Graphical Information and Risk Perception: The Effect of Price Charts and Return Bar Charts on Financial Risk Perception

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ABSTRACT

The existing literature shows that individuals are systematically influenced by the characteristics of price charts displaying the past performance of an asset. It appears that the shape of a price path exhibited in the price chart affects risk perception and, ultimately, financial investment decisions. In this study, the effect of differently shaped price paths in combination with return bar charts has been analyzed to find out to what extent the provision of additional investment information affects perceived risk on the part of (retail) financial investors. An experimental survey shows that different price path elements, such as ending point, salience of peak (trough), turning point, and price trend, all significantly affect the risk perception. The inclusion of supplementary return bar charts causes significant changes to risk perception when controlling for financial knowledge. This research contributes a more holistic perspective on a wide range of risk perception studies as it considers additional information sources that could be used by (retail) financial investors to assess their financial investments.

Keywords: price paths, price charts, return bar charts, past performance, investment decision, investor behavior, risk perception, behavioral finance, experimental finance

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CONTENT

1 INTRODUCTION

A stock price is determined when supply meets demand for a particular stock. Three major forces influence the behavior of a stock price, namely fundamental factors, technical factors, and market sentiment (Mcclure, 2020). Investors always strive to make informed investment decisions that help them to make a profit when trading in the stock market. Therefore, according to the traditional economics and financial literature, market participants are rational if they base their investment decisions on all available information in the market. In the financial market setting, rationality can be described as "correctly updating beliefs," according to Bayesian law, while market participants are wealth-maximizers (Al Mamun et al., 2015).

To attract more investors, financial investment funds establish confidence by ensuring that financial information is provided adequately, voluntarily, and in a timely fashion. For this reason, the use of press announcements, corporate reports, and investor presentations allows financial investors to make more informed investment decisions and to predict earnings more accurately (Breu et al., 2015). According to Breu et al. (2015), listed companies use investor presentations to "inform the financial investors about matters such as organizations' activities, earnings and strategies." Consequently, investor presentation formats play a significant role in financial markets because they permit financial investors to appropriately predict the risk of financial assets before making any investment decision.

However, abundant literature suggests that the investment decisions taken by financial investors are far from rational. This is the case even when financial agents are provided with information on which their decisions should be rational. Economic research by Kahneman and Tversky (1979), Levis (1989), or, more recently, List and Millimet (2008) showed that markets and their participants are not rational, certainly not in the way described by traditional economic theories. One of these irrationalities is the way in which price charts are used by market participants in the investment decision-making process.

Seemingly, price and return charts are extensively used as information sources by institutional and retail investors (Glaser et al., 2019). Over the years, different studies have conducted research on price path developments and investor behavior (Nolte & Schneider, 2018; Borsboom & Zeisberger, 2020; Grosshans & Zeisberger, 2018). On the other hand, other studies have looked at the presentation formats of price charts and their influence on financial investors (Diacon & Hasseldine, 2007; Huber & Huber, 2019; Borsboom et al., 2020). Research by Nolte and Schneider (2018) showed that differences in price path developments play an important role in the investment decision process as they influence the perceived attractiveness of an asset. This is true even though these price paths do not contain any information relevant to these individuals. Further, experimental research by Borsboom and Zeisberger (2020) found that price path characteristics significantly affect the risk perception of financial investors. A more recent study by Borsboom et al. (2020) concluded that changing the display horizons of price charts affects the trading volume and frequency while having no influence on risk taking behavior. Moreover, Huber and Huber (2019) provided evidence that different scaling of the axes of price and return charts affects the risk perception of individuals. This study suggests that ‘’narrowing the vertical axis results in a higher perceived risk of an asset, both for price and return charts, even though the volatility remains constant across different graphs’’ (Huber & Huber, 2019). Similarly, Diacon and Hasseldine (2007) showed that individuals have different risk perception depending on the graphical format displayed to them. It appears that individuals perceive the return charts as more risky than the price charts of an investment fund.

The topic of risk perception and presentational formats has been covered extensively over the last few years. Despite this fact, prior studies have mainly focused on the elements of price charts and return bar charts that could affect the risk perception of individuals, for example differences in the shape of price paths, time horizons, or scaling of the axes. However, there is still a piece missing from the puzzle in this discussion. Previous research dealt with each of these elements separately, forgetting that financial investors do not only consider past performance represented in one graphical format, such as price charts or return bar charts, when making financial decisions; rather, they can consult different financial information sources simultaneously. For this reason, this study does not merely replicate previous studies to find out how different price path characteristics influence the risk perception of (retail) financial investors. The objective of this study is to estimate the impact of additional return information alongside price charts on the perceived risk of a retail financial investor.

For this reason, the following question unfolds in this experimental research:

“To what extent do price charts in conjunction with return bar charts influence the risk perception of a retail financial investor compared to price charts alone?”

This research question was addressed by conducting an incentivized online experiment in which participants were randomly divided into two treatment groups, one of which received price charts while the other received price charts and return bar charts simultaneously. Each participant was shown 8 out of 16 artificially created return bar charts and/or price charts. The price paths included in the price charts were described using Geometric Brownian Motion (GBM) while controlling for the price process in order to create desirable characteristics, that is, increasing or decreasing price trends, salient troughs or peaks, turning points, and maximum or minimum price. Lastly, the subjects were asked to score the riskiness of the displayed graphs of a stock investment between 0 and 10 on a Likert scale.

In line with previous studies, this study shows that risk perception depends significantly on different types of price path shape. By focusing on the components of the price paths that play a major role in the perceived riskiness of an asset, this study contributes to the current literature by identifying that individuals prefer price paths that end above their initial starting point as these lead to lower risk perception. Similarly, subjects perceived price paths that first rise and then fall (up-down) as more risky than price paths that first fall and then rise (down-up). Furthermore, it proves that individuals perceive lower risk when price paths have more gradual price trends or early turning points. Ultimately, this study demonstrates that provision of additional return information in conjunction with price charts significantly affects the individual´s risk perception when controlling for financial knowledge.

This study gives a more holistic perspective on a wide range of risk perception studies as it takes both a theoretical and an experimental perspective. From a theoretical point of view, this study is relevant for further research as it extends the current literature by showing that risk perception changes as soon as additional return information is displayed to individuals. From a practical point of view, these findings are useful for policy makers because it has been shown that provision of the same information in different form alters the risk perception of retail financial investors. This implies that retail financial investors could be susceptible to manipulation and make entirely different investment decisions if information is withheld from them or provided in a different presentational format. This study also proves the importance of financial risk communication such as the Key Investor Information Document (KIID), and, hence, that proper information provision is necessary to prevent retail financial investors from detrimental financial investment decisions.

2 THEORETICAL FRAMEWORK

2.1 Capturing Financial Risk

According to Verma (2021), ‘’financial risk occurs due to instability in the asset market triggered by changes in share prices, currencies, and interest rates’’. These are the most common risks in all enterprises and could be categorized into market risk, credit risk, liquidity risk, and operational risk (Verma, 2021).

The Capital Asset Pricing Model (CAPM) is a well-known model that attempts to capture the risk of financial assets. This model builds upon the portfolio choice theory developed by Markowitz in 1952 and assumes that an investor selecting a portfolio is risk-averse and cares only about the mean and variance when constructing their optimal portfolio (Fama & French, 2004), i.e., an investor prefers a higher return but dislikes higher risk. For this reason, in traditional finance, individuals are assumed to be rational and immune to cognitive errors, while the financial markets are efficient. However, different behavioral theories and models reject variance as the only source that shapes the risk perception of investors while at the same time allowing for market imperfections (Statman, 2014).

Behavioral finance advocates for bounded rationality, which place restrictions on the availability of information and the capability of individuals to analyze available information. Moreover, decisions in the financial markets are not always optimal but only meant to satisfy traders within the limitations on their capabilities. Given these constraints, financial investors are likely to use mental heuristics to evaluate riskiness (Kahneman, 2003). As visual information is widely used by financial investors in the decision-making process (Nolte & Schneider, 2018; Glaser et al., 2019; Borsboom & Zeisberger, 2020) and their decisions are sub-optimal due to information and time constraints, the graphical presentation has a significant effect on how risk is perceived by them (Diacon & Hasseldine, 2007).

