the question which percent of €10.000 subjects would like to invest was also used by Borsboom & Zeisberger (2020).

When participating in the survey, subjects were divided in four different treatment groups. Each treatment group was shown four different price charts and asked the subjects how risky they perceived the asset to be and how willing they were to invest in the asset, based on the price chart. The order in which the price charts were shown was fixed. Subjects always first got to see a price chart without manipulations, then a price chart with only the trendline manipulation, then a price chart with only the crypto label manipulation and last, a price chart with both the trendline and crypto label manipulation. In this way, participants got to see all the possible manipulations, which

was necessary because this experiment tests subjective variables. So, in order to make a fitting and fair comparison between the datapoints, subjects had to be encountered with all the different possible manipulations. This argument also applied for which price paths were shown as well: subjects were always shown a price path with an up-down and a down-up movement with an early and late turning point. In addition to that, in order to prevent an experimental demand effect and thus a situation in which the participants would adjust their responses because the manipulations of the price paths would be too obvious, the manipulations were divided over the four different price paths. In other words: all subjects would be encountered with four different price paths and four different manipulations.

Considering the critical points of the paragraph above, the choice of the order in which the price charts were shown was based on the following argument: keeping the possibility of an experimental demand effect in mind, the order of price charts was chosen in such way that up-down and down-up price paths would alternate. The same line of thought was applied to the trendline, since it is a more visual outspoken manipulation than the crypto label in the price path itself. Combining all these considerations and choices resulted in the different treatments, visualized by table 3:

***Table 3**: Treatments and shown price charts*

	Shown price chart 1 No manipulation	Shown price chart 2 Trendline manipulation	Shown price chart 3 Crypto manipulation	Shown price chart 4 Trendline & crypto manipulation
Treatment 1	Up-Down Early/1	Down-Up Late/14	Up-Down Late/7	Down-Up Early/12
Treatment 2	Up-Down Late/5	Down-Up Early/10	Up-Down Early/3	Down-Up Late/16
Treatment 3	Down-Up Early/9	Up-Down Late/6	Down-Up Late/15	Up-Down Early/4
Treatment 4	Down-Up Late/13	Up-Down Early/2	Down-Up Early/11	Up-Down Late/8

Note: The first row indicates which price charts are shown first, second, third and fourth. There are four treatments, each one showing different price charts. The table indicates which price chart is shown by stating their movement (up-down or down-up) and turning point (early or late), followed by / and a number which corresponds with table 2, showing exactly which properties the price chart has.

After the questions that concerned the evaluation of assets based on a shown price chart, some demographic and personal questions were asked (APPENDIX C). These questions were similar to

the questions asked by Borsboom & Zeisberger (2020) and concerned some demographic elements like gender, age and education as well as investment experience (in common assets or cryptocurrencies) and willingness to take risks. As has been noted, all created and used price charts are to be found in APPENDIX A, the questions about risk perception and willingness that were asked in APPENDIX B (as well as, to provide an illustration, the shown price charts of treatment 1) and the personal and demographic questions in APPENDIX C.

4. Results

This chapter explains how the data retrieved from the Qualtrics survey environment was processed and interpretated using Stata17. Section 4.1 discusses demographics and the randomization process between the treatments. Section 4.2 elaborates on the descriptive statistics of the results. Section 4.3 shows the regression models that were used to investigate the effect of the trendline and crypto label variables on risk perception and willingness to invest. Last, robustness checks and the (possible) effects of the recent cryptocurrency crash of May 2022 are discussed.

4.1 Demographics and Randomization Process

In total, the survey was answered by 149 respondents. 61% of them was male, 38% was female, and 1% preferred not to say. There was a clear majority of people that had an academic background: 54% had an university degree, 26% a HBO (higher vocational education) degree, 11% a MBO (post-secondary vocational education) degree and 9% had a high school or elementary degree. In the age category there was also a clear majority: 52% of the respondents was between 18 and 24 years old, 14% between 24 and 30 years old, 8% between 31 and 40 years old, 8% between 41 and 50 years old, 16% between 50 and 65 years old and 3% was older than 65 years. Furthermore, 57% of the subjects had experience in trading common assets. 37% had experience in trading cryptocurrencies. In total, there were 596 observations, divided over 16 different price charts.

Table 4 depicts the per group division of the subjects over the treatments. The survey was designed so that all participants had an equal chance of being placed in either treatment 1, 2, 3 or 4. Table 4 does not show the results of the division between manipulations (trendline and/or crypto label), since this is unnecessary: all subjects, regardless of the treatment, got to see all four manipulations. Since the sample size of some of the groups was outright small (for example: there were only four participants with age >65, and there was only one participant with education ‘basisschool’) the age and education group were split in two groups: youth and non-youth and low education and high education. For the same reason, the risk preference group was also divided in two (since the three highest risk preference categories all contained less than 10 participants): low risk preference and high risk preference.

We chose not to explicitly use statistical tests to check whether the randomization process succeeded. This is because this method nowadays is considered to be misleading and inappropriate by the American Statistical Organisation. What is investigated later in this chapter however, are

the differences in effects between certain groups. Or more specific: between the groups with different trading experience. The personal and demographic variables are thus accounted for in the eventual regression models further on in this chapter. However, a basic visual analysis points out that the subjects were divided properly, since none of the percentages depicted in table 4 indicates a tremendous deviation from the 25% distribution across the treatments.

***Table 4**: Division of subjects between the treatments*

Group	Treatment 1 N (percentage)	Treatment 2 N (percentage)	Treatment 3 N (percentage)	Treatment 4 N (percentage)
Gender				
Men	26 (29%)	24 (26%)	21 (23%)	20 (22%)
Women	10 (18%)	11 (19%)	18 (32%)	18 (32%)
Age				
Youth (age =<30)	24 (25%)	24 (25%)	25 (26%)	24 (25%)
Non-youth (age >30)	12 (23%)	11 (21%)	15 (29%)	14 (27%)
Education				
Low (=<MBO)	6 (19%)	11 (35%)	4 (12%)	10 (32%)
High (=>HBO)	30 (25%)	24 (20%)	36 (31%)	28 (24%)
Investing experience				
No	13 (20%)	19 (29%)	21 (32%)	12 (18%)
Yes	23 (27%)	16 (19%)	19 (22%)	26 (30%)
Crypto trading experience				
No	19 (20%)	24 (26%)	28 (30%)	23 (24%)
Yes	17 (31%)	11 (20%)	12 (22%)	15 (27%)
Risk preference				
Low (0-5)	24 (21%)	29 (25%)	31(26%)	33 (28%)
High (6-10)	12 (38%)	6 (19%)	9 (28%)	5 (15%)

Note: The first term indicates the absolute number of participants in a group, in brackets that absolute number is expressed in percentages considering the distributions across the different treatments

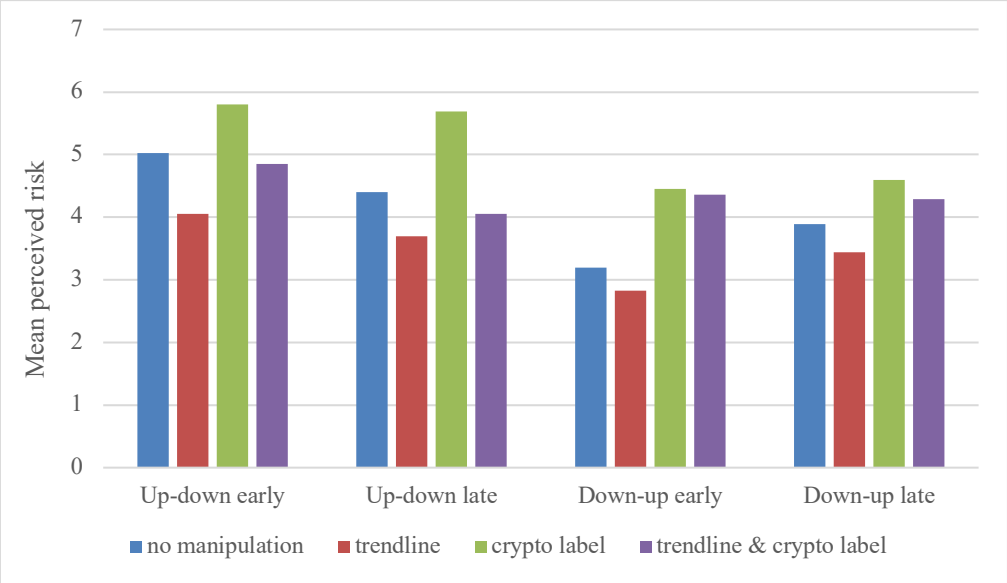
4.2 Descriptive Statistics

Figure 1 shows the mean perceived risk per shown price chart and figure 2 shows the mean willingness to invest per shown price chart. In this case, we chose not to depict the mean values per treatment, since the research focusses on the effect on the different price path manipulations which are scattered throughout the four treatments. There are multiple considerable variations in mean values visible. First of all, in figure 1, there is a clear deviation in mean risk perception when we differentiate for the different price paths. Not taking any manipulations into account yet, the mean risk perception of the price paths with an up-down movement are 5.02 (early) and 4.40 (late), while the mean risk perception of the price paths with a down-up movement are 3.20 (early) and 3.89 (late) (see APPENDIX D for the detailed numbers). This means that there could be a significant relation between movement of a price path and risk perception, as shown by the literature discussed in chapter 2 (i.e., Grosshans & Zeisberger, 2018; Nolte & Schneider, 2018; Borsboom & Zeisberger, 2020). Furthermore, we can observe big differences in perceived risk when looking at the different manipulations. In all cases, the price charts with a trendline (crypto label) manipulation have substantially lower (higher) means than the price charts with no manipulation. However, when a price chart contains both the trendline and crypto label manipulation, the observations are less consistent: for the down-up price paths, the risk perception means for this specific manipulation are slightly lower than the means for the crypto manipulation. But for the up-down price paths, this difference in means between the two manipulations is substantially larger.

When considering a more general effect of the manipulations on risk perception (which are of course explicitly investigated further on in this chapter) and not taking the different movements of the price paths into account, we can observe the following mean values per manipulation: the mean risk perception for the shown price charts with no manipulation is 4.10, with the trendline manipulation is 3.52, with the crypto manipulation is 5.11 and with both the trendline and crypto manipulation is 4.40. Important to note is that these values are not visible in figure 1. Here, again a clear deviation of the price paths that contained a trendline and a crypto label from the no manipulation risk perception mean is visible. The mean risk perception for the price charts that contained a trendline (crypto label) is substantially lower (higher) than the mean risk perception of the no manipulation price charts. And here as well, there is no clear distinctive deviation in mean

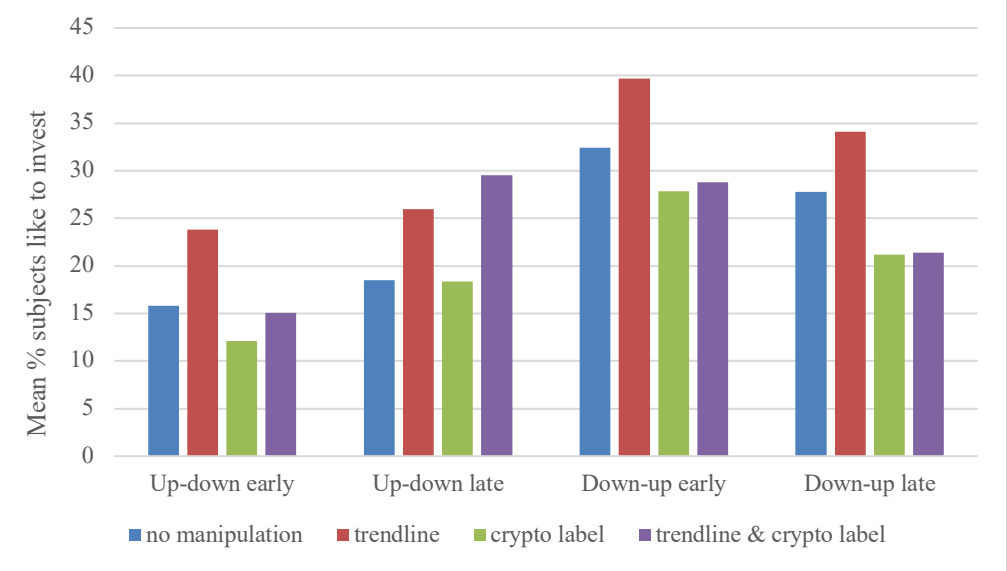
risk perception of the combined trendline and crypto manipulation price charts from the no manipulation price charts.

***Figure 1**: Mean perceived risk per price chart*



Note: table with corresponding numbers are to be found in APPENDIX D

***Figure 2**: Mean % of 10.000 subjects like to invest per price chart*



Note: table with corresponding numbers are to be found in APPENDIX D

When zooming in on the means of willingness to invest and figure 2, there are also a few remarkable elements that stand out. First of all, again not taking the manipulations into account yet, the differences in mean between the up-down and down-up price paths are clearly visible. Where the up-down price paths willingness to invest means are 15.81 (early) and 18.46 (late), the means of the down-up price paths are 32.43 (early) and 27.79 (late); a substantial difference that is also directly in line with the already discussed literature (again, i.e., Grosshans & Zeisberger, 2018; Nolte & Schneider, 2018; Borsboom & Zeisberger, 2020). These results seem to run parallel with the results of figure 1, where the down-up price path risk perception means are lower than the risk perception means of the up-down price paths. What also stands out, are the effects of the manipulations. In all cases, the means of the price charts with a trendline are higher than the no manipulation means. This observation also seems to run parallel to the results of figure 1, where all trendline means are lower than the no manipulation means in terms of risk perception. The same goes for the means of the price charts in which crypto labels are shown: mean willingness to invest in all cases is clearly lower when the crypto manipulation is applied, except for the up-down late price path. What also seems to be the case, is that there is, again, no clear relation between the mean willingness to invest when a price path contains a crypto label and a trendline and the no manipulation mean values. However, the behaviour of these specific means is comparable to that of the means in figure 1: they are more or less equal to the means of the crypto manipulation when applied on price paths with a down-up movement. Not taking in account the differences of the manipulations per type price path, the following mean values for willingness to invest are visible: 23.95% for the no manipulation price charts, 30.60% for the trendline manipulation charts, 20.06% for the crypto manipulation price charts and 23.54% for the combined trendline and crypto manipulation price charts. Again, these numbers also mirror the mean risk perception values. That means that there is a clear difference in mean willingness to invest between the trendline and crypto manipulation and the no manipulation price chart. And here as well there is no distinctive result for the combined trendline and crypto manipulation.

The main takeaway of these descriptive statistics thus is that there seem to be substantial differences in mean values of risk perception and willingness to invest between different price paths (up-down and down-up movement) and between different manipulations (trendline, crypto label or both). The exact effects of these (and other) different relevant variables are investigated in the next section. Furthermore, there is clear mirroring behaviour of mean values between risk

perception and willingness to invest: the higher risk perception, the lower willingness to invest and the other way around. We tested this negative relationship with a correlation test, that indeed indicated that the variables were significantly negatively correlated (with a correlation coefficient of -0.45) with each other.

4.3 Regression Models

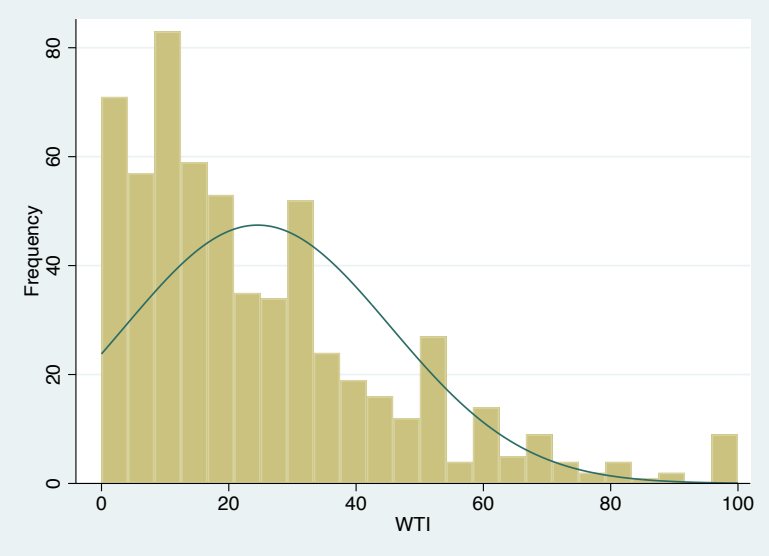
The function of this section is to evaluate whether the posed hypotheses in chapter 2 can be verified. It will do so by running various regressions that test the effects of trendlines and crypto labels on investor's risk perception and willingness to invest. First, section 4.3.1 elaborates on general effects of the trendlines and crypto labels. After that, each section will investigate in more detail, more specific effects that occur in more specific surroundings, using interaction terms and price path property variables. In that way, other relevant effects can also be observed and tested, like the influence of a steep trendline in contrast to no or a flat trendline or the influence of turning points and price path movements.

4.3.1 Overall Effect of Trendlines and Crypto Labels

This section tests the general effects of the manipulations (trendline and crypto label) on the variables risk perception and subjects' willingness to invest. The effects are regarded as 'general' because in the models there is no discrimination between the four different manipulations, unlike in the next section. There are multiple regressions at our disposal that can be used to test the presumed effects. An important notion to keep in mind while choosing the right regression, is that the dependent variables are not measured at interval level. Namely, risk perception is measured using a Likert scale from 1 to 7, and willingness to invest is measured using a slider bar with a scale from 1 to 100. Grosshans & Zeisberger (2018) used a linear regression model (OLS) to test the effect of various factors on investor satisfaction, which in their research ranged from -4 to +4 (on a 9-point Likert scale). Then, a t-test was used to test for the gap between treatments. On the other hand, Borsboom & Zeisberger (2020) used an ordered logistic regression model to test the effects of various variables on risk perception, for which also a Likert scale (on a scale from 1 to 10) was used. To test the effect of various variables on investment propensity (which was measured on a scale from 0 to 100) a tobit regression was used.

The problem that rises when using an OLS-regression on non-interval data is that the assumptions that come along with the OLS-regression are violated. A better fit for analysing Likert-scale data (that applies to the measurement of risk perception in this thesis) is the ordered logistic regression model (or ologit regression) that Borsboom & Zeisberger (2020) also use. This is because an ologit regression is better able to process ordinal variables that are dependent on an arbitrary scale, just as risk perception in this thesis. That is why we choose to apply the ologit regression when investigating the effects on risk perception. Additionally, a tobit regression is used in cases in which variables are used that are limited at either the left or right side. In this thesis, that is the case with the variable willingness to invest: that cannot be lower than 0 and not higher than 100. A tobit regression also considers that subjects might fill in the same number, and that that number does not necessarily mean the same to the subjects: the meaning of their filled in values depends on their subjective judgement (as figure 3 depicts: the data on WTI is extremely right-skewed, and subjects could interpretate the low percentages substantially different). More concrete: 24% of 10.000 for example, might feel as a lot for one person while it does not for another person.

***Figure 3**: Histogram of data points willingness to invest*



We could have also applied an OLS-regression when investigating willingness to invest. However, an OLS-regression might provide inconsistent estimates of the parameters, resulting in a situation in which the coefficients will not take their true form. Another reason to choose the tobit regression is the fact that willingness to invest was measured in percentages, not absolute numbers, also

influencing participants' perception of meaning. All these considerations thus resulted in the choice of using a tobit regression to investigate willingness to invest. The control variables that are used in the regressions are gender, age, education, investing experience, crypto investing experience and risk preference. Also, subject fixed effects were added.

***Table 5**: Overall effect of trendline and crypto label manipulation*

	Risk perception (ologit)	Willingness to invest (tobit)
	β	β
Trendline	-1.034***	5.155***
	(-6.62)	(4.52)
Crypto label	1.523***	-5.311***
	(9.44)	(-4.66)
Cons		-2.92
		(-0.24)
N	596	596
Pseudo R^2	0.035	0.004
Control variables	Yes	Yes
Subject fixed effects	Yes	Yes

Note: t-statistics in parentheses, * p<0.05, ** p<0.01, *** p<0.001. We apply subject-fixed effects. Control variables are gender, age, education, investing experience, crypto investing experience and risk preference.

Table 5 depicts the results of the ologit regression and the tobit regression on respectively risk perception and willingness to invest. The models test the overall effect of showing trendlines and/or crypto labels in a price chart, while not taking other aspects (like the deviation in steepness of the trendline and the different movements of price paths) into account. First, we discuss the results of the ologit-regression. It seems that the trendline and the crypto label coefficients are significant, both having a p-value of <0.001. The trendline coefficient takes the value of -1.034, meaning that the ordered log-odds of being in a higher risk perception category (from 1 to 7) decrease with 1.034 when a trendline is present in the shown price chart compared to the situation in which a trendline is not present. The crypto label coefficient takes the value of 1.523, meaning the odds of being in a higher risk perception category increase when a crypto label is present in the shown price chart

compared to the situation in which no crypto label is present. These findings result in the conclusion that in general, in a price path setting, trendlines negatively influence risk perception and crypto labels do so positively.

The second notable element that can be observed in the ologit regression is the difference in effect of the trendline and the crypto label manipulations. The effect of the trendline manipulation seems to be somewhat weaker than the effect of the crypto label manipulation. Despite both coefficients having a significant value, it is clear that adding a crypto label to a price chart positively affects risk perception in a stronger way than a trendline does negatively. This result might be counterintuitive, since a trendline is a manipulation with a stronger visual presence than a crypto label. And visual information, just as explained in chapter 2, substantially influences investor attitude (Glaser et al, 2019; Shaton, 2017; Borsboom et al., 2022; Gigerenzer & Gaissmaier, 2011). Given this observation however, we should keep in mind that the trendline variable in this model includes both the steep and the flat trendlines that were used in the experiment. It is possible that these different trendlines have different effects that could put the results depicted in table 5 into perspective. This matter is addressed later in this chapter.

Zooming in on the tobit model that investigates the effects of the trendlines and crypto labels on willingness to invest, we also can observe that the trendline and crypto label coefficients are significant, both with p-value <0.001. The coefficients in this case are more or less equal in magnitude (5.155 compared to -5.311). At least the difference here is smaller than in the ologit-regression. Table 5 shows that if a trendline (crypto label) is present in a price chart, the expected percentage of €10.000 subjects would like to invest, increases (decreases) with 5.155 (5.311) percentage points compared to a price chart with no manipulations. Just like the last paragraph indicated, these findings could be put in perspective when zooming in on more specific circumstances. However, based on the insights and outcomes of both models in table 5, it can be concluded that:

Result 1: Subjects perceive a price chart with a positive trendline as less risky than a price chart without a positive trendline.

Result 2: Subjects perceive a price chart with a crypto label as riskier than a price chart without a crypto label.

Result 3: Subjects are willing to invest more in an asset with a price chart that contains a positive trendline than with a price chart that does not contain a positive trendline.

Result 4: Subjects are willing to invest less in an asset with a price chart that contains a crypto label than in an asset with a price chart that does not contain a crypto label.

As has been stated in chapter 2, there does not seem to be concrete and directly applicable literature (yet) that we can compare these findings with. However, it turns out that, according to our expected believes based on the relevant available literature, indeed the effect of a trendline in a price path setting is negative on risk perception and positive on willingness to invest. These findings are in line with the literature on the preference for improving sequences (Loewenstein & Prelec, 1993; Read & Powell, 2002). Apparently, subjects have a concrete preference for positive trend indicating visual instruments (in the form of a trendline) on which they can base their investment decisions on. The trendline as a positive trend indicator also seems to influence the way individuals perceive risk, as would be in line with the findings of Schmitt & Westerhoff (2021) and Hommes (2021).

Additionally, the crypto label manipulation positively affects risk perception and negatively affects willingness to invest. These findings also confirm our expectations based on the limited amount of literature that was available. It seems subjects associate cryptocurrencies with substantial risk and are less willing to invest in them compared to 'normal' or more common assets. The reason for this could be that crypto's and their technology and platforms are not known well enough to most of the population and therefore are associated with uncertainty and risk. Which could also cause subjects' limited willingness to invest in them. However, these considerations are still speculative thoughts, as there seems to be lacking research on this specific topic. Nevertheless, the effect of a crypto label in a price path context is clearly visible in these results.

4.3.2 Separate Effects of the Manipulations

This section seeks to investigate the analysis of the previous section further by replacing the trendline and crypto label variables in the previous regression models with three variables that specifically capture the different manipulations (trendline, crypto label or both). This in contrast to the previous section, were the general effects of the trendline and crypto variables were investigated, not differentiating for each of the manipulations. The exact difference with the

previous analysis thus is that now the four different manipulations are strictly separated: manipulation 0 only contains price charts without a trendline or crypto label, manipulation 1 only contains price charts with a trendline and no crypto label, manipulation 2 only contains price charts with a crypto label and no trendline and finally manipulation 3 only contains price charts with both a trendline and a crypto label. The models are to be found in table 6. Manipulation 0 is excluded from the regressions since it is used as the reference category. We could also have chosen to run a regression with an interaction term between the trendline and the crypto label variable as an alternative. However, this would result in a regression model in which the coefficients are intertwined and hard to interpret. Strictly separating the manipulations makes for an easier method in this case. This makes it less difficult to reach the goal of this section: investigating the distinct effect of manipulation 3.

***Table 6**: Effects of the four manipulations*

	Risk perception (ologit)	Willingness to invest (tobit)
	β	β
Manipulation 1	-0.880***	6.676***
(Trendline)	(-4.05)	(4.15)
Manipulation 2	1.681***	-3.791*
(Crypto label)	(7.49)	(-2.36)
Manipulation 3	0.481*	-0.155
(Trendline, crypto label)	(2.30)	(-0.10)
Cons		-3.682
		(-0.31)
N	596	596
Pseudo R^2	0.1834	0.0899
Control variables	Yes	Yes
Subject fixed effects	Yes	Yes

Note: t-statistics in parentheses, * p<0.05, ** p<0.01, *** p<0.001. We apply subject-fixed effects. Control variables are gender, age, education, investing experience, crypto investing experience and risk preference.

First, we zoom in on the risk perception model or the ologit regression. All the manipulations are significant, meaning they all have a distinctive effect on risk perception. Furthermore, the results concerning the separate effects of the trendline (manipulation 1) and the crypto label (manipulation 2) are similar to those of general trendline and crypto label variables used in the models of table 5. The direction of the coefficients remains the same (negative for the trendline and positive for the crypto label). In magnitude, there are also no big deviations: the effect of the trendline slightly decreases (from -1.034 to -0.880) while the effect of the crypto label somewhat increases (from 1.523 to 1.681). The coefficient of manipulation 3 (with both a trendline and a crypto label incorporated in the price charts) is also significant and takes a positive value. Meaning: when both a crypto label and a trendline are present in a price chart, it positively influences risk perception. This result illustrates that the effect of the crypto label could be stronger than the effect of the trendline. It could also be that the specific fusion of these two elements sparks a whole bunch of separate, distinctive thoughts in the mind of the subjects. In any case, it is clear that a combination of the manipulations in the end leads to higher risk perception.

Zooming in on the tobit regression, the same patterns as in the ologit regression are visible. The direction of the coefficients of manipulation 1 and manipulation 2 also remains the same compared to the general trendline and crypto variables in table 5. And in terms of magnitude, the results are quite similar to the outcomes of the last section. Here the effect of the trendline slightly increases (from 5.155 to 6.676) while the effect of the crypto label decreases (from -5.311 to -3.791). Moreover, the manipulation 2 coefficient loses some significance compared to the crypto label coefficient. However, it is still clear that, also according to this model, adding a trendline (crypto label) has a positive (negative) effect on investors' willingness to invest compared to not adding them to a price chart. The manipulation 3 coefficient is, other than in the ologit model, not significant. That means there is no distinctive effect of the combination of a trendline and a crypto label in a price chart on willingness to invest. This is a remarkable outcome, since there was an effect of manipulation 3 on risk perception. Considering all the results above, the following can be concluded:

Result 5: Subjects perceive a price chart with the simultaneous depiction of a trendline and a crypto label as riskier than a price chart without both of those manipulations (or: no manipulation).

Result 6: There is no significant effect of the simultaneous depiction of a trendline and a crypto label in a price chart on investors' willingness to invest compared to a price chart without both of those manipulations (or: no manipulation).

For the rest of this chapter, until the presentation of the holistic models in section 4.3.5, we chose to run the regressions with the general trendline and crypto label variables, as we did in section 4.3.1 and table 5. This in contrast to the models of this section. The choice was based on the thought that is this way, the effects of the variables are easier to compare to each other. This is because with the general trendline and crypto label variables there is a more distinct separation of the effects of these elements compared to the situation in which there is a separate category included in which both the trendline and crypto label are present as manipulations. Moreover, the regression models become less difficult to grasp and understand with the inclusion of more general variables that capture the trendline and crypto label manipulations.

4.3.3 Effect of Steep Trendlines

In the survey, two different trendlines that varied in steepness were used. This section seeks to investigate whether this difference in steepness also played a role in influencing subjects' risk perception and willingness to invest by extending the regression model of table 5 with an interaction term that captures the situations in which the trendline was strongly positive. That was the case when the trendline was added to the up-down late and the down-up early price paths. The reason we did not add a variable that captures the cases when a flat trendline was present, is to avoid multicollinearity. This is because in every case there is a steep trendline, there is no flat trendline and in every case there is no trendline at all, there are of course also no steep and flat trendlines. Also, it should be noted that the general trendline variable still captures both the steep and the flat trendlines that were used in this experiment.