2.2 Positive versus Negative

Individuals pay attention to a limited amount of information shown to them (Kahneman, 1973), implying that not all information will be used to assess an investment decision. Meanwhile, individuals will only pay attention to information that appears salient to them (Shaton, 2017). One of the features of presentational formats that grab the attention of individuals is the achieved return of an investment during an investment horizon. It is not surprising that investors’ risk perception is significantly affected by overall return, as they believe investments with high returns to be less risky (Borsboom & Zeisberger, 2020). Similarly, stocks with overall positive returns bring higher satisfaction than stocks with overall negative returns (Grosshans & Zeisberger, 2018). Based on these insights, the following hypothesis is formulated:

H_1: An individual will perceive a price path that ends above its initial price as <u>less risky</u> than a price path that ends below its initial price when this individual is confronted with the price chart of the underlying asset.

Abundant literature has reviewed how different (elements of) presentational formats affect investors' financial risk perception (e.g., Diacon & Hasseldine, 2007; Nolte & Schneider, 2018; Borsboom & Zeisberger, 2020; Huber & Huber, 2019). However, none of these studies considered how financial risk perception changes as soon as an individual receives additional return information about a financial investment. Sobolev and Harvey (2016) showed that financial risk sensitivity changes as soon as an individual is shown additional price information, that is, price changes, alongside price levels. At the same time, provision of price changes makes risk assessment much easier for the individuals. It appears as well that extra numerical information, such as average return, current price, and purchase price, has an impact on perceived satisfaction with a financial investment (Grosshans & Zeisberger, 2018). Therefore, it could be argued that displaying additional return information can reinforce the effect on perceived risk. Based on these insights, the following hypothesis is formulated:

H_2: An individual will perceive a price path that ends above its initial price as <u>even less risky</u> than a price path which ends below its starting price when this individual is shown the price chart and return bar chart simultaneously than when shown only the price chart of the underlying asset.

2.3 Improving Sequences

According to Loewenstein and Prelec (1993), individuals become farsighted when choosing which sequence of outcomes will occur. Their study showed that individuals would rather postpone more favorable outcomes so they occur after less favorable ones, as they dislike sequences that decline in value due to negative time preferences. Similarly, Huber and Huber (2019) showed that rising price paths tend to be perceived as less risky than decreasing price paths. Moreover, Mussweiler and Schneller (2003) stated that investors are more likely to invest in stocks that have a stronger upward trend than in those with a stronger downward trend as they expect higher prices in the future. Therefore, investors should opt for up-down over down-up price paths if these trends are visible to them. This result is in line with Nolte and Schneider (2018) and Grosshans and Zeisberger (2018), whose research subjects were more attracted to down-up than up-down price paths. From these arguments, the following hypothesis is formulated:

H_3: An individual will perceive a price path that first falls and rises afterwards (down-up) as <u>less risky</u> than a price path that first rises and falls afterwards (up-down) when shown the price chart of the underlying asset.

The literature discussed above only takes account of price path development in the evaluation of the riskiness or attractiveness of a particular price path. Therefore, providing additional information investment information over a given trading horizon might lead individuals to evaluate stock riskiness diametrically differently, as shown in Sobolev and Harvey (2016). It is possible that displaying return information about an asset could lead to the equalization of perceived riskiness between assets with up-down and down-up trend. Given this argumentation, the following hypothesis is formulated:

H_4: An individual will perceive a down-up and up-down price path as <u>equally risky</u> when simultaneously shown the price chart and return bar chart than when only shown the price chart of the underlying asset.

2.4 Peaks and Troughs

Price charts are among the information sources most frequently used by financial investors (Borsboom et al., 2020). Price charts attract investors' attention and affect their investing behavior (Borsboom & Zeisberger, 2020; Borsboom et al., 2020; Nolte & Schneider, 2018; Glaser et al., 2019; Bose et al., 2020). Moreover, it has been shown that individuals try to observe patterns in the price paths presented in price charts and predict future price developments from this information (Fama, 1995). Therefore, the way in which price charts is used is not rational, as indicated by traditional economics. Due to bounded rationality, individuals selectively analyze the information displayed to them when making investment decisions. An individual only pays attention to the information that attracts its attention, that is, salient information, therefore, changing the attention focus of an individual would affect their investment decision-making process (Shaton, 2017).

Providing investors with price paths that are identical but have differently scaled vertical axes (wide versus narrow) significantly affects risk perception. It seems that a narrow price path with clearly visible volatility is perceived as more risky than a wide price path with a less recognizable volatility pattern (Huber & Huber, 2019). Similarly, Huddart et al. (2009) provided evidence that extreme prices in price paths affect the investment decisions made by financial investors. It appears that trading volume increases as soon as the stock price passes its latest upper or lower price limit. On the other hand, Raghubir and Das (2010) demonstrated that a stock with a longer run length, that is, greater extrema, is perceived to be more risky than one with less visible peaks or troughs even if the stocks are identical. Consequently, the following hypothesis can be formulated:

H_5: An individual will perceive a price path with a salient peak (trough) as more risky than a price path where no salient peak (trough) is visible when shown the price chart of the underlying asset.

The literature suggests that risk perception depends on risk communication to financial investors, for example price levels or return bar charts. At the same time, risk perception is one of the factors affecting investment decisions as it significantly influences risk-taking behavior (Weber et al., 2005). Undoubtedly, additional investment information affects the risk perceived by financial investors. For example, Sobolev and Harvey (2016) show that displaying price-change information alongside price charts significantly affects how risk is evaluated, while, Diacon and Hasseldine (2007) argue that risk perception is greater when an individual is confronted with return bar charts rather than value charts (price charts).

However, studies by Sobolev and Harvery (2016) and Diacon and Hasseldine (2007) did not compare the changes to risk perception when both return bar charts and price charts were shown simultaneously and price charts were shown alone. In Diacon and Hasseldine (2007), the sample population received a treatment of price charts and return bar charts and in repeated examen return bar charts. However, the authors did not explicitly examine risk perception differences between these two treatment groups. Moreover, neither study controlled for different price path characteristics, which could have a significant influence on risk perception. For this reason, it is not evident how risk perception changes as soon as an individual receives additional return information about an investment. It could be the case that individuals feel more confident when receiving additional investment information, even though, it does not provide any relevant information. Hence, as stated earlier, additional return information could equalize risk perception differences between the price paths with and without salient peaks (troughs). Therefore, the following hypothesis can be formulated:

H_6: An individual will perceive a salient peak (trough) price path as <u>equally risky</u> as a price path where the salient peak (trough) is not visible when simultaneously shown the price chart and return bar chart than when only shown the price chart of the underlying asset.

2.5 Turning Points

Another point that should be addressed in the context of presentational formats is the turning points of price paths. The evidence shows that investors have preferences for specific sequences (Loewenstein & Prelec, 1993). However, some scholars assume that, besides this phenomenon, recent developments play an important role in the context of investor behavior. For example, Bailey et al. (2011) showed that biased investors prefer investments with more recent positive or high returns, while Glaser et al. (2019) demonstrated that more recent past returns are extrapolated by investors when forecasting price levels whereas more distant ones are ignored when forming expectations. Also, de Bondt (1993) showed that individuals forecast future stock prices based on recent trends in the stock market. These studies are closely connected with the recency bias, defined as a tendency to overweight the most recent information, where individuals are more likely to base their (financial) decisions on the latest information while ignoring more distant one. This bias is clearly visible in Grosshans and Zeisberger (2018), but these authors come to totally different conclusions. Their findings show that subjects prefer an early turning point in down-up price paths and a late turning point in up-down price paths. However, the latter effect was found to be insignificant.