The ologit and tobit regression show that the steep trendline coefficients are significant. It turns out that the addition of a steep trendline also influences risk perception and subjects' willingness to invest: individuals perceive a price chart with a steep trendline as less risky and are more willing to invest in the underlying asset compared to a price chart without a steep trendline. This also means that the effect on willingness to invest of the steep trendline is stronger compared to the flat trendline. Namely the effect of the steep trendline can be described by both the steep

trendline variable and the general trendline variable in these models. And as it seems, the general trendline variable has a lower coefficient compared to the steep trendline coefficient (1.577 vs. 7.155).

***Table** 7: Effect of steep trendlines*

	Risk perception (ologit)	Willingness to invest (tobit)
	β	β
Trendline	-0.715***	1.577
	(-3.79)	(1.15)
Crypto label	1.557***	-5.311**
	(9.59)	(-4.74)
Steep trendline	-0.663**	7.155***
	(-3.01)	(4.52)
Cons		-2.922
		(-0.25)
N	596	596
Pseudo R^2	0.1870	0.0934
Control variables	Yes	Yes
Subject fixed effects	Yes	Yes

Note: t-statistics in parentheses, * p<0.05, ** p<0.01, *** p<0.001. We apply subject-fixed effects. Control variables are gender, age, education, investing experience, crypto investing experience and risk preference.

The coefficients of the trendline and crypto label manipulation remain significant for risk perception, despite the addition of this new explanatory variable. That is not the case for willingness to invest: the addition of the steep trendline variable makes the more general trendline variable insignificant. That means that the addition of a positive trendline in general does not influence willingness to invest, however the addition of a steep trendline does. These observations lead to the following results:

Result 7: Subjects perceive a price chart with a steep positive trendline as less risky than a price path without a steep positive trendline.

Result 8: Subjects are willing to invest more in an asset with a price chart that contains a steep trendline than with a price chart that does not contain a steep trendline.

Again, these results are consistent with the literature on the preference for improving sequences and trend following behaviour (Loewenstein & Prelec, 1993; Read & Powell, 2002; Anufriey & Hommes, 2012; Hommes, 2012; Schmitt & Westerhoff, 2021). A steeper trendline namely indicates a more positive trend, resulting in a more positive reaction and perception of the subjects. And exactly this result is observable in table 7.

4.3.4 Effect of Different Price Path Properties

***Table 8**: Effect of a different price path properties*

	Risk perception (ologit)	Willingness to invest (tobit)
	β	β
Trendline	-1.233***	5.531***
	(-7.69)	(5.14)
Crypto label	1.741***	-5.311***
	(10.48)	(-4.94)
Down-up movement	-1.494***	9.258***
	(-9.18)	(8.61)
Early turning point	0.032	-0.162
	(0.21)	(-0.15)
Cons		-7.658
		(-0.67)
N	596	596
Pseudo R^2	0.2238	0.1028
Control variables	Yes	Yes
Subject fixed effects	Yes	Yes

Note: t-statistics in parentheses, * p<0.05, ** p<0.01, *** p<0.001. We apply subject-fixed effects. Control variables are gender, age, education, investing experience, crypto investing experience and risk preference.

As has been extensively explained in chapter 2, the literature on the effect of different price path properties, as up-down or down-up movements, turning points and final returns on investor attitudes (like risk perception and willingness to invest) is abundant. That is why in the regression models in table 8 the effect of the trendline and crypto label manipulations is investigated, while also investigating the effect of price path movements and the timing of the turning points, to see whether the effects that were observed earlier in this chapter still hold. Beside the trendline and crypto label variables, a variable that captures the situation in which a price path had a down-up movement and a variable that captures when a price path had an early turning point were added to the model. Again, we do not add variables that capture the situations that are opposite to the down-up movement and early turning point because then we would encounter multicollinearity problems. The models show that all trendline and crypto label coefficients remain significant. The down-up variable also has a significant p-value for both the risk perception and willingness to invest model. The turning point variable is not significant for both models and thus has no explanatory power with respect to the dependent variables. Interestingly, this section thus could not confirm that the turning point variables also had an effect on risk perception and willingness to invest, while the literature explicitly finds such an effect (Grosshans & Zeisberger, 2018). These findings mean that the influence of the manipulations remains present even if price path property variables (like movement and turning point) are added to the model. More specific: the direction of the trendline and crypto label coefficients stays the same and the magnitudes are more or less equal to the original model.

The fact that the down-up movement variable is significant, does not come as a surprise, since Grosshans & Zeisberger (2018) and Nolte & Schneider (2018) already found that price paths with a down-up movement yield more investor satisfaction and a higher willingness to invest. Table 8 depicts results that are exactly in line with those findings. Additionally, our model finds that price paths with a down-up movement negatively influences risk perception. Important to note is that the findings concerning the down-up movement are to be compared to the price charts with an up-down movement. Meaning: if the effect of a down-up movement in a price chart on risk perception is negative, then it is more negative compared to a price chart with an up-down movement. In other words: the chance of being in a higher perceived risk category (1 to 7) is lower when you are shown a down-up price path in comparison to an up-down price path. Furthermore, if a subject is shown

a down-up price path, the expected percentage of 10.000 you would like to invest, rises with 9.258 percentage points compared to when you are shown a price path with an up-down movement. The observations and findings above lead to the following results:

Result 9: Subjects perceive a price chart that contains a price path with a down-up movement as less risky than a price chart with an up-down movement.

Result 10: Subjects are willing to invest more in an asset with a price chart that contains a price path with a down-up movement than with a price path that contains an up-down movement.

4.3.5 Holistic Model and Robustness Checks

This last section of the chapter first seeks to test the significant results of the previous sections by adding them together in one model. The goal is to check whether the significant variables remain significant and to investigate how the coefficients behave when they are put together in one explanatory model. In total, we run two holistic models. The first one includes the trendline, crypto and the other found significant variables, while the second model includes the manipulation 1, 2 and 3 variables and the other significant variables. This choice was made to illustrate and investigate the differences that might exist between the more general effects of the trendline and crypto variables and the specific effects of the four different manipulations within the context of a 'holistic' model.

***Table 9**: Holistic model 1*

	Risk perception (ologit)	Willingness to invest (tobit)
	β	β
Trendline	-0.861***	1.953
	(-4.54)	(1.51)
Crypto label	1.788***	-5.311***
	(10.69)	(-5.04)
Steep trendline	-0.807***	7.155***
	(-3.64)	(4.80)
Down-up movement	-1.539***	9.258***
	(-9.38)	(8.78)
Cons		-7.739
		(-0.69)
N	596	596
Pseudo R^2	0.2299	0.1071
Control variables	Yes	Yes
Subject fixed effects	Yes	Yes

Note: t-statistics in parentheses, * p<0.05, ** p<0.01, *** p<0.001. We apply subject-fixed effects. Control variables are gender, age, education, investing experience, crypto investing experience and risk preference.

First, we zoom in on holistic model 1: the trendline, crypto label, steep trendline and down-up movement variables all remain significant, except for the trendline variable in the willingness to invest model (as we could also observe in section 4.3.3). This means that, in a price path context, trendlines, crypto labels, steep trendlines and down-up movements significantly influence risk perception. And crypto labels, steep trendlines and down-up movements significantly influence investors' willingness to invest. When zooming in in risk perception, the effect of the crypto label is positive, while the effects of the other variables are negative. For willingness to invest, the effects are reversed in this regard; obviously revealing the clear negative relationship between risk perception and willingness to invest, which was already discussed earlier in this chapter

***Table 10**: Holistic model 2*

	Risk perception (ologit)	Willingness to invest (tobit)
	β	β
Manipulation 1	-0.723**	3.473*
(Trendline)	(-3.04)	(2.09)
Manipulation 2	1.937***	-3.791*
(Crypto label)	(8.42)	(-2.55)
Manipulation 3	0.915***	-3.358*
(Trendline, crypto label)	(3.77)	(-2.02)
Steep trendline	-0.795***	7.155***
	(-3.59)	(4.81)
Down-up movement	-1.540***	9.258***
	(-9.39)	(8.79)
Cons		-8.499
		(-0.76)
N	596	596
Pseudo R^2	0.2303	0.1075
Control variables	Yes	Yes
Subject fixed effects	Yes	Yes

Note: t-statistics in parentheses, * p<0.05, ** p<0.01, *** p<0.001. We apply subject-fixed effects. Control variables are gender, age, education, investing experience, crypto investing experience and risk preference.

When looking at the second holistic model, there are some noticeable deviations from the first holistic model. First of all, when adding a variable that controls for the situations in which both a trendline and a crypto label are present in a price chart, the separate effect of the trendline (manipulation 1 variable) slightly decreases (from -0.861 to -0.723) and the effect of the crypto label (manipulation 2 variable) slightly increases (from 1.788 to 1.937) for the risk perception model (the ologit regression). For the willingness to invest model (the tobit regression) it means that the separate effect of the trendline increases (from 1.953 to 3.473) and the separate effect of the crypto label decreases (from -5.311 to -3.791). Furthermore, in the tobit regression all three manipulation coefficients are significant. That means that in this model the separate effect of the trendline does significantly influence risk perception as well as willingness to invest. In holistic model 1 this was not the case because there the general trendline variable only significantly influenced risk perception and not willingness to invest. In holistic model 2 thus both the (sperate) trendline as well as the steep trendline variables influence willingness to invest. Important to note, again, is that the general trendline variable of holistic model 1 as well as the separate trendline variable of holistic model 2 both contain all possible trendlines: the steep ones and the flat ones. The fact that the trendline variable (manipulation 1) is significant for willingness to invest in holistic model 2 (in contrast to holistic model 1) is thus probably due to the fact that the four manipulations are separated.

Concerning the manipulation 3 coefficients, they now indicate (unlike in the earlier model of section 4.3.2) a significant effect on both risk perception and willingness to invest. It seems that combining the trendline and the crypto label also has a distinctive influence. The coefficients of manipulation 3 are comparable in some dimensions to the coefficients of manipulation 2. First of all, they have the same direction: a positive relation with perceived risk and a negative relation with willingness to invest. Second, their magnitudes in the willingness to invest model are almost equal (-3.791 and -3.358). Where the coefficients explicitly differ, is in the magnitude of their effect on risk perception (1.937 and 0.915). So, if we would follow the in section 4.3.2 posed idea that the coefficients of manipulation 3 show that the effect of the crypto label is stronger than the trendline when they are combined, we have to conclude that this is more the case for willingness to invest than for perceived risk. This because the coefficient of manipulation 3 hardly deviates from the coefficient of manipulation 2 in the tobit regression, while it deviates to a greater extend from the manipulation 2 coefficient in the ologit regression. The question then rises: why would

the relative effect between the two models differ in such a way if there would actually be a stronger effect of the crypto label compared to the trendline? In other words: if the explanation that the effect of the crypto label would get the upper hand over the trendline effect is true, why is there such a difference in risk perception and willingness to invest? Obviously, these are questions that require more research on the mechanism that lays behind individual decision making in the context of the factors that were investigated in this thesis. Another explanation for the coefficients of manipulation 3 (and their differences with those of manipulation 1 and 2), is that the combination of the trendlines with crypto labels sparks an idiosyncratic perspective in the minds of the subjects on the shown price chart. This explanation would also require more and deeper research on the specific effect of the combined manipulations in a price path setting. Despite the differences in deviation with the manipulation 2 coefficients in the different models, the fact remains that the manipulation 3 coefficients also have a positve relation with risk perception and a negative relation with willingness to invest. This in contrast to the direction of the trendline coefficients, which have the reverse direction. It is plausible that the crypto label effect indeed has the upper hand over the trendline effect when these two elements are combined. However, how this exact relation should be explained in the context of different investor attitudes like risk perception and willingness to invest, is not within the reach of this thesis.

Robustness checks

To test whether the results above are due to obvious differences in trading experience between the subjects, we rerun the analysis of table 9 (holistic model 1) and exclude specific observations. In this way, we can discover if the findings until thus far apply to certain (non-)experienced groups only. In the regressions beneath, experienced and non-experienced traders in 'normal assets' are separated as well as experienced and non-experienced traders in cryptocurrencies. Table 11 depicts the results for the risk perception models and table 12 for the willingness to invest models. There are four regressions on risk perception (RP) in table 11 that each include only non-experienced investors, experienced investors, non-experienced crypto traders, or experienced crypto traders (in that order from left to right). The same goes for to table 12, but applied on willingness to invest (WTI). Important to note is that if there are differences, we do not test their significance; we only seek to observe if there are notable deviations between the groups, just as Borsboom & Zeisberger (2020) also do. And if not, the previous found results are most likely to be robust.

Compared to the original holistic model (1), the results of all four regressions of table 11 hardly change. The directions of the trendline, crypto label, steep trendline and down-up movement variables are the same and the magnitudes of the coefficients are more or less equal. There are furthermore, no remarkable deviations in significance visible. A small detail that is noticeable is that for the experienced (normal asset) traders, the trendline and crypto label have a stronger effect and the steep trendline and down-up variable a weaker effect on their risk perception, compared to the non-experienced (normal asset) traders. Interestingly, the effects of all the variables for experienced crypto traders are stronger compared to the non-experienced crypto traders, except for the trendline variable. It thus seems that adding a trendline in a price chart affects the risk perception of experienced crypto traders less than non-experienced crypto traders. But for all other variables in the model, it is the other way around. The main takeaway here is that there are some minor differences in effects, but the overall existence of the effects still holds.

***Table 11**: Comparison RP between experienced and non-experienced (crypto)traders*

	RP No inv. exp. β	RP Investing exp. β	RP No cryp. exp. β	RP Crypto exp. β
Trendline	-0.777**	-0.903***	-0.934***	-0.738*
	(-2.74)	(-3.49)	(-3.91)	(-2.33)
Crypto label	1.531***	1.993***	1.698***	1.991***
	(6.16)	(8.64)	(8.15)	(6.97)
Steep trendline	-0.959**	-0.731*	-0.681*	-1.024**
	(-2.87)	(-2.41)	(-2.43)	(-2.79)
Down-up movement	-1.608***	-1.500***	-1.356***	-1.927***
	(-6.46)	(-6.81)	(-6.68)	(-6.76)
N	258	338	374	222
Pseudo R^2	0.1968	0.2587	0.2006	0.2864
Control variables	Yes	Yes	Yes	Yes
Subject fixed effects	Yes	Yes	No	Yes

Note: t-statistics in parentheses, * p<0.05, ** p<0.01, *** p<0.001. We apply subject-fixed effects. Control variables are gender, age, education, investing experience, crypto investing experience and risk preference.