Converting these insights into a risk perception framework, it could be argued that more recent price developments impact risk perception more severely than more distant ones. This means that a turning point could offer a certain cut-off capturing the part of a price path before the turning point as more distant while a part of the price path after the turning point as more recent. Based on these arguments, the following hypothesis can be formulated:

H_7: An individual will perceive a price path with a late turning point as <u>less risky</u> than a price path with an early turning point when shown the price chart of the underlying asset.

According to rational economics, a rational agent should ignore price development when considering a financial investment. However, individuals exhibit bounded rationality, meaning that they are not able to process all the information provided to them. In other words, when subjects are given a particular information format, they base their decision solely on that format. It might happen that shifting the focus of attention could lead them to make an entirely different decision, even if the information displayed is exactly the same (Borsboom & Zeisberger, 2020). Moreover, Glaser et al. (2019) showed that subjects have totally different expectations when faced with price charts than when shown return charts. Similarly, Sobolev and Harvey (2016) found that providing additional price information affects the risk perception of an individual. Therefore, in this case as well, it can be argued that the provision of return information in conjunction with price information could equalize the perceived risk between assets with the same price trends but different turning points. Given these insights, the following hypothesis has been formulated:

H_8: An individual will perceive a price path with an early and late turning point as equally risky when simultaneously shown the price chart and return bar chart than when only shown the price chart of the underlying asset.

3 METHODOLOGY

3.1 Data Collection & Survey

The main aim of this research was to compare how risk perception changes as soon as financial retail investors receive return information about a certain asset alongside the price chart of an underlying asset. For this reason, two treatment groups were asked to evaluate the perceived riskiness of a particular stock based on the return bar charts and price charts displayed to them.

In this experiment both Amazon Mechanical Turk (MTurk) as inner circle (students, friends, etc.) were recruited to gather as many survey responses as possible. As Amazon MTurk provides similar results to those found in previous decision-making studies, it was considered a reliable source for data collection and to ensure a representative sample (Goodman et al., 2012).

There are three different approaches to incentivizing individuals to do what they are asked to. Read (2005) mentions cognitive extortion, motivational focus, and emotional triggers. It would be extremely difficult to use motivational focus or an emotional trigger to guarantee a decent effort from participants and a high response rate. Therefore, the only option left was a monetary incentive, i.e., cognitive extortion. However, there are still trade-offs when considering a financial incentive. First of all, paying each participant for their participation could incur enormous costs, which was not feasible due to financial constraints. Moreover, the possibility of limited realism in incentivized tasks remains a problem, because a monetary incentive is only feasible when an experiment is realistic as well as its payoff (Read, 2005). In order to not discriminate between different participants and to keep the stimulus the same, both MTurk and inner circle respondents were offered the chance to participate in a lottery in which three randomly chosen participants would receive a payoff of 50 Euros each. Including a lottery in the survey brought a higher response rate but could not guarantee realism in the payoff due to budget constraints.

At the beginning of the survey, participants were asked to answer demographic and personal questions related to financial knowledge, willingness to take financial risks, and statistical skills (Appendix A). These opening questions not only allowed an evaluation of self-stated risk perception differences among subjects but ensured that the target group of this study (i.e., retail financial investors) was well defined.

To evaluate perceived riskiness, a similar approach was used to that applied in Duxbury and Summers (2018). The participants evaluated the perceived riskiness of charts using a slider bar on a scale of 0 (not risky at all) to 10 (extremely risky). In total, 16 price charts with corresponding return bar charts were created (Appendix B). Further, participants were randomly divided in two groups of similar size; the first treatment group received a survey with 8 out of 16 randomly selected price charts while the second treatment group received 8 out of 16 randomly selected price charts and corresponding return bar charts. It should be stressed that participants in the second treatment group received both charts simultaneously on their computer screens.

In total, the survey was answered by 223 respondents. However, two cases were deleted from the dataset because these participants did not complete the main part of survey, namely questions about perceived risk based on the graphs they viewed. Moreover, one respondent took only 12 seconds to answer all the questions, which is far below the median time needed (130 seconds). This entry was classified as an outlier and deleted from the dataset as well, yielding a total of 220 respondents on which data analysis was conducted.

A small number of participants did not answer all the demographic or personal questions but gave response to risk perception questions. These entries were not omitted from the data as they were considered useful for statistical analysis. However, to rule out the possibility that these missing values could significantly drive the results, "dummy variable adjustment" was used.

3.2 Chart Characteristics

All price paths created in this study are characterized by four dichotomous characteristics. These four characteristics are (1) positive or negative ending point, (2) up-down or down-up trend, (3) salient peak (trough) or no peak (trough), and (4) late or early turning point. Table 1 provides an overview of these price paths with their corresponding characteristics.

As regards the first category, this study takes a similar approach to Grosshans and Zeisberger (2018), where all the price paths have the same starting point but can have two different ending points. For the *positive* category, eight different price paths end above a starting point at 110 while another eight price paths in the *negative* category end at 90, hence below the starting point of 100. Therefore, each of the created price paths is allowed to have either an overall positive or negative return of 10%.

Table 1: characteristics of price paths

Type	Positive	Up-down	Peak (Trough)	Late
Price Path 1	1	1	1	1
Price Path 2	1	1	0	1
Price Path 3	1	0	1	1
Price Path 4	1	0	0	1
Price Path 5	1	1	1	0
Price Path 6	1	1	0	0
Price Path 7	1	0	1	0
Price Path 8	1	0	0	0
Price Path 9	0	1	1	1
Price Path 10	0	1	0	1
Price Path 11	0	0	1	1
Price Path 12	0	0	0	1
Price Path 13	0	1	1	0
Price Path 14	0	1	0	0
Price Path 15	0	0	1	0
Price Path 16	0	0	0	0

Note: 1 implies that the given price path possesses characteristics such as positive end point, late turning point, downward sloping after turning point occurs (up-down), or peak (trough), while 0 implies that the price path has the opposite characteristics, i.e., negative end point, early turning point, upward sloping after turning point occurs (down-up), or no peak (trough). The price charts are included in Appendix B.

According to Fiske and Taylor (1978), the point of view of an agent determines what they would consider salient information. It is also argued that salient information is the type that is overrepresented in a set of information. Studies show that salient information is more likely to be adopted because individuals use the most salient sample points from an "infinite amount of information" in order to decrease the complexity of information processing (Raghubir & Das, 2010). However, a review of the literature on price paths shows, remarkably, that there is no standard definition of the salience of peaks and troughs. For example, Mussweiler and Schneller (2003) demonstrated that, from a psychological point of view, extreme values in a price chart are those that would be used in the formation of future price expectations that eventually influence investment behavior. In their research, however, no rationalization was given for defining how extreme these values should be, for example, as a percentage above or below purchase price, a percentage of the purchase price, or something else. Likewise, Bose et al. (2020) showed that subjects attribute more importance to returns that are notably higher than those which surround them. Similarly, other studies on price paths, such as Grosshans and Zeisberger (2018), Nolte and Schneider (2018) and Borsboom and

Zeisberger (2020), focused to some extent on salient information, that is, peaks and troughs. However, none of these authors prescribed how high (low) these peaks (troughs) should be to be called salient, and, most importantly of all, they did not provide any explanation of why particular values were chosen. The size of salient peaks (troughs) in Grosshans and Zeisberger (2018) was described as a 30% increase (30% decrease) in the purchase price. At the same time, price paths in their study showed a more gradual development, with no sharp price changes. Their robustness checks on peak and trough sizes showed that, even if they are less salient, the same pattern would be found as in the baseline experiment with peaks and troughs of greater size; that is, in robustness checks, the minima is 20% below while the maxima is 20% above the purchase price. These results show that the satisfaction or attractiveness of a particular price path does not depend on the relative size of the peak and trough as long as these are considered salient by an individual (Grosshans & Zeisberger, 2018).

Nevertheless, the definition of peaks and troughs, as in Raghubir and Das (2010), and their size, as in Grosshans and Zeisberger (2018), needs to be adjusted for the purpose of this study because it could cause confusion to distinguish between price paths with down-up and up-down trends and price paths with peaks and troughs. In this study, the peak is the largest value while the trough is the lowest value that a particular price sequence can take, similarly to Raghubir and Das (2010). However, all price paths in this experiment have up-down or down-up price developments with visibly sharp or more gradual price trends. Therefore, to distinguish between price paths with and without a salient peak (trough), different measures were taken. Firstly, price paths without a salient peak (trough) have a visible increasing and decreasing trend, but their price developments are gradual and no sharp price changes were allowed within a small period of time. The appearance of these price paths is similar to those shown in Huber and Huber (2019), Nolte and Schneider (2018) or Grosshans and Zeisberger (2018). Secondly, the price paths without a salient peak (trough) can reach a maximum (minimum) price of 130 (70). Thirdly, the price paths with a salient peak (trough) are allowed to increase (decrease) beyond the price of 130 (70) to maximum price of 150 (minimum price of 50). Fourthly, peak (trough) price paths are those in which the price sharply increases and decreases (decreases and increases) within a span of two consecutive months. Hence, a price path is considered to have a salient peak (trough) if its price is above (below) 130 (70) for at least one month.

The literature shows that the most recent information is overweighted in the decision-making process or expectation formation (Bailey et al., 2011; Glaser et al., 2019; de Bondt, 1993) and that this situation is closely related to turning points. As noticed by Grosshans and Zeisberger (2018), the timing of these turning points yields different emotions among individuals. To mimic the real world, Grosshans and Zeisberger (2018) chose to have two different turning points – after the third and ninth month of the observation period – because a switching point which fell exactly in the middle of an observation period could look artificial. However, as noted by Huddart et al. (2005), there is no standard definition of where "the salient price levels should be located." Therefore, this study took a similar approach to Grosshans and Zeisberger (2018). A turning point is defined as a switching point between the increasing and decreasing (or decreasing and increasing) parts of a price path. At the same time, the early turning point took place between the third and fourth month of the observation period, while the late turning point took place between the ninth and tenth month of the observation period.

3.3 Simulations & Other Consideration

Another important consideration in the construction of price paths is the design of price charts and return bar charts. Huber and Huber (2019) considered how different axis scales and presentation formats affect the risk perception of individuals. Based on their results, it appears that variation in the vertical scale of a chart significantly affects the risk perception of individuals in that a narrower scale implies greater perceived risk. This result seems to be present in presentational formats of prices (price charts) and returns (return bar charts). Research by Duxbury and Summers (2018), Lawrence and O'Conner (1992), and, more recently, Borsboom et al. (2020), provided evidence that changes in price chart characteristics significantly affect investor behavior. Therefore, to assess the change in risk perception as a result of different price path characteristics and different presentational formats, it is important that the graphical elements of price charts and return bar charts are as harmonized as possible. Otherwise, these elements could influence the risk perception as well as the characteristics of price paths which are part of this research.

In this study, the scaling of the vertical axis as well as the horizontal axis was adjusted along all charts. Moreover, the timelines in both price charts and return bar charts were adjusted and depicted in months instead of days, as a monthly timeline is more easily visible to subjects. Also, returns were calculated as monthly price changes so it would be easier to link them back to prices in the price charts with a monthly rather than a daily timeline. The vertical axis depicting stock prices had steps of 10. Similarly, the numerical provision was equalized for price charts with positive and negative returns, meaning that the vertical axes had a size of 80 for all the price charts created. The distance from the starting price to the highest and lowest numbers visible in the graphs was equal for price charts with up-down (60 above the initial price) and down-up (60 below the initial price) development. This approach is similar to Nolte and Schneider (2018), where the vertical axes of price charts were also of the same size. To harmonize price paths even further, the highest (lowest) realized values of peak (trough) price paths and no peak (trough) price paths had the same vertical distance to highest (lowest) value visible in the chart. Namely, a distance of 10 for price paths with peak (trough) and of 30 for the price paths with no peak (trough). Similarly, the location of turning points was adjusted so they occurred at exactly the same time, that is, between the third and fourth month or the ninth and tenth month. A similar logic as described above was applied to the return bar charts, whose vertical axes were of the same size, i.e., between 25% and -25%, with equal steps of 5%.

Another visual aspect that should be addressed is the color used in graphs. The financial literature shows that different colors have a significant effect on individuals' behavior and affect risk preferences, investment decisions, and future price expectations (Bazley et al., 2021). Moreover, it has been shown that risk attitude can be manipulated by using color coding (Kliger & Gilad, 2012). Apparently, green can be implicitly associated with something good, creating a feeling that a certain price chart or return bar chart is less risky. Similarly, red can be associated with something bad, implicitly giving a feeling that a certain price chart or return bar chart is more risky. To avoid color bias, the price paths in the price charts and the returns in the return bar charts were depicted in blue, which seems to elicit neutral feelings and should therefore not affect investors' behavior (Bazley et al., 2021)

In order to make the appearance of the price paths as realistic as possible, they were characterized by irregular development, as stylized price paths seem to increase perceived risk (Duxbury & Summers, 2018; Pincus & Kalman, 2004), and in a real-world setting, price paths have irregular development (Grosshans & Zeisberger, 2018; Borsboom & Zeisberger, 2020). Therefore, in this study the simulated price paths had an irregular development, but at the same time other characteristics, such as peaks (troughs), down-up and up-down trends, or turning points, were clearly recognizable for subjects. To achieve irregular development, each price path was based on 252 observations with one price tick per observation period, i.e., one business day. Meanwhile the number of observations – 252 days – corresponds to the number of days in a trading year. This feature brings more real-world into this experiment as it has been shown that investors use a 12-month horizon to evaluate their actual investments (Benartzi & Thaler, 1995).

In constructing the price paths, this study used a similar approach to Nolte and Schneider (2018), in which price developments were described using Geometric Brownian

Motion (GBM). In order to simulate price paths (charts) as well as return bar charts, STATA 16 was deployed (Appendix C).

To construct price shapes that fulfilled all the characteristics described earlier in a computing-efficient way, the observation period was divided into 12 intervals of 21 days each. In each of these intervals, the value was created around which a particular price path should wander in the given interval. For the first period, the starting point was always 100, whereas the ending point was created manually for each of the 12 observation intervals. This method allowed to simulate price paths with specific properties in the period desired. For example, if a price path had a peak between the ninth and tenth month, then the ending points of the eight and tenth period were considerably lower than the ending point of the ninth period. Finally, the program was encoded to generate random price paths in a loop until it found fractional price paths for each period that described the desired price development.

In total, 160 different price paths were created, 10 per price chart, from which 16 were chosen that reproduced the given characteristics in the most convincing way (Appendix B). The parameters describing price development in the GBM model were held constant for all price paths, i.e., $\mu = 0.01\%$ for drift rate and $\sigma = 1\%$ for shock rate. These values were used as they offered the most fruitful results. The trial-and-error method applied to determine these values showed that a higher drift rate offered very "shaky" price developments with less distinguishable characteristics. While technical difficulties emerged when changing values for the shock rate, i.e., for some price paths, it took too much time to simulate the price paths with the required characteristics and, in some cases, it was impossible to complete the simulation.

STATA 16 was also used to create the return bar charts (Appendix C). These returns were calculated as the relative price change at the end of each month compared to the price the month before (in percent). The corresponding return bar charts for each price chart are shown in Appendix B.

4 RESULTS

4.1 Demographic Analysis

Some respondents did not answer all the demographic and personal questions, resulting in missing values. As can be seen in Table 2, out of 220 surveys used for the analysis, five participants did not provide answers to the questions about gender and age and four did not state their current occupation or whether they own financial products. In three cases, answers were missing for financial knowledge, and in two cases, no answers were given to questions about willingness to take financial risks and statistical skills.