Zooming in on table 12, the results are also similar to the results depicted in table 9. Again, the coefficients do not seem to differ much in magnitude and not in direction at all. However, there is a deviation in significance compared to the original holistic model. Namely, the crypto label coefficient is not significant for the experienced crypto traders. In other words, adding a crypto label does not influence the willingness to invest of subjects that are experienced in trading cryptocurrencies. There is another interesting result that does not relate to significance. Namely there seems to be a remarkable difference in the effect of the steep trendline and the down-up movement variables between non-experienced (normal asset) traders and experienced (normal asset) traders (9.666 vs 5.350 and 11.860 vs 7.200). It looks like the experienced investors are less affected by adding a steep trendline in the price chart and by price paths that have a down-up movement. Despite this finding, there still remains a profound and clear positive effect.

***Table 12**: Comparison WTI between experienced and non-experienced (crypto) traders*

	WTI No inv. exp. β	WTI Investing exp. β	WTI No cryp. exp. β	WTI Crypto exp. β
Trendline	1.901	1.792	3.271	0.117
	(0.95)	(1.07)	(1.97)	(0.06)
Crypto label	-4.740**	-5.386***	-6.892**	-2.563
	(-2.87)	(-3.92)	(-5.08)	(-1.55)
Steep trendline	9.666***	5.350**	7.225***	6.329**
	(4.14)	(2.76)	(3.76)	(2.70)
Down-up movement	11.860***	7.200***	9.523***	9.022***
	(7.27)	(5.27)	(7.01)	(5.49)
N	258	338	374	222
Pseudo R^2	0.1110	0.1065	0.1136	0.0967
Control variables	Yes	Yes	Yes	Yes
Subject fixed effects	Yes	Yes	Yes	Yes

Note: t-statistics in parentheses, * p<0.05, ** p<0.01, *** p<0.001. We apply subject-fixed effects. Control variables are gender, age, education, investing experience, crypto investing experience and risk preference.

***Table 13**: Mann-Whitney U testing for differences between experienced and non-experienced (crypto) traders*

Group (N) p-value	Mean values RP (p-value)	Mean values WTI (p-value)
Investing experience		
No (65)	4.25	25.24
Yes (84)	4.31	23.99
p-value	(0.80)	(0.84)
Crypto experience		
No (94)	4.38	24.72
Yes (55)	4.11	24.21
p-value	(0.04)	(0.53)

Note: Table depicts mean values as well as the results of the Mann-Whitney U tests that were conducted to test whether there is a significant difference in risk perception and willingness to invest between experienced and non-experienced traders. The number of observations shows the number of participants per group; the number depicts the aggregated data per participant.

The results that indicate somewhat different effects of the dependent variables on risk perception and willingness to invest between experienced and non-experienced groups should be complemented by the findings depicted in table 13. Namely, Mann-Whitney U tests suggest that there is no significant overall difference in mean perceived risk and willingness to invest between groups that differ in trading experience. But there seems to be a significant difference in mean risk perception between experienced crypto traders and non-experienced crypto traders. It thus seems that experienced traders have an overall lower risk perception. This result does not change or affect the previous findings of this chapter and the answer to the main research question, however. This because table 11 and 12 show that the direction of the coefficients of the experienced and non-experienced crypto traders are the same and that their magnitudes are comparable. Combining all results on the robustness of the regression models, we can conclude that the findings of the holistic model, depicted in table 11, are likely to be robust to the degree of experience in trading 'normal' assets as well in cryptocurrencies. This because all the minor differences that were found, do not contradict the main effects of the trendlines, crypto labels, steep trendlines and price path

movement. The main effects of the independent variables that were investigated all throughout this chapter thus are probably more deeply rooted in the psychology of the subjects than differences in trading experience.

The recent cryptocurrency crash of May 2022

During the conduction of the survey (from 23/04/2022 until 12/05/2022) a crash occurred in price of the most known and (in)famous cryptocurrency, the Bitcoin. Between 4 and 9 May, the price of the Bitcoin decreased with almost 24%. After the crash, the crypto coin stabilized around the new, lower price. If subjects were aware of this news, there is a possibility that the crash would have influenced their answers. Table 14 depicts the results of the Mann-Whitney U tests that were conducted to check whether or not the mean risk perception and willingness to invest values differed between subjects that participated before and after may 8th. In doing so, only the observations of risk perception and willingness to invest that correspond with price charts that contain the crypto label were included:

Table 14*: Mann-Whitney U testing for significant differences between subjects that participated before and after the crash*

Groups (N)	Mean value RP (crypto) (p-value)	Mean value WTI (crypto) (p-value)
Participated…		
Before the crash (40)	5.07	23.06
After the crash (35)	4.39	20.38
p-value	(0.00)	(0.87)

Note: Table depicts mean values as well as the results of the Mann-Whitney U-tests that were conducted to test whether there is a significant difference in risk perception and willingness to invest between subjects that participated before and after May 8th. The number of observations shows the number of participants per group; the number depicts the aggregated data per participant.

As the findings show, in the willingness to invest model there seems to be no significant difference in mean between the subjects from before and after the crash. For the risk perception model however, there is a significant difference: subjects that participated before the crash have a higher mean perceived risk than subjects that participated after the crash. This result is obviously

extremely counterintuitive, since a crash should lead to higher perceived risk because of the severe negative outcomes it exposes. Given that fact, the concerning significant difference between mean risk perception is probably due to other factors, or just plain coincidence. One of those factors could be that the majority of the participants after the crash were recruited through LinkedIn, on which more academically schooled people are active that probably have more than average financial knowledge and experience. We tested this presumption. It turns out that, in this case, the percentage of experienced (normal asset) traders before the crash was 62.03% and after the crash 50%. The percentage of experienced crypto traders before the crash was 64.56% and after the crash 35.44%. Therefore, the explanation of the results of table 14 probably cannot be found in difference in trading experience. The same goes for education: before the crash 83.54% of the subjects was highly educated, and after the crash 74.29% was.

To get even further into the analysis of the possible effects of the crash, we run other Mann-Whitney U tests and leave the subjects out that participated during the crash (4-8 May). It should be noted that this exclusion of observations only concerns 8 participants. The results of the tests turned out to be practically identical to the tests in which they were not excluded. The fact thus remains that there is a significant difference in risk perception (for the crypto charts) between the groups that participated before and after the crash that cannot be explained by investing experience or education. Therefore, there must be another explanation that is beyond our ability to explain or that is the consequence of pure coincidence.

***Table 15**: Mann-Whitney U testing for significant differences between subjects that participated before and after the crash*

Groups (N)	Mean value RP (non-crypto) (p-value)	Mean value WTI (non-crypto) (p-value)
Participated…		
Before the crash (40)	4.25	27.58
After the crash (35)	3.31	26.93
p-value	(0.00)	(0.78)

Note: Table depicts mean values as well as the results of the Mann-Whitney U-tests that were conducted to test whether there is a significant difference in risk perception and willingness to invest between subjects that participated before and after May 8th. The number of observations shows the number of participants per group; the number depicts the aggregated data per participant.

For completion, we also conducted the same tests as above, but for the non-crypto assets. As table 15 depicts, the results are again similar to those of table 14: there turns out to be a significant difference in mean risk perception between the participants before and after the crash. When the tests are done again leaving the 8 subjects that participated during the crash, the same result holds again. This finding thus also indicates that the difference between the participants before and after the crash is coincidence or has an explanation that we are not able to discover for now.

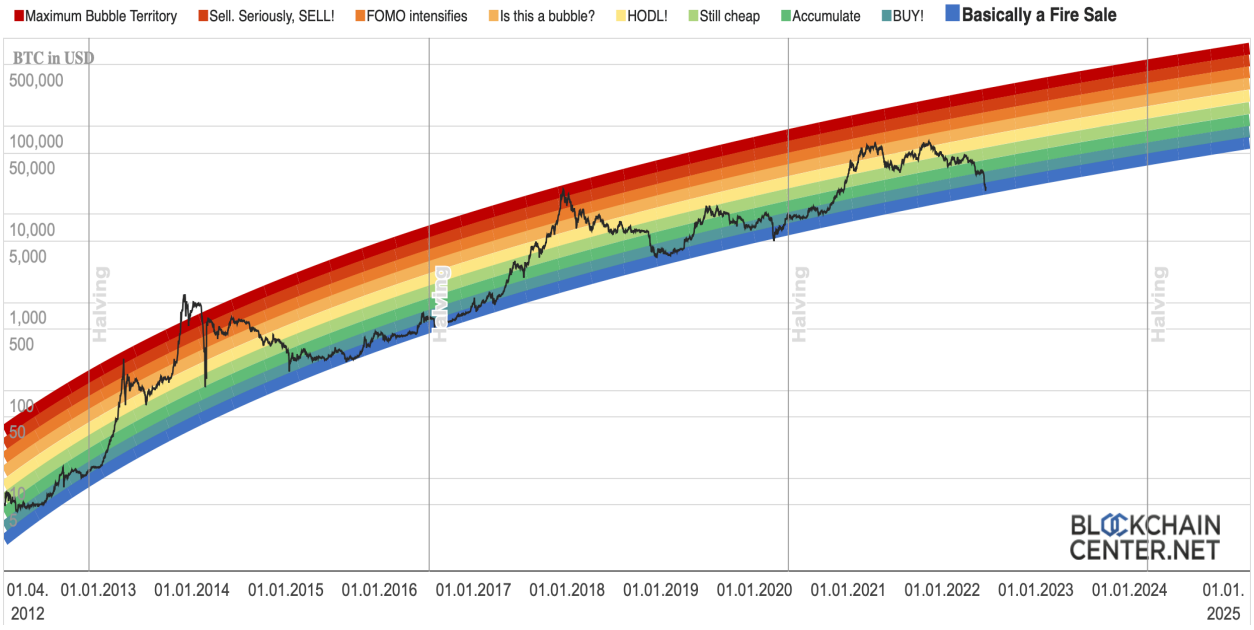
5. Conclusion and Discussion

Visual information is a popular tool used for evaluating investment opportunities, and that is why it is often used by listed companies to communicate with their (potential) clients (Lurie & Mason, 2007; Breau et al., 2015; Glaser et al., 2019). The problem with visual information, however, is that the way in which it is presented can influence investor attitudes like risk perception, willingness to invest, satisfaction, expectations, risk taking and trading activity. Examples of visual factors that are found to be of influence on these factors are loss probability, maximum loss, scale deviations of graphs, time horizons, the choice between depicting bars and charts and the choice between depicting prices and returns (Holzmeister et al., 2019; Zeisberger, 2022; Duxbury & Summers, 2004; Diacon & Hasseldine, 2007; Huber & Huber, 2019; Glaser et al., 2019; Borsboom et al., 2022). The most important example of the presentation of economic information in a visual way is the price path, which is used to find patterns and predict future developments of the prices of assets (Nolte & Schneider, 2018; Fama, 1995). Moreover, the way a price path is depicted is also found to affect investor attitudes like return beliefs, trading behaviour, investment decisions, satisfaction and risk perception. Some specific elements on which the distinct shape of a price path depends that cause these effects are found to be returns (positive or negative), turning points and improving (or decreasing) sequences (Grosshans & Zeisberger, 2018; Borsboom & Zeisberger, 2020; Bhootra & Hur, 2013; Lin, 2018; Baily et al., 2011; Mussweiler & Schneller, 2003; Glaser et al., 2019; Huber & Huber, 2019; Nolte & Schneider, 2018).

So, while there is abundant literature on the effects of the shape of a price path (affected by the returns, turning points and improving/decreasing sequences) and other framing elements like loss probability, scale deviations and time horizons, there seems to be lacking literature on certain other (visual) elements that also could affect investor attitudes like risk perception and willingness to invest. Two examples of those elements that could be of significant influence in a price path setting, are trendlines and crypto labels. Since the use of graphical tools like trendlines and the trading volume of cryptocurrencies are both becoming more popular, investigating their effect in a price path context could be highly relevant for consumers, policy makers and businesses. For consumers, because they can be made more aware of the possible effects of the use of graphical tools like trendlines and the effects of trading in and coverage of cryptocurrencies on their attitude towards investment opportunities. In other words: when consumers know the effect of certain elements that can influence and cloud their decision making, they might make better and well-

funded choices for themselves. This will improve the economic consciousness of investors, leading to a more enlightened environment in which traders can make better and more deliberate choices. For policymakers, secondly, because they might want to regulate (online) brokers or banks that make use of the elements investigated in this thesis, and thus provide graphical tools like (positive) trendlines or a platform on which cryptocurrency trading is possible. Policymakers might want to restrict the use of graphical elements like trendlines because they lead to a distorted perception of (potential) investors. Crypto platforms might be regulated for the same reason. However, if a crypto label leads towards higher perceived risk and lower willingness to invest, there might be less reason to do so if the effects of the trendline are reversed since the public than needs less protection. For businesses lastly, because they might want to improve their services and provide a more diverse selection of graphical tools or trendlines if that influences potential clients in their favour (leading to lower perceived risk and higher willingness to invest). There already is a wide range of different graphical tools available (figure 4 depicts a remarkable example), but with this thesis businesses will have concrete evidence on which they can base further choices concerning the use of trendlines and perhaps other trend indicating tools as well, on.

***Figure 4**: Bitcoin rainbow price chart*



Note: Image was retrieved from blockchaincenter.net and depicts the price development of the Bitcoin, complemented with investment advice connected to bandwidths in the form of a rainbow, which indicates a positive trend.

Research on the effects of crypto labels can also be relevant for businesses, because the results might help them to decide whether or not they want to provide crypto trading services. If a crypto label leads to higher perceived risk and lower willingness to invest, a business might not want to take the risk of developing such a platform. On the other hand, if businesses already provide crypto trading services, they might want to make changes according to the findings of this thesis. For example: crypto labels in a price path setting could be revealed to a lesser extent or not at all, possibly leading to lower risk perception and higher willingness to invest.

Because of the reasons above, this thesis seeks to extend the current literature by providing a detailed analysis of the influence of trendlines and crypto labels on risk perception and investors' willingness to invest. It does so by analysing the evaluations of 16 different price charts with a realistic design. The price charts differ in movement (down-up of up-down), turning point (early or late), trendline (present or not and steep or flat) and crypto label (present or not). Using a survey experiment, we are able to discover if the addition of trendlines and crypto labels in a price path context has a profound effect on risk perception and willingness to invest. Moreover, conducting the experiment with price paths that differ in properties which are proven to influence investor attitude, makes the research more robust and realistic.