Table 2: descriptive statistics of the sample respondents

Variable	N	Percent/Mean	Std. Dev.	Min	Max
Gender					
Female	215	.34	.48	0	1
Age:					
0-17	215	.00	.07	0	1
18-25	215	.33	.47	0	1
26-35	215	.41	.49	0	1
36-45	215	.18	.38	0	1
46-55	215	.06	.23	0	1
56-65	215	.02	.15	0	1
Education:					
High school or lower	220	.12	.32	0	1
Bachelor	220	.64	.48	0	1
Master or higher	220	.25	.43	0	1
Status:					
Employed	216	.80	.4	0	1
Unemployed/inactive	216	.05	.21	0	1
Student	216	.15	.36	0	1
Retired	216	.00	.07	0	1
Personal questions:					
Own financial product	216	.75	.44	0	1
Financial knowledge	217	6.49	2.23	0	10
Financial risk willingness	218	6.25	2.45	0	10
Statistical skills	218	6.56	2.18	0	10

More males than females took part in the experiment, i.e., 66% males versus 34% females. The majority of the respondents were between the age of 26–35 (41%), followed by the age groups of 18–25 (33%) and 36–45 (18%). Almost 9% of the participants fell in the following age groups: 0–17 (1 participant), 46–55 (12 participants), and 56–65 (5 participants). At the time of taking the survey, 88% of the participants had completed at least a bachelor's degree, while 80% of the participants reported being employed. Further, the majority of respondents (75%) stated that they possessed financial products such as stocks, bonds, or options. On a scale from 0 to 10, the self-stated financial knowledge, willingness to take financial risks, and statistical skills were 6.49, 6.25, and 6.56, respectively.

For all further analyses, the dataset was reshaped from a wide format (each row containing a respondent) to a long format (each row containing a particular price path evaluated by a particular respondent). This method allowed to compute the mean risk perception for each category within demographic groups as well as in relation to the personal questions asked. Moreover, ANOVA tests were used to determine whether perceived risk mean values between different groups were significantly different from each other for given demographics and personal questions.

In order to calculate averages for personal questions, all these variables were converted to dichotomous variables. In the case of *Own financial product*, this was not necessary as this variable is already dichotomous, i.e., an individual can either own or not own a financial product. For the other three questions, the median was used as a cut-off value to divide groups between low or high financial knowledge, low or high willingness to take financial risk, and low or high statistical skills.

As can be seen in Table 3, the mean perceived risk was higher for individuals who own financial products than for those who do not. Likewise, mean values for willingness to take financial risks deviated significantly between those people willing to take moderate risks and those willing to take higher ones. Apparently, those who are willing to take more financial risk are also those who have a higher risk perception. This is a surprising result as it could be expected that individuals who are less willing to take financial risks would perceive higher risk than those more willing to take financial risks. It also appears that there is a significant difference in average values for self-stated confidence in financial knowledge and statistical skills. In this study, individuals who declared to have higher financial knowledge and statistical skills stated to have higher risk perception, on average. These outcomes are conceivable as individuals with higher financial knowledge and statistical skills can be more capable of evaluating the riskiness of financial investments. Moreover, it could be the case that they feel more insecure when taking financial risks, leading to increased risk perception when taking financial investment decisions. On the other hand, it could be argued that individuals who believe themselves to be more knowledgeable in finance and statistics are overconfident about their skills and knowledge, resulting in more reckless financial behavior and, potentially, lower risk perception.

Table 3: mean perceived risk for personal questions (ANOVA tests)

Group	N	Mean perceived riskiness	F	P
Own financial product	1704		23.882	0.000
No (0)	432	5.986		
Yes (1)	1272	6.607		
Financial knowledge	1713		74.206	0.000
Low (0-6)	720	5.915		
High (7-10)	993	6.858		
Financial risk willingness	1720		118.218	0.000
Low (0-6)	826	5.844		
High (7-10)	894	7.004		
Statistical skills	1720		91.434	0.000
Low (0-6)	775	5.876		
High (7-10)	945	6.906		

Note: N is not the number of participants but the total amount graphs showed to these participants grouped per personal question asked in the survey.

Similarly, Table 4 provides results for mean values for perceived risk, but across different demographic groups. Seemingly, only education and status are significantly related to the perceived risk of an individual. For both *Education* and *Status*, there is a statistically significant difference in average risk perception, depending on the highest degree of education attained by an individual as well as their current occupation. An eye-catching result is that the mean risk perception is substantially lower for respondents with high-school or lower education level (5.702) than for individuals with a bachelor degree (6.561) or master or higher degree (6.542). Neither of the other two demographic characteristics, gender and age, is correlated to risk perception. However, males have, on average, a higher mean risk perception than females when it comes to financial investments, while for different age groups, there is a non-linear pattern in the mean risk perception.

Table 4: mean perceived risk across demographic groups (ANOVA tests)

Group	N	Mean perceived riskiness	F-value	p-value
Gender:	1696		4.959	0.026
Men	1116	6.529		.
Women	580	6.267		.
Age:	1696		2.818	0.015
0-17	8	8.500		.
18-25	559	6.354		.
26-35	691	6.376		.
36-45	303	6.726		.
46-55	95	6.389		.
56-65	40	6.900		.
Education:	1736		13.006	0.000
High school or lower	208	5.702		.
Bachelor	1111	6.561		.
Master or higher	417	6.542		.
Status:	1706		4.649	0.003
Employed	1372	6.504		.
Unemployed/inactive	70	6.757		.
Student	256	5.996		.
Retired	8	7.500		.

Note: N is not the number of participants but the total amount graphs showed to these participants grouped per demographic characteristic.

4.2 Randomization Checks

In this experimental study, a total of 16 different price charts (price paths) with corresponding return bar charts were constructed. On the one hand, this research checked how different characteristics of price paths affect the perceived riskiness of a retail investor. On the other hand, it aimed to show how the risk perception of retail financial investors changes as soon as they receive additional information about a financial asset, i.e., return bar charts. In this study, different versions of the survey – mix of 16 types of price charts or/and return bar charts – were randomly assigned among participants. The first treatment group was shown 8 out of 16 randomly selected price charts, while the second treatment group received 8 out of 16 randomly selected price charts with corresponding return bar charts. Moreover, each participant had an equal chance of being included in one of the treatment groups.

This approach, permutated block randomization, guaranteed the even and random division of the sample population between two treatment groups. It also assured that within a particular category, the treatment was evenly divided among subjects with a particular characteristic.

Table 5: balance tests

Group	Positive (p-value)	Late (p-value)	Up-Down (p-value)	Peak (p-value)
Gender:				
Men (N=1116)	50.6	48.3	49.9	50.4
	(0.70)	(0.27)	(0.98)	(0.79)
Women (N=580)	49.0	52.6	50.3	49.7
	(0.65)	(0.23)	(0.90)	(0.90)
Age:				
18-25 (N=559)	50.4	50.6	50.3	48.5
	(0.87)	(0.80)	(0.93)	(0.50)
26-35 (N=691)	49.9	47.9	50.9	51.1
	(1.00)	(0.29)	(0.65)	(0.59)
36-45 (N=303)	49.8	51.2	48.5	51.2
	(1.00)	(0.73)	(0.65)	(0.73)
46-55 (N=95)	50.5	53.7	47.4	50.5
	(1.00)	(0.54)	(0.68)	(1.00)
56-65 (N=40)	52.5	50	45	52.5
	(0.87)	(1.00)	(0.64)	(0.87)
Education:				
High school or lower (N=208)	50	49.0	51.9	49.0
	(1.00)	(0.84)	(0.63)	(0.84)
Bachelor (N=1111)	49.3	50.2	49.3	49.3
	(0.67)	(0.90)	(0.67)	(0.67)
Master or higher (N=417)	53.0	49.6	50.6	52.8
	(0.24)	(0.92)	(0.84)	(0.28)
Status:				
Employed (N=1372)	50.1	49.6	49.7	50.6
	(0.94)	(0.81)	(0.85)	(0.69)
Unemployed (N=70)	57.1	52.9	61.4	51.4
	(0.28)	(0.72)	(0.07)	(0.90)
Student (N=256)	47.3	49.6	49.6	46.5
	(0.42)	(0.95)	(0.95)	(0.29)

Note: The table shows the proportion of the observations in each subsample for which the price path had a certain characteristic compared to not having this characteristic. The p-values report binomial tests that test whether the proportion significantly differs from the expected 50 percent under perfect randomization. The cases are price paths (not respondents). Subsamples with less than 20 cases are not shown.

The randomization made it possible to avoid spurious correlation between treatment variables, e.g., positive versus negative, etc., and observed and unobserved individual characteristics, e.g., gender, age, motivation, etc. This experimental method severely reduced the risk of bias in the estimation of the effect of price chart and return bar chart characteristics on the perceived risk.

In order to check whether the treatment randomization was successful, balance checks were conducted, as provided in Table 5. The sample size *N* refers to the number of graphs displayed to subjects for a given individual characteristic category. Within each of these categories, the percentage was calculated of price paths (price charts) with a given characteristic that was shown to that given subcategory. For example within the category *gender,* subcategory *men,* 50.6% saw a price path with a positive ending point, whereas 49.4% saw a price path with a negative ending point.

If the treatment randomization was successful, there should be no significant difference in percentages of graphs displayed for different subcategories of individual characteristics and, since the price path characteristics are dichotomous, each characteristic is assigned to a price chart and return bar chart with a probability of 50%. Indeed, the balance checks show that for each price path, the corresponding graphs were evenly distributed for each individual characteristic. For example, within age category 18–25, 50.6% of respondents received the price path with the late turning point, whereas 49.4% saw the price path with an early turning point. The p-value for this particular subcategory equals 0.8 (>0.05), meaning that there was no significant difference in the percentage of graphs with late turning point versus those with an early turning point shown to the age group 18–25.

Table 5 provides that, for each price path characteristic, the differences in percentages of graphs displayed within each individual characteristic group were not significant as all p-values are greater than 0.05. Therefore, it can be concluded that, within each individual characteristic category, the treatment was divided evenly, hence, there was no spurious effect of individual characteristics on the risk perception of an individual.

4.3 Visual Analysis

Figure 1 presents the average risk perception for the price charts with and without the return chart bars constructed for the purpose of this study. Simple one-to-one visual inspection of these averages yields some interesting insights. To see which price charts and return bar charts were compared, please consult Appendix D.

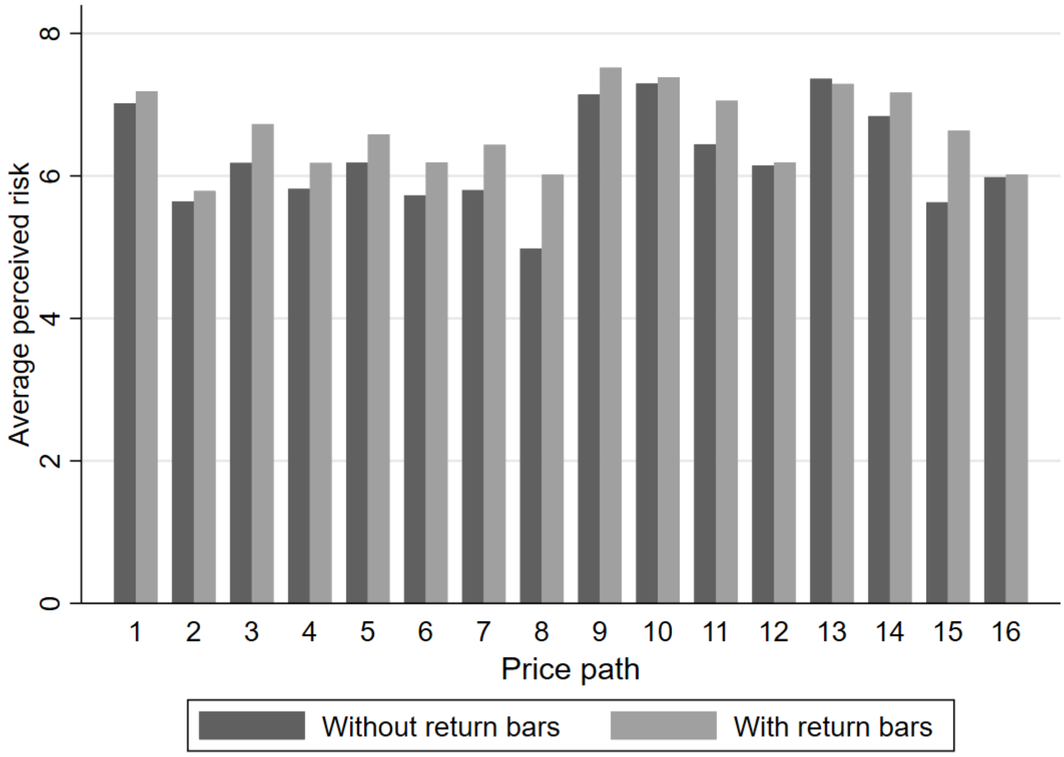
It has been argued that the risk perception of retail financial investors depends on price path characteristics that are visible in the price charts displayed to them. Therefore, it is not surprising to see that across all 16 price charts *without return bars*, the average risk perception varied across price paths. Keeping all other characteristics constant, it was expected that the perceived risk for the price charts with a positive ending point (Price Path 1–8) would be lower than for those with a negative ending point (Price Path 9–16). Checking price charts on this particular characteristic shows that this was indeed true for all price path pairs (Price Path 1 versus 9, Price Path 2 versus 10, etc.) except for the Price Path 15 versus 7. Therefore, price paths in the positive domain, i.e., a positive ending point, were, on average, perceived as less risky than those within negative domain, i.e., a negative ending point

Another eye-catching outcome was found when comparing price charts on the salient peak (trough) versus no peak (trough) characteristic. The literature review indicated that price paths with a salient peak (trough) would be perceived as riskier than those with no visible peak (trough). Comparing pairs of price charts with and without a peak (trough) within the positive domain confirms this expectation. As shown in Figure 1, price paths with positive return and no salient peak (trough), namely Price Paths 2, 4, 6, and 8, were, on average, perceived as less risky than their counterparts with a salient peak (trough), namely Price Paths 1, 3, 5, and 7. Within the negative domain, similar results were found, with two exceptions, i.e., Price Path 9 versus 10 and 15 versus 16. For these two pairs, it appears that price paths with a peak (trough) were, on average, less risky than those with more gradual price trends. These findings partly confirm the earlier expectation that, on average, price paths with a salient peak (trough) are perceived to be more risky than price paths with no visible peak (trough), but only if the price paths have a positive ending point, while for price paths with a negative ending point, these results are mixed.

Further, checking the price paths on their down-up and up-down trends across different pairs shows that, for this particular characteristic, the earlier expectations were also fulfilled As can be seen in Figure 1, in the positive domain almost all the up-down Price Paths, i.e., 1, 2, 5 and 6, were, on average, perceived to be more risky than their down-up counterparts, i.e., 3, 4, 7 and 8. There is one exception to this rule – Price Path 2 versus 4 – as it appears that the latter (the down-up price path) is perceived, on average, to be slightly more risky than the former (up-down). Apart from this exception, overall, the previous expectations were met that, on average, up-down price paths would be considered more risky than down-up ones.

The last characteristic discussed in this study was an early versus a late tuning point. It has been stated that an individual would perceive price paths with an early turning point as more risky than those with a late turning point due to recency bias or the overweighting of more recent information. Again, forming different pairs of price paths with the same characteristics, except for a turning point, did not show entirely straightforward results. In the positive domain, individuals perceived the price paths with a late turning point (1 and 3) to be more risky, on average, than those with an early turning point (5 and 7), if they had a salient peak or trough. However, if an up-down price path with a late turning point had no salient peak (Price Path 2), it was, on average, perceived to be slightly less risky than a price path with an early turning point (Price Path 6). For down-up price paths with no peaks (troughs), in contrast, it appears that, on average, an early turning point (Price Path 8) was perceived to be less risky than a late turning point (Price Path 4).