The results indicate, first of all, that there is a significant effect of positive trendlines on the investor attitudes risk perception and willingness to invest. This effect however, depends on different factors. When not strictly separating the manipulations, as we did in holistic model 1, we find a general significant effect of trendlines on risk perception but no such effect on willingness to invest. But when we do strictly separate the manipulations, we find an effect of trendlines on risk perception and willingness to invest. Meaning: these effects exist when separating the situations in which the trendline manipulation, the crypto label manipulation or both manipulations are present in a price chart, like in holistic model 2. Moreover, we tested the effect of steep trendlines (in contrast to not present or flat trendlines) and found that their effect on risk perception and willingness to invest was significant in each model. Important to note is that this effect of the steep trendline coexist with the previous described effects; the general trendline variable in holistic model 1 and the manipulation 1 variable in holistic model 2 namely contain both the flat and steep trendlines. All these results are in line with the literature on the preference for improving sequences (Loewenstein & Prelec, 1993; Read & Powell, 2002), on the preference for price path trends that rise and price paths that have a down-up movement (Huber & Huber, 2019; Grosshans &

Zeisberger, 2018; Nolte & Schneider, 2018) and on trend-following behaviour (Anufriev & Hommes, 2012; Hommes, 2021; Schmitt & Westerhoff, 2021). It turns out that the preference for improving sequences and trend following behaviour also translates into a preference (in the form of a lower perceived risk and a higher willingness to invest) for price charts that contain a positive (steep) trendline. That means that the hypotheses posed in chapter 2 concerning these effects can be confirmed. Moreover, we find significant differences in mean risk perception between experienced and non-experienced crypto traders. However, the difference in effect of the trendline on risk perception hardly deviates in magnitude between both groups. Besides that, it does not contradict the main results of the regression models. Therefore, the main result that a trendline in general does influence risk perception is most likely to be robust. Based on these observations, there is clearly room for future research. This because while this thesis does reveal that there is an effect of positive trendlines on investor attitude, the question remains if this effect holds when also controlling for different situations. For example, the effect of trendlines with more different slopes could be investigated. The effect of trendlines in different kinds of settings, with price paths that take other shapes than the ones used in this experiment, could also contribute to a more holistic view of the subject. The effect of a negative trendline also makes for a good future topic to investigate. The effect of other trend indicating graphical elements (like in figure 4) whether or not in a price path setting, finally, might also be an interesting and logical topic for following research.

The other major finding of this thesis concerns the effect of the crypto label. Adding a crypto label to a price chart turns out to significantly affect risk perception and willingness to invest. This effect is present when taking the situations into account in which the crypto label is simultaneously depicted with a trendline (holistic model 1), and also in the situations in which that is not the case (holistic model 2). This result is line with our expectations and hypotheses, that were not based on comparable literature, since there does not seem to be any specific research on the effect of crypto labels in price path settings yet, to the best of our knowledge. We based our expectations and hypotheses on (mostly negative) media coverage of cryptocurrencies, the fact that cryptocurrencies differ in many ways from normal assets (Liu et al., 2018), the fact that a great part of the public lacks knowledge about cryptocurrencies and the technology behind it (McMorrow & Seyed Esfahani, 2021) and the combination of these factors with loss aversion (Kahneman & Tversky, 1979). It turns out that individuals perceive price charts with a crypto label as riskier and that they are less willing to invest in the asset that these charts represent. This result potentially

reveals that the subjects prefer 'normal' assets over cryptocurrencies in terms of the investigated dependent variables. However, also in this aspect there is abundant room for future research. Maybe the effects of the crypto label deviate between different (known and lesser known) crypto assets. Also, the effect of the crypto label, as well as the previous mentioned trendline effect, could be investigated in situations with different price paths that visually deviate from the ones we used in this thesis. A more general investigation of preferences and investor attitudes towards cryptocurrencies and -labels would also contribute to a more holistic view of the subject.

Beside the effects of the trendlines and crypto labels on risk perception and willingness to invest, this thesis also found additional effects on these investor attitudes of price path properties to be significant. Exactly in line with Grosshans & Zeisberger (2018) who found that investors are more satisfied with price paths that have a down-up movement than with price paths that have an up-down movement and Nolte & Schneider (2018) who found that individuals are more willing to invest in price paths with a down-up movement compared to price paths with an up-down movement, we found that price paths with a down-up movement are perceived as less risky than price paths with an up-down movement. Moreover, we found, just as Nolte & Schneider (2018) that our subjects are willing to invest more in assets with price paths with a down-up movement. Our findings thus confirm the results of previous research on the subject. In contrast to the significant differences in effect of price path movement, we did not find, as Grosshans & Zeisberger (2018) did, significant effects of early or late turning points. In this aspect the thesis cannot confirm previous research on the topic.

Despite the significant results that were found, this thesis has some limitations. First of all, there is the obvious observation that the number of variations used for trendlines and crypto labels as well as for the different price path shapes was limited. Future research can focus on more different forms of price paths, crypto labels and their combination with more different shapes of price paths. Second, the subjects that participated were not in all aspects a fair representation of the actual population. Most of the participants were highly educated and young, which is not the case for the general demographic of the Netherlands. Third, there is the problem of possible experimental demand effects. In chapter 3 we explained how we tried to prevent such effects, but this thesis was probably not able to completely eliminate the chance of subjects filling in answers that they think were desired. There is still a chance that subjects deliberately indicated higher perceived risk and lower willingness to invest when shown price charts with a crypto label for

example, overthinking the assessment. The question is how much experimental demand effects have contributed to the results. Because the trendline and crypto label manipulations were combined with price paths that each had a distinctive shape, we think we minimized experimental demand effects. This because the presence of multiple salient elements in the shown price charts leads to the presumption that it is not obvious that subjects solely focused on the treatments and filled in their answers accordingly. Conclusion: experimental demand effects are undoubtedly a limitation of this thesis, but do probably not cause the findings to be mainly the result of subjects filling in desired answers. However, future research on this subject could use more deception if a questionnaire is used. In line with that: posing the questions that were asked in another way could also help to further minimize experimental demand effects. Finally, the results of the thesis rely on hypothetical questions which consist of non-real investment opportunities, answered by subjects who were not incentivized in any way. The risk of those in-subject questions is that in practice a different result can arise which is not in line with the findings of this thesis. The effect of trendlines and crypto labels could, alternatively, be investigated using trading data from the real world, discovering patterns in how much traders are actually willing to invest. Data that describes the timing of buying and selling (crypto) assets could reveal the consequences of risk perception. Given the popularity of cryptocurrencies, are investors willing to overcome the risk they perceive? Or do investors actually like the risk that comes along with those types of assets? This line of thought can also be applied to the effect of trendlines. For example: if a trading platform automatically provides a (positive) trendline, does trading traffic increase? This is just an example of the many research questions that can be posed in this regard. The problem with investigating the effect of trendlines and crypto labels in a price path setting with this kind of real-world data however is that retrieving and interpreting it could be extremely difficult. Moreover, this kind of data might not even exist (yet).

There are several lessons we can learn from the results of this thesis. First, it turns out that trend following behaviour is found in multiple ways within a price path context; not only the distinctive shape of a price path in the form of an upward trend is of influence, as established by for example Huber & Huber (2019), but also trendlines also are found to be an example of a trend indicating graphical element that influences investor attitude. In this context, this thesis provides a valuable contribution to the knowledge concerning the subject (see the explanation above). Furthermore, this thesis showed the influence of crypto labelling and maybe even a more general

aversion (in terms of investor attitude) against cryptocurrencies. It is clear that there is a profound effect of displaying crypto labels on individuals' risk perception and willingness to invest which could be the consequence of lacking knowledge, negative media reportage, a bad reputation of the assets or other mechanisms that we are not able to grasp at this time in this thesis. The fact remains that the results reveal the role that the perception of cryptocurrencies can play in assessing risk and making investment choices. This thesis thus could be the starting point of more, additional research on how individuals view cryptocurrencies and how that influences their attitude towards investment opportunities.

References

Anufriev, M., & Hommes, C. (2012). Evolutionary Selection of Individual Expectations and Aggregate Outcomes in Asset Pricing Experiments. *American Economic Journal: Microeconomics*, *4*(4), 35–64.

Beattie, V., & Jones, M. J. (2000). Impression management: the case of inter-country financial graphs. *Journal of International Accounting, Auditing and Taxation, 9*(2), 159-183.

Bailey, W., Kumar, A., & Ng, D. (2011). Behavioral biases of mutual fund investors. *Journal of Financial Economics*, *102*(1), 1–27.

Benartzi, S. and Thaler, R. (1995). Myopic loss aversion and the equity premium puzzle. *The Quarterly Journal of Economics, 110*, 73–92.

Bhootra, A. and Hur, J. (2013). The timing of 52-week high price and momentum. *Journal of Banking and Finance, 37(*1), 3773-3782.

Borsboom, C., Janssen, D-J., Strucks, M., Zeisberger, S. (2022). History Matters: How Short -Term Price Charts Hurt Investment Performance. *Journal of Banking and Finance*, 2021.

Borsboom, C. and Zeisberger, S. (2020). What Makes an Investment Risky? An Analysis of Price Path Characteristics. *Journal of Economic Behavior &Organization 169*, 92-125.

Bose, D., Cordes, H., Nolte, S., Schneider, J.C., Camerer, C.F. (2022). Decision Weights for Experimental Asset Prices Based on Visual Salience, *The Review of Financial Studies*, hhac027, https://doi.org/10.1093/rfs/hhac027.

Breu, C., Schönbohm, A., & Löcher, M. (2015, December). Impact of investor presentations on share prices: Evidence from DAX 30 companies from 2010–2012. *Working Papers 88, IMB Institute of Management Berlin, Berlin School of Economics and Law*, 1–25.

Brown, A.L., Imai, T., Vieider, F. and Camerer, C. F. (2021). Meta-Analysis of Empirical Estimates of Loss-Aversion. *CESifo Working Paper,* 8848.

Diacon, S., & Hasseldine, J. (2007). Framing effects and risk perception: The effect of prior performance presentation format on investment fund choice. *Journal of Economic Psychology*, *28*(1), 31–52.

Duxbury, D., & Summers, B. (2004). Financial risk perception: Are individuals variance averse or loss averse? *Economics Letters, 84*(1), 21–28.

Fama, E. F. (1995). Random walks in stock market prices. *Financial Analysts Journal, 51*(1), 75–80.

Gigerenzer, G., & Gaissmaier, W. (2011). Heuristic decision making. *Annual Review of Psychology, 62*, 451–482.

Glaser, M., Iliewa, Z., & Weber, M. (2019). Thinking about prices versus thinking about returns in financial markets. *The Journal of Finance*, *74*(6), 2997-3039.

Grosshans and Zeisberger (2018): All's well that ends well? On the importance of how returns are achieved. *Journal of Banking and* Finance, 87, 397-410.

Hidajat, T. (2019). Bahvioural Biases in Bitcoin Trading. *Fokus Ekonomi: Jurnal Ilmiah Ekonomi. 14*. 337-354.

Holzmeister, F., Huber, J., Kirchler, M., Lindner, F., Weitzel, U., Zeisberger, S. (2020). What Drives Risk Perception? A Global Survey with Financial Professionals and Laypeople. *Management Science 66*(9):3977-4002.

Hommes, Cars. (2021). Behavioral and Experimental Macroeconomics and Policy Analysis: A Complex Systems Approach. *Journal of Economic Literature, 59* (1): 149-219.

Huber, C., & Huber, J. (2019). Scale matters: risk perception, return expectations, and investment propensity under different scalings. *Experimental Economics*, *22*(1), 76 100.

Kahneman, D., & Tversky, A. (1979). Prospect theory: An analysis of decision under risk. *Econometrica, 47*(2), 263–292.

Li, J. & Yu, J. 2012. Investor attention: psychological anchors, and stock return predictability. *Journal of Financial Economics* 104:41-19.

Lin, M.-C. (2018). The effect of 52-week highs and lows on analyst stock recommendations. *Accounting and Finance, 58*(1), 375-422.

Liu, Y., Tsyvinski, A. and Tsyvinski, A. (2018). Risks and Returns of Cryptocurrency. *Available at SSRN*:

Loewenstein, G. F., & Prelec, D. (1993). Preferences for sequences of outcomes. *American Psychological Association, Inc.*, *100*(1), 91–108.

Lurie, N. H., & Mason, C. H. (2007). Visual representation: Implications for decision making. *Journal of Marketing, 71*(1), 160–177.

McMorrow, J. & Seyed Esfahani, M. (2021). An Exploration into People's Perception and Intention on using Cryptocurrencies. *Journal of Business and Public Administration. 12*, 109-144.

Murdock Jr., B.B. (1962). The serial position effect of free recall. *Journal of Experimental Psychology,* 64, 482-488.

Nolte, S. and Schneider, J.C. (2018). How price path characteristics shape investment behavior. *Journal of Economic Behavior & Organization, 154*, 33-59.

Raghubir, P., & Das, S. R. (2010). The Long and Short of It: Why Are Stocks with Shorter Runs Preferred? *Journal of Consumer Research*, *36*(6), 964–982.

Read, D. and Powell, M. (2002). Reasons for sequence preferences. *Journal of Behavioral Decision Making, 15*:433–460.

Roppelt, J.C. (2019) Security risks surrounding cryptocurrency usage: a study on the security risks of cryptocurrencies and how security perception affects usage.

Schmitt, N., Westerhoff, F. (2021). Trend followers, contrarians and fundamentalists: Explaining the dynamics of financial markets, *Journal of Economic Behavior & Organization, 192*, 117-136.

Shaton, M. (2017). The Display of Information and Household Investment Behavior. *Finance and Economics Discussion Series*, *2017*(043).

Spiller, S., Reinholtz, N., Maglio, S. Judgments Based on Stocks and Flows: Different Presentations of the Same Data Can Lead to Opposing Inferences. *Management Science, 66*(5), 2213-2231.

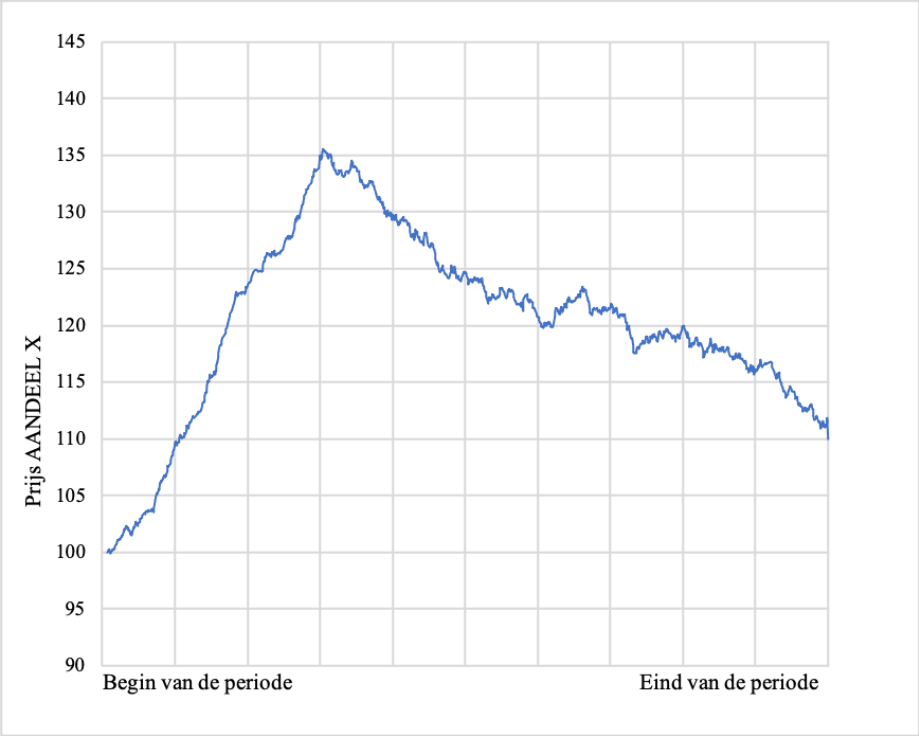
Tversky, A., & Kahneman, D. (1992). Advances in prospect theory: Cumulativerepresentation of uncertainty. *Journal of Risk and uncertainty, 5*(4), 297-323.