Figure 1: average perceived risk for price charts and return bar charts



Note: the price charts and return bar charts with corresponding characteristics are detailed in Table 1.

In the negative domain, the results were even more mixed than in the positive domain. Figure 1 shows that the up-down price path with a salient peak and a late turning point (Price Path 9) was considered less risky, on average, than the price path with a salient peak and an early turning point (Price Path 13). However, an up-down price path with no salient and late turning point (Price Path 10) was perceived as more risky, on average, than a similar price path with an early turning point (Price Path 14). For a price path with a down-up trend, meanwhile, a late turning point (Price Path 11 and 12) was perceived to be more risky, on average, than counterparts with an early turning point (Price Paths 15 and 16), regardless of whether the price path had a trough or not.

Looking at the price charts in conjunction with the return bar charts also gives some interesting results. In previous sections of this article, it has been argued that risk perception should change when an individual receives additional return information alongside price information. One-to-one comparison for the same assets between price charts with and without return bar charts shows that providing return bar charts alongside price charts leads to an increased average risk perception.

Further, a comparison of price path pairs on their ending points showed similar results to those described earlier. However, there were three noticeable changes. Firstly, the average risk perception for Price Path pair 7 versus 15 appeared to be consistent with expectations. Hence, the price path with a positive return (Price Path 7) was perceived as less risky, on average, than the price path with a negative return (Price Path 15). Secondly, the risk perception between price paths with a positive return (Price Path 8) and a negative return (Price Path 16) was almost equalized, while it was expected that risk perception differences would increase after additional return information was displayed to the individuals. Thirdly, for Price Paths 4 and 12, it appears that, on average, the former (positive return) was perceived to be more risky than the latter (negative return). This observation is inconsistent with common sense, that is, it is peculiar that a price path with a negative return could be perceived as less risky than a price path with a positive return. As stated earlier, it was expected that the risk perception gap between different pairs would increase after the return bar chart was provided alongside the price chart of an underlying asset. However, this figure does not support such a conclusion. In general, it can be said that, on average, price paths with a positive return are perceived less risky than those with a negative return, with the exception of two price path pairs.

Further, Figure 1 shows that the provision of additional return information did not lead to an equalization of the average risk perception for all pairs constructed in the case of down-up versus up-down price paths. Quite extensive differences remained visible between different price path pairs, with the exception of Price Path 5 versus 7, 6 versus 8, and 9 versus 11. The visual analysis brought more optimistic results for the peak (trough) versus no peak (trough) characteristic even though in three pairs, the average risk perception differs a lot for Price Paths 1 versus 2, 11 versus 12, and 15 versus 16. For the last characteristic, that is, late versus early turning point, the findings are most satisfying, as in each price path pair, the average risk perceptions were very close to each other. Based on these results, it seems that the provision of a return bar chart as well as a price chart can lead to the equalization of perceived risk between price paths with an early and late turning point.

4.4. Regression Models

To evaluate the hypotheses stated in a previous section of this study and determine whether different price path characteristics, as well as return bar charts, hold any explanatory power to explain risk perceived by retail financial investors, the different regression models found in Table 6 are discussed in this section.

The first model (Model 1) examines whether the four price path characteristics and return bar charts have any significant influence on the risk perception of retail financial investors. This model shows that three of four characteristics have a significant effect at a 0.01% significance level, while one characteristic, i.e., turning point, is significant at a 1% significance level. It seems that a positive ending point and the up-down trend result in the highest difference in perceived risk. For price sequences, up-down price path results, on average, in a 0.627-point higher risk perception than price path with down-up trend, if the other price path characteristics are held constant. Next, price paths with a positive ending point lead to a lower perceived risk of 0.601 points, on average, compared to price paths with a negative ending point, that is, i.e., those with an overall negative return over their observation horizon. These two characteristics are followed by price paths with a salient peak (trough) and price paths with a late turning point. Price paths with salient peak (troughs) lead to a higher perceived risk by retail financial investors – by 0.488 points – compared to price paths which have more gradual price trends. For turning points, in contrast, it appears that price paths with a late turning point are considered more risky than those with an early turning point. Price paths with a late turning point result in a risk perception of 0.304 points higher than price paths with an early turning point. This regression model confirms earlier expectations that these four dichotomous price path characteristics significantly influence retail investors' risk perception.

However, only three of these characteristics have the hypothesized effect, namely ending point, price sequences, and salient peak (trough). The statistical analysis proves the opposite to be true for turning points, as subjects perceived price paths with an early turning point to be, on average, less risky than their counterparts with a late turning point. Based on these insights it can be concluded that:

<u>Result 1</u>: retail financial investors perceive a price path that ends above its initial price as less risky than a price path that ends below its initial price when they are confronted with the price chart of the underlying asset.

<u>Result 2</u>: retail financial investors perceive a price path that first falls and rises afterwards (down-up) to be less risky than a price path that first rises and falls afterwards (up-down) when confronted with the price chart of the underlying asset.

<u>Result 3</u>: retail financial investors perceive a price path with a salient peak (trough) to be more risky than a price path whose peak (trough) is not visible when confronted with the price chart of the underlying asset.

<u>Result 4</u>: retail financial investors perceive a price path with a late turning point to be more risky than a price path with an early turning point when confronted with the price chart of the underlying asset.

These findings are in line with prior research showing that price path development significantly affects the risk perception of financial investors. The literature shows that investment satisfaction and risk perception depends on the return that an investment yields over the investing horizon (Brosboom & Zeisberger, 2020; Grosshans & Zeisberger, 2018). The findings of this study confirm these results, that price paths ending above their initial price (positive return) are considered to be less risky than those which end below their initial price (negative return). Moreover, Model 1 confirms previous findings that the price paths with down-up trend are preferred because they are considered less risky than those with up-down trend (Mussweiler & Schneller, 2003; Nolte & Schneider, 2018; Grosshans & Zeisberger, 2018; Huber & Huber, 2019). Similarly to previous studies (Borsboom & Zeisberger, 2020; Borsboom et al., 2020; Nolte & Schneider, 2018; Glaser et al., 2019; Bose et al., 2020), this study demonstrates that the salience of price paths plays an important role in investment decisions and the investment behavior of financial investors. Statistical analysis showed that sharp price changes (peaks and troughs) significantly affect the risk perception of an individual, as found by Huber and Huber (2019), Borsboom and Zeisberger (2020), and Raghubir and Das (2010).

The only discussion point are turning points, as the opposite has been hypothesized and described in the financial literature. In this study, it was found that price paths with a late turning point were perceived as more risky by subjects than the equivalent price paths with an early turning point. While, prior studies have shown that investors base their financial decisions on recent rather distant information (Bailey et al., 2011; Glaser et al., 2019; de Bondt, 1993). More precisely, Bailey et al. (2011) found that investors prefer recent positive returns over more distant ones, whereas Glaser et al. (2019) and de Bondt (1993) argued that more recent trends are extrapolated by investors to forecast future returns or stock prices. On the other hand, Grosshans and Zeisberger (2018) demonstrated that investor satisfaction with a given price path depends on the interaction effect of both price path trend (down-up versus up-down) and its turning point. They found that subjects preferred an early turning point in down-up price paths and a late turning point in up-down price paths, with the former effect being significant.

Before moving on, it should be noticed that Model 1 only looks at the differences in the main effect of displaying price charts with return bar charts and price charts alone. To see how the price path characteristics affect the risk perception of individuals within each treatment group, please consult Appendix E where separate regression analysis has been conducted on the subsamples of this research. Further, as can be seen in Model 1, provision of return bar charts in conjunction with price charts does not lead to significant difference in risk perception compared to displaying price charts alone. Moreover, showing both price charts and return bar charts to subjects results, on average, in higher risk perception (0.390). It should be noted, however, that the effect of the return bar charts is only slightly not significant (p-value 0.051) and perhaps it is better to conclude that the effect is marginally significant.