Weber, E.U., Siebenmorgen, N., Weber, M., 2005. Communicating asset risk: how name recognition and the format of historic volatility information affect risk perception and investment decisions. *Risk Anal. 25* (3), 597–609.

Zeisberger, S., 2022. What is Risk? How Investors Perceive Risk in Return Distributions (March 30, 2022). *https://ssrn.com/abstract=2811636 or http://dx.doi.org/10.2139/ssrn.2811636*.

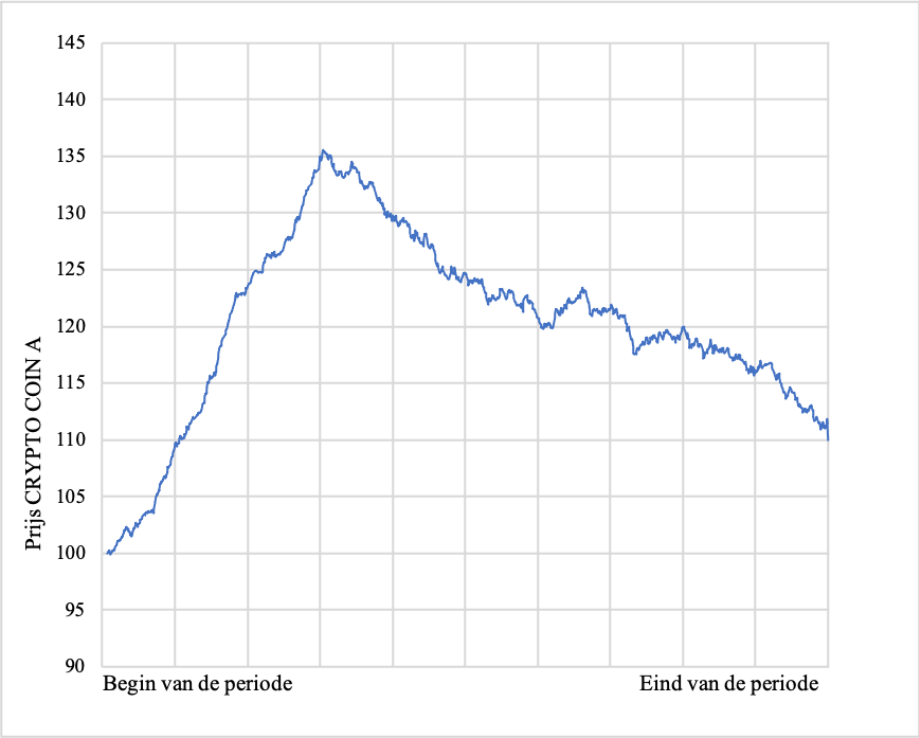
APPENDIX A Price Charts

Price Chart 1

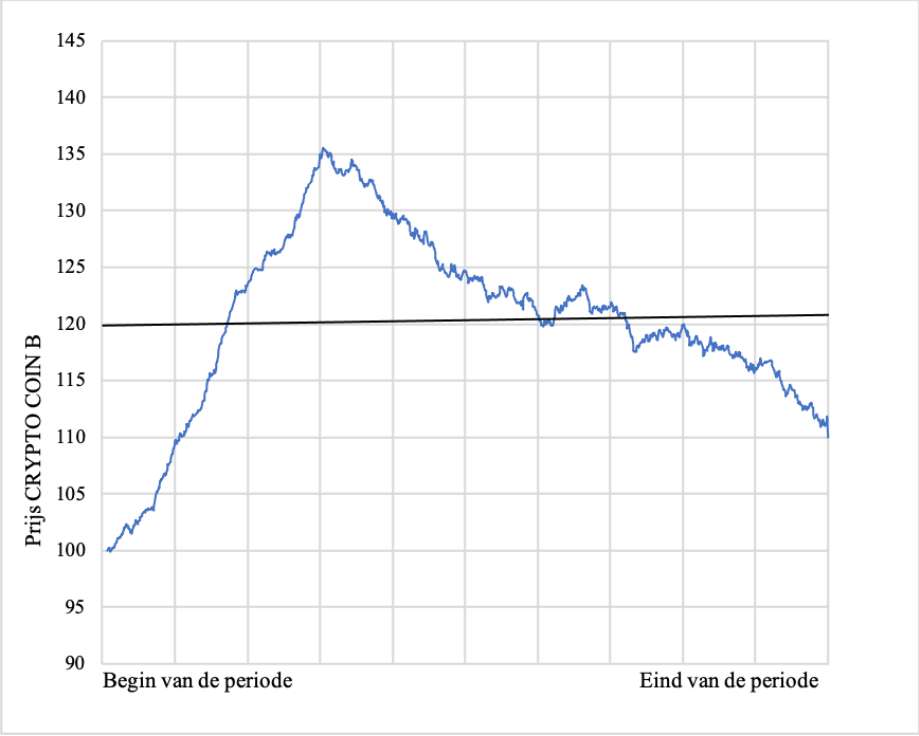


Price Chart 2

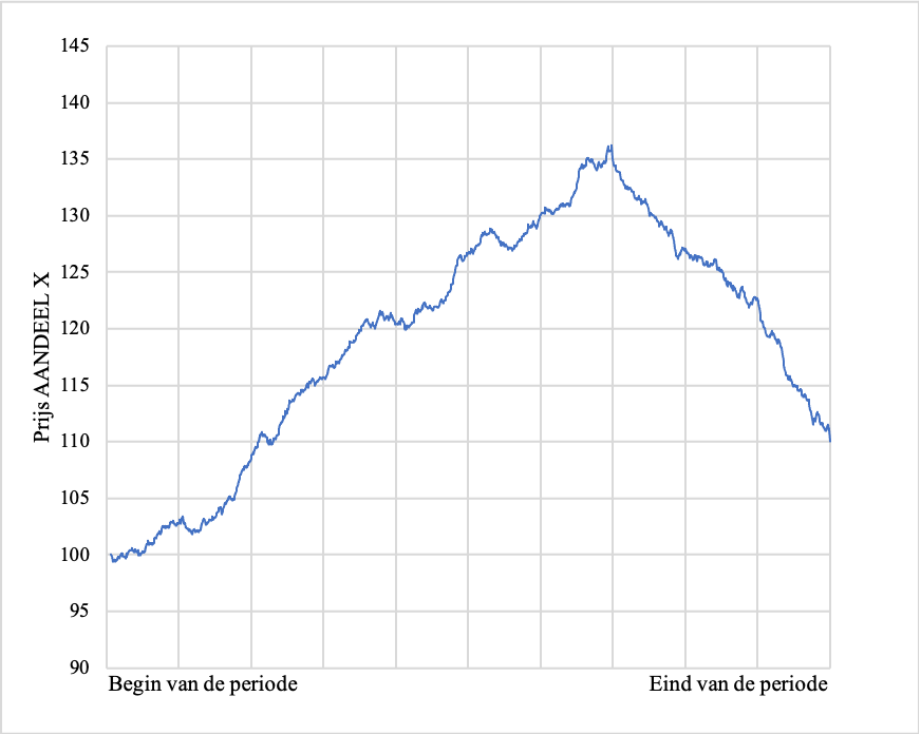
Price Chart 3



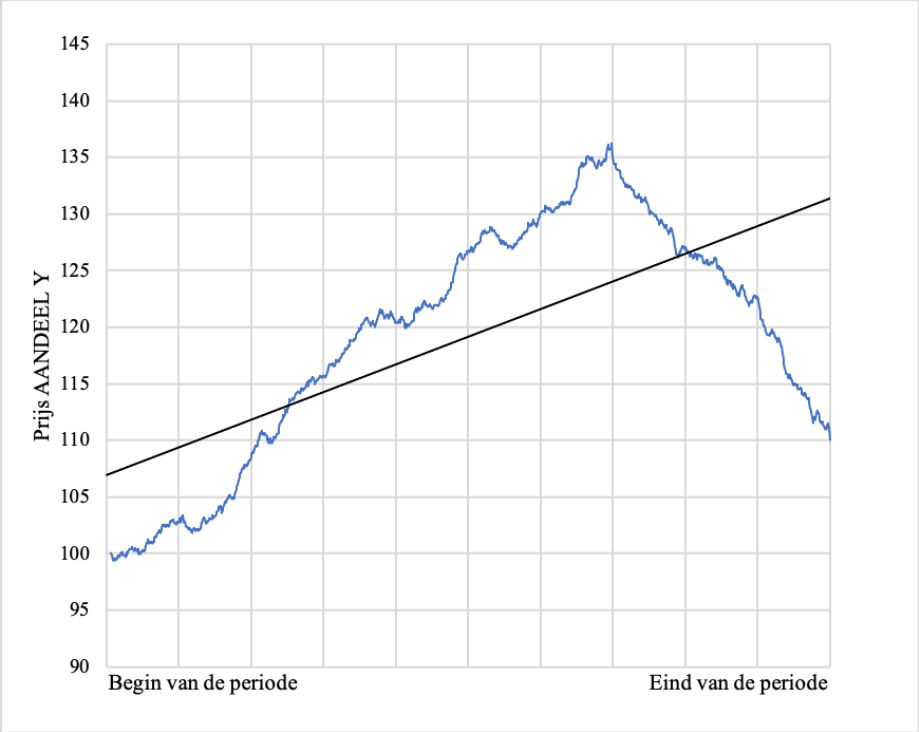
Price Chart 4



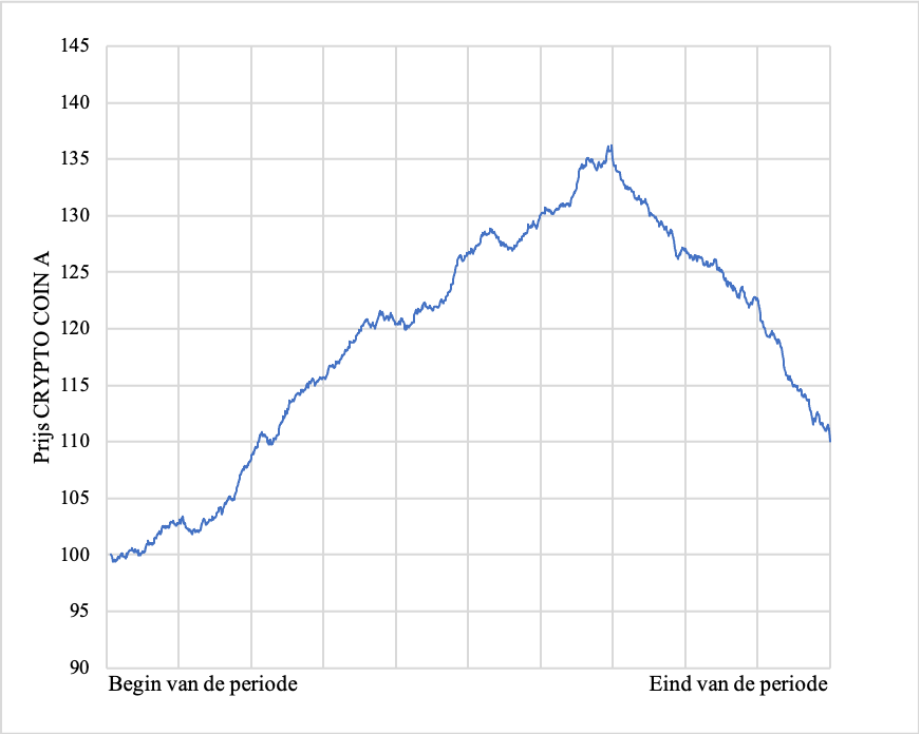
Price Chart 5



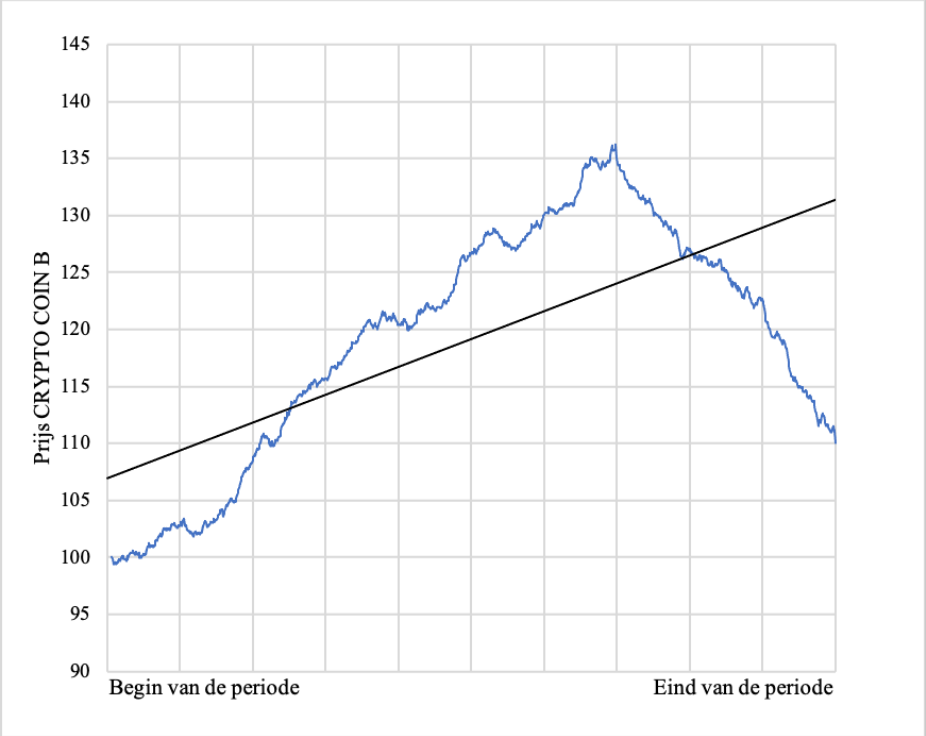
Price chart 6



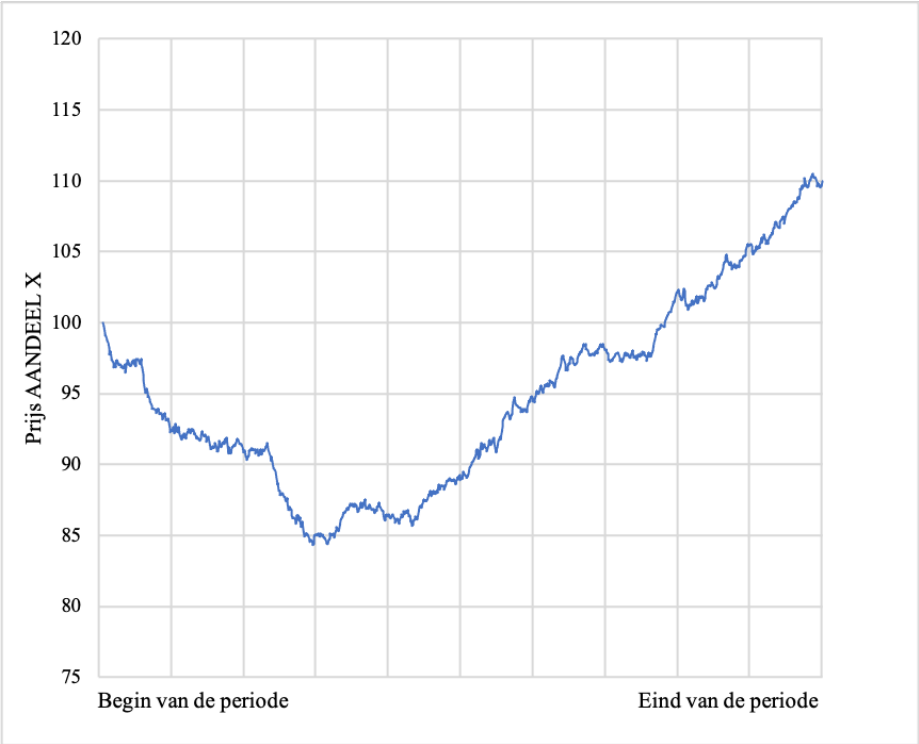
Price chart 7



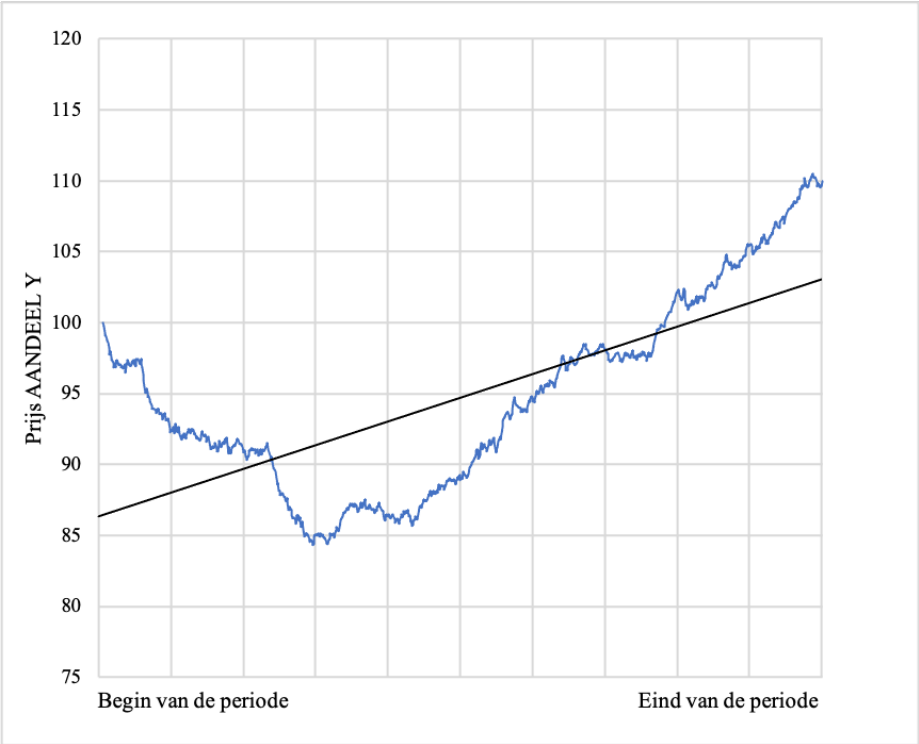
Price chart 8



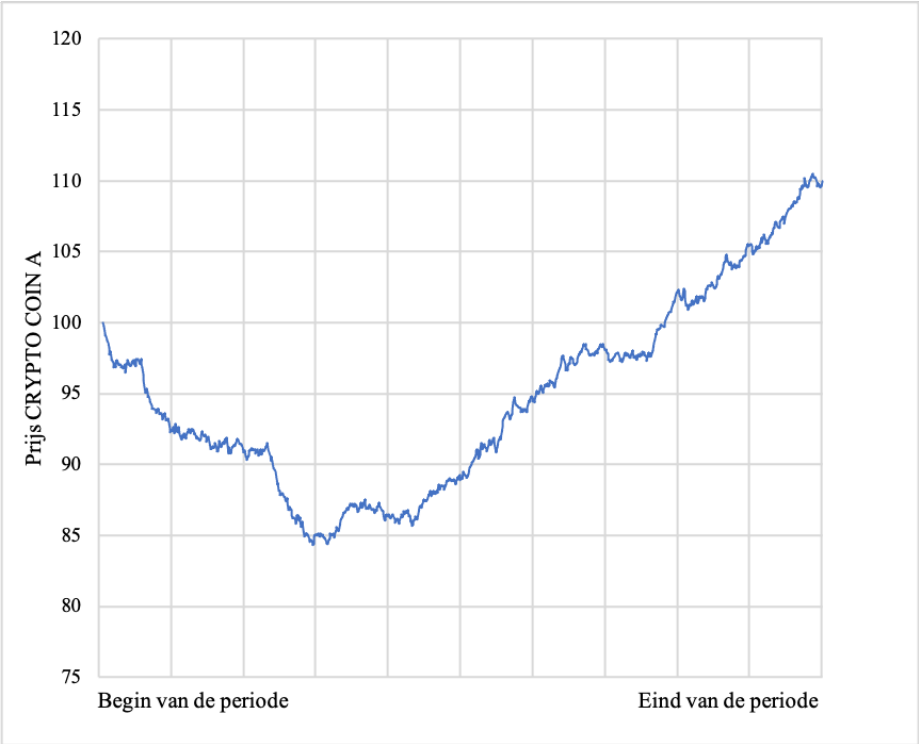
Price Chart 9



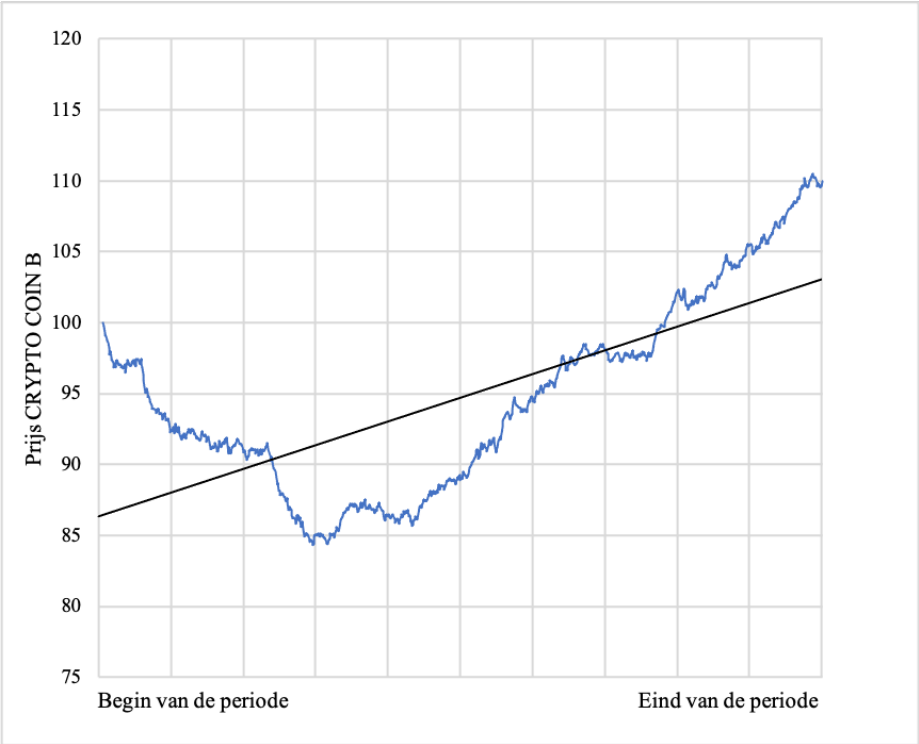
Price chart 10



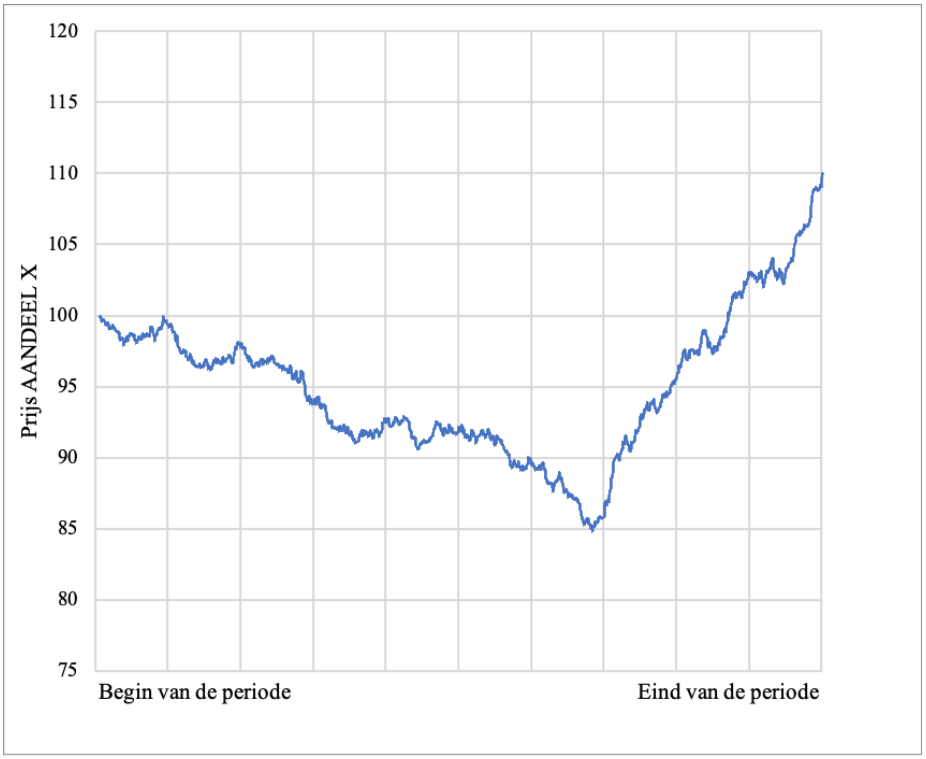
Price chart 11



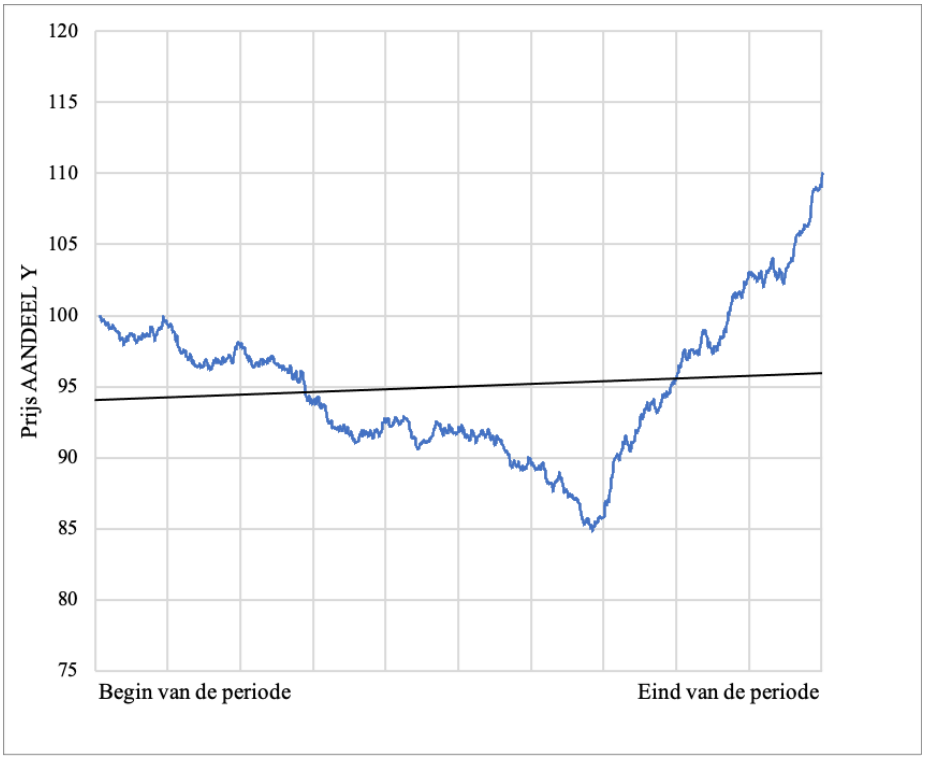
Price chart 12



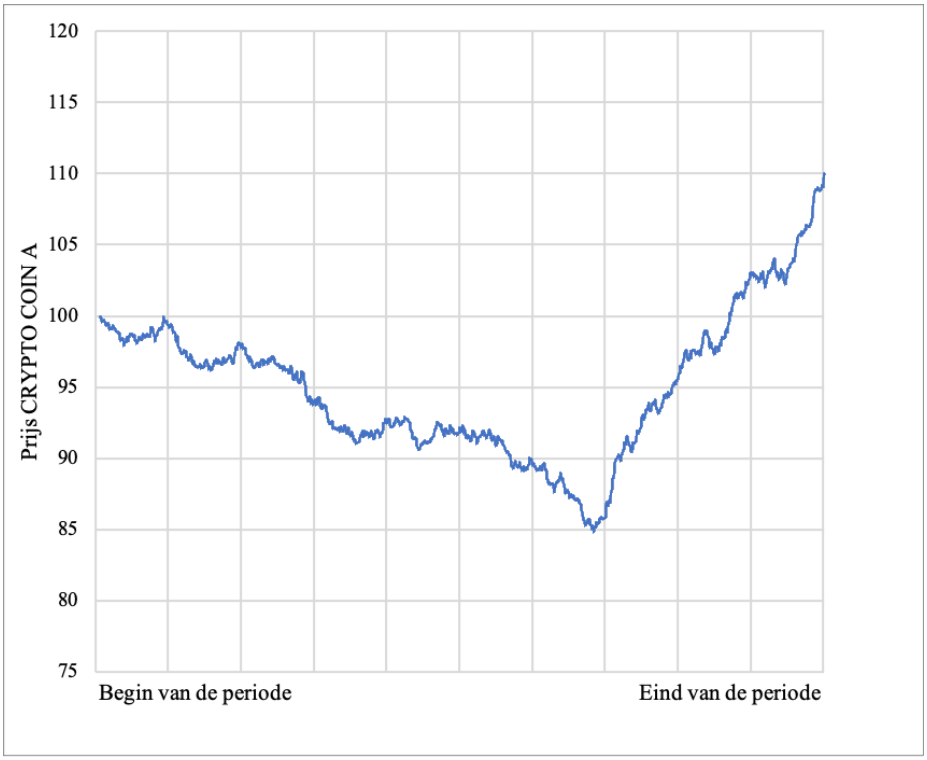
Price chart 13



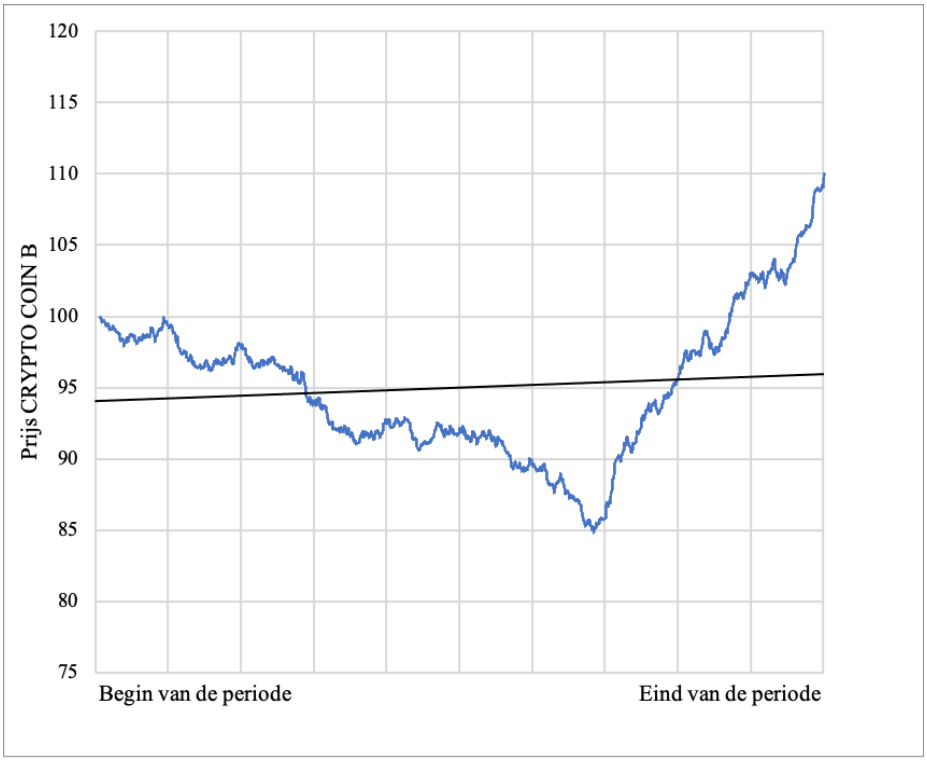
Price chart 14



Price chart 15



Price chart 16



APPENDIX B Survey I (Risk perception, Willingness to Invest)

General announcement

Welkom!
Bedankt voor uw deelname aan deze enquête over beleggingsgedrag en risicoperceptie voor mijn masterscriptie. Tijdens deze enquête worden er 4 verschillende prijsgrafieken aan u getoond. Deze prijsgrafieken tonen de prijsontwikkeling van verschillende soorten aandelen in een tijd van precies 1 jaar. De namen van de aandelen zullen niet expliciet genoemd worden.

Voor elk van de getoonde prijsgrafieken vragen wij u om aan te geven:
1) Hoe riskant de investering is volgens u
2) Uw bereidheid om in het betreffende aandeel te investeren

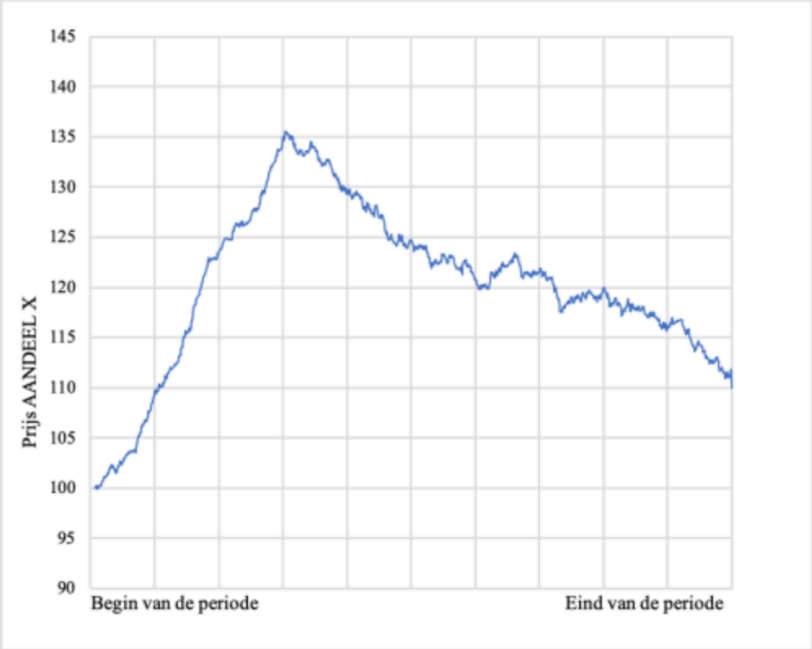
De aandelen die getoond worden kunnen normale beursaandelen zijn, of crypto munten. Crypto munten zijn digitale valuta, zoals Bitcoin, Dogecoin of Ethereum, die tegenwoordig enorm in populariteit toenemen.

Soms wordt er in de prijsgrafiek een duidelijk zichtbare zwarte lijn weergegeven. Dit is een trendlijn. Een trendlijn is een lijn die de richting van een prijsontwikkeling aangeeft.

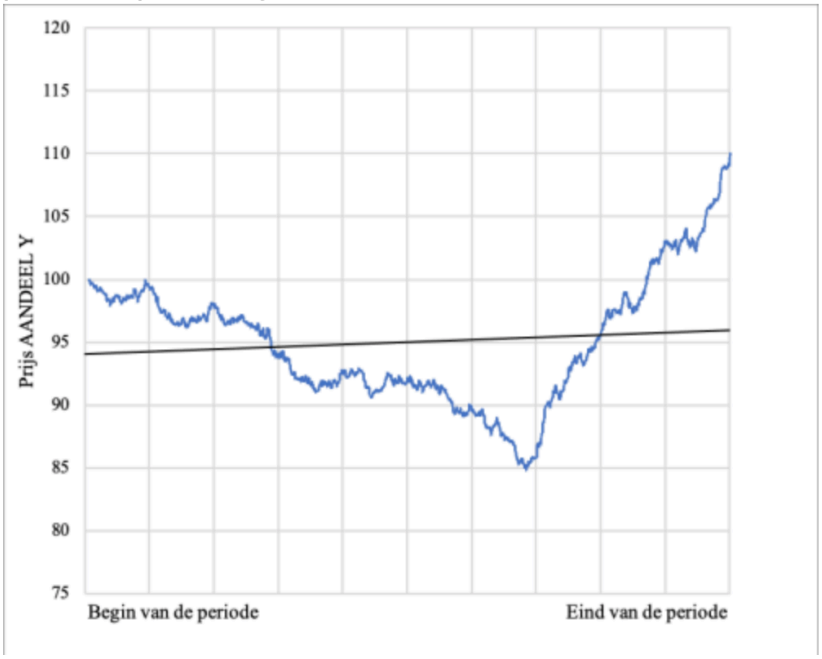
Bekijk de grafieken telkens goed en probeer u in te beelden dat het een echte kans om te beleggen is! Het maakt niet uit of u daadwerkelijk in aandelen belegt of niet. Iedereen kan deze vragen beantwoorden. Daarnaast gaat u met het invullen van deze enquête akkoord met het verzamelen van de door uw ingegeven data. Deze zullen alleen voor deze scriptie worden gebruikt.

Treatment 1: Shown price charts

Dit is de prijsgrafiek van **AANDEEL X**. De tijd die verstreken is van het begin tot het eind van de periode is precies 1 jaar.

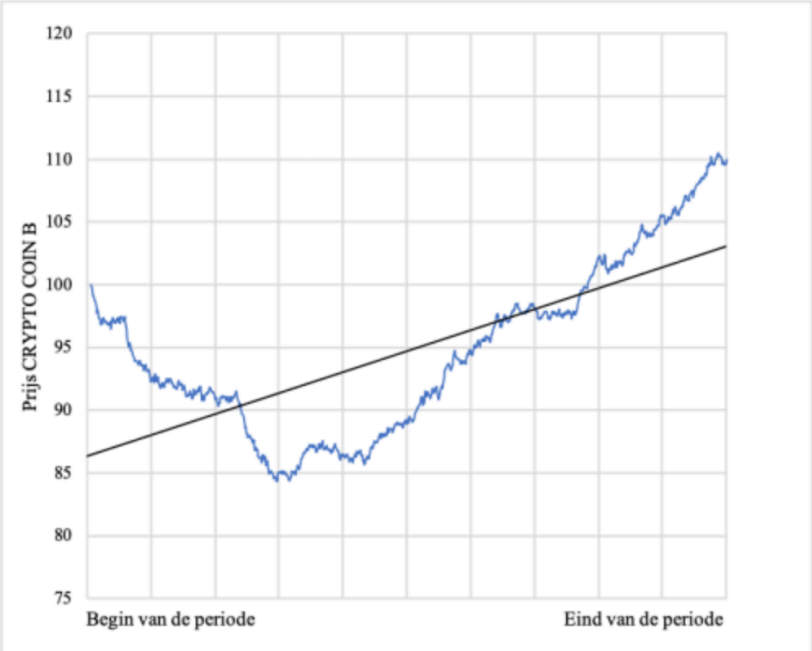


Dit is de prijsgrafiek van **AANDEEL Y**. De tijd die verstreken is van het begin tot het eind van de periode is precies 1 jaar.



Dit is de prijsgrafiek van een crypto munt, **CRYPTO COIN A**. De tijd die verstreken is van het begin tot het eind van de periode is precies 1 jaar.

Dit is de prijsgrafiek van een crypto munt, **CRYPTO COIN B**. De tijd die verstreken is van het begin tot het eind van de periode is precies 1 jaar.

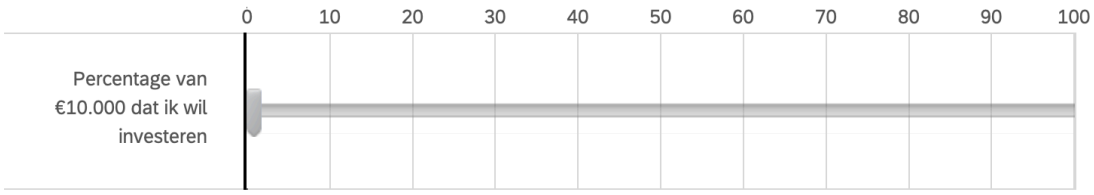


Posed questions by every shown graph

Hoe risicovol vindt u deze investering? U kunt dit aangeven op een schaal van 1 tot 7, waarbij 1 staat voor 'zeer laag risico' en 7 voor 'zeer hoog risico'

	Zeer laag risico						Zeer hoog risico
	1	2	3	4	5	6	7
Waargenomen risico	○	○	○	○	○	○	○

Stel dat u 10.000 euro tot uw beschikking zou hebben om te investeren, welk percentage zou u bereid zijn om te investeren in de hierboven weergegeven investeringsmogelijkheid?



APPENDIX C Survey II (Personal & Demographic Questions)

General questions

Wat is uw geslacht?

- Man
- Vrouw
- Zeg ik liever niet

Wat is uw hoogst genoten opleiding?

- Basisschool
- Middelbare school
- MBO
- HBO
- Universiteit/WO
- Anders

Wat is uw leeftijd?

- 18-24 jaar
- 24-30 jaar
- 31-40 jaar
- 41-50 jaar
- 51-65 jaar
- >65 jaar

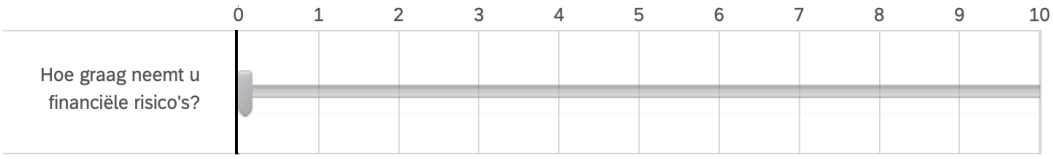
Heeft u ooit geld in financiële producten belegd (bijvoorbeeld aandelen, obligaties, etc.?)

- Nee
- Wel eens, maar momenteel niet
- Ja

Heeft u ooit geld belegd in cryptocurrencies of crypto munten? (Bijvoorbeeld Bitcoin, Ethereum, Doge Coin, etc?)

- Nee
- Wel eens, maar momenteel niet
- Ja

Op een schaal van 1 tot 10, hoe graag neemt u financiële risico's? Met 0 "Helemaal niet" en met 10 "Heel erg graag"



APPENDIX D Additional Tables

Mean perceived risk per price chart

	Up-down early	Up-down late	Down-up early	Down-up late
No manipulation	**5.02**	**4.40**	**3.20**	**3.89**
Trendline	**4.05**	**3.70**	**2.83**	**3.44**
Crypto label	**5.80**	**5.69**	**4.45**	**4.60**
Trendline & crypto label	**4.85**	**4.05**	**4.36**	**4.29**

Mean % of 10.000 subjects are willing to invest per price chart

	Up-down early	Up-down late	Down-up early	Down-up late
No manipulation	**15.81**	**18.46**	**32.43**	**27.79**
Trendline	**23.81**	**25.98**	**39.66**	**34.08**
Crypto label	**12.09**	**18.36**	**27.82**	**21.20**
Trendline & crypto label	**15.05**	**29.50**	**28.75**	**21.40**

Effect of demographic and personal factors

	Risk perception	Willingness to invest
	β	β
Trendline	-0.766***	5.155***
	(-5.17)	(3.12)
Crypto label	1.090***	-5.311***
	(7.23)	(-3.31)
Man	0.384*	-2.037
	(2.25)	(-1.07)
High education (=>HBO)	0.245	-5.690**
	(1.33)	(-2.78)
Youth (age<31)	0.224	-2.493
	(1.40)	(-1.38)
Investing experience	0.146	-0.592
	(0.86)	(-0.31)
Crypto trading experience	-0.552**	1.370
	(-3.11)	(0.68)
High risk preference (6-10)	0.165	0.618
	(0.83)	(0.28)
cons		20.00***
		(10.81)
N	596	596
Pseudo R^2	0.0410	0.0059
Control variables	No	No

Note: t-statistics in parentheses, * p<0.05, ** p<0.01, *** p<0.001.