Result 5: provision of additional return information alongside a price chart of the underlying asset leads to a marginally significant difference in risk perception compared to when only the price charts are provided to retail financial investors.

Nevertheless, this finding contradicts previous studies where risk perception significantly depends on the way in which information is provided to individuals. For example, Grosshans and Zeisberger (2018) and Sobolev and Harvey (2016) stated that displaying supplementary information about a financial investment has an impact on financial investors when it comes to their perceived investment satisfaction or the perceived riskiness of financial investments. Similarly, Diacon and Hasseldine (2007) argued that risk perception depends on the graphical presentation of information, whereas Borsboom and Zeisberger (2020) indicated that shifting the focus of attention could results in entirely different investment decisions.

In order to give a better understanding of the impact of return bar charts on risk perception, the second model (Model 2) extends the analysis with interaction effects between return bar charts and price path characteristics. This model allowed to measure the effect of return bar charts when simultaneously provided with price charts on risk perception when taking different price path characteristics into account.

Table 6: the effect of price path characteristics on perceived risk (regression analysis)

	Model 1 b/se	**Model 2** b/se	**Model 3** b/se	**Model 4** b/se	**Model 5** b/se
Positive	-.601***	-.688***	-.623***	-.677***	-.634***
	(.115)	(.179)	(.110)	(.176)	(.109)
Late	.304**	.393**	.289**	.384**	.221*
	(.097)	(.144)	(.092)	(.135)	(.086)
Up-Down	.627***	.775***	.671***	.786***	.687***
	(.135)	(.203)	(.131)	(.196)	(.142)
Peak	.488***	.419**	.505***	.525***	.516***
	(.101)	(.144)	(.100)	(.145)	(.101)
Bars	.390	.472	.379*	.557*	
	(.199)	(.309)	(.179)	(.269)	
Bars*Positive		.174		.108	
		(.229)		(.224)	
Bars*Late		-.181		-.191	
		(.194)		(.186)	
Bars*Up-Down		-.300		-.233	
		(.269)		(.260)	
Bars*Peak		.139		-.040	
		(.201)		(.202)	
Female			-.334	-.325	
			(.196)	(.196)	
Bachelor			-.200	-.199	
			(.348)	(.346)	
Master or higher			-.255	-.248	
			(.408)	(.406)	
Age: 0-17			4.306***	4.288***	
			(.490)	(.492)	
Age: 18-25			.146	.146	
			(.268)	(.268)	
Age: 36-45			.284	.274	
			(.253)	(.254)	
Age: 46-55			-.164	-.179	
			(.302)	(.300)	
Age: 56-65			.624	.618	
			(.765)	(.769)	
Unemployed			.348	.364	
			(.419)	(.420)	
Student			-.238	-.239	
			(.355)	(.356)	
Retired			.691	.663	
			(.736)	(.739)	
Own Financial Product			-.131	-.135	
			(.253)	(.253)	
Financial Knowledge			.173**	.174**	
			(.061)	(.061)	
Financial Risk Willingness			.081	.081	
			(.056)	(.056)	
Statistical Skills			.093	.093	
			(.067)	(.067)	
Missing: Female			.728*	.730*	
			(.318)	(.319)	

Missing: Age			-.056	-.094	
			(.314)	(.314)	
Missing: Status			1.089	1.083	
			(.934)	(.930)	
Missing: Owning Financial Product			.271	.246	
			(.502)	(.498)	
Missing: Financial Knowledge			-.516	-.466	
			(.703)	(.699)	
Constant	5.854***	5.812***	3.890***	3.800***	5.108***
	(.204)	(.252)	(.376)	(.398)	(.096)
Individual fixed effects	No	No	No	No	Yes
R-squared	.06	.06	.17	.17	.48
N (price paths)	1736	1736	1736	1736	1736

Note: * p<.05; ** p<.01; *** p<.001. Standard errors (in parentheses) are clustered at the individual respondents. The reference categories are male for gender, high school or lower for education, 26-35 years old for age and employed for status.

The findings seem to be consistent across Model 1 and Model 2. However, there are some minor changes in the size of effects of the main explanatory variables as well as their significance. This regression model shows that each main explanatory variable has an even greater effect on the risk perception, while the significance only changed for the variable *peak*, decreasing from a 0.01% to a 1% significance level. This model proves that price chart characteristics are still robust when adding interaction variables as they have the same sign as previously while holding their significant effect on perceived risk. The expansion of Model 2 with interaction terms shows, however, that provision of the return bar charts alongside the price charts does not lead to significant changes in risk perception. It appears that the increased number of explanatory variables makes its effect even more insignificant than in Model 1.

However, interaction effects offer more fruitful findings. Model 2 shows that adding return bar charts reduces the effects (in absolute value) of each of the price path characteristics because the coefficients of the interaction terms have the opposite sign to the main effect. Moreover, the interaction-effect variables are of no significance on perceived risk by retail financial investors. In line with previous statements, provision of the additional return bar chart should enlarge the difference in the risk perception between the price paths that end above (positive return) and below (negative return) their starting point. However, Model 2 does not provide a straightforward result because it seems that simultaneous provision of the return bar chart and the price chart leads to increased risk perception for price paths with a positive ending. At the same time, this regression model implies that provision of the additional return information does not have any significant effect on risk perception differences between price paths with different ending points. Thus, this outcome contradicts what was hypothesized, that the risk perception gap between price paths with positive and negative returns would enlarge due to the provision of the additional return information.

For the other three characteristics, the findings are in line with the hypotheses. It was claimed that simultaneous provision of the return bar charts and price charts would equalize the risk perception between different price paths. Apparently, when the return bar chart is provided in conjunction with the price chart there is no significant difference in the perceived risk. This is the case when keeping all other characteristics constant and discriminating the price paths on one of the characteristics, i.e., early versus late turning point, down-up versus up-down or salient peak (tough) versus no peak (trough). Therefore, giving individuals the additional return bar charts together with price charts wipes out the effect of different price path characteristics on the risk perception, thereby equalizing the risk perception within dichotomous characteristics.

Result 6: in comparison to the situation where only the price chart of the underlying asset is displayed, the simultaneous provision of the return bar chart in conjunction with the price chart of the underlying asset does not significantly increase the risk perception gap between the price path that ends above its initial point and the one that ends below its initial point.

Result 7: in comparison to the situation where only the price chart of the underlying asset is displayed, there is no significant difference in perceived risk between the price path which first falls and then rises (down-up) and that which first rises and then falls (up-down) if an individual is provided simultaneously with the price chart and return bar chart of the underlying asset.

Result 8: in comparison to the situation where only the price chart of the underlying asset is displayed, there is no significant difference in the perceived risk between the price path with a salient peak (trough) and that without a salient peak (trough) if an individual is provided simultaneously with the price chart and return bar chart of the underlying asset.

Result 9: in comparison to the situation where only the price chart of the underlying asset is displayed, there is no significant difference in the perceived risk between the price path with an early turning point and that with a late turning point if an individual is provided simultaneously with the price chart and return bar chart of the underlying asset.

In order to test the robustness of these results, two additional models (Model 3 and Model 4) were estimated to control for the observed characteristics of respondents. In the survey, respondents were asked about their personal characteristics, i.e., demographics and personal questions. The introduction of personal characteristics as control variables should rule out that the findings of Model 1 and Model 2 are significantly driven by these personal characteristics. For example, results could be driven by the individuals with relatively high willingness to take financial risk or those that own financial products. This is all true with the exception of financial knowledge, as this study deliberately included subjects with some financial knowledge to mimic retail financial investors. As a few participants did not answer some personal characteristic questions or demographic questions, these two models were adjusted by means of "dummy variable adjustment" to account for those missing values.

Adding control variables to Model 3 proves that the findings of Model 1 are robust because the effect of different price path characteristics on risk perception is the same, and these variables hold the same level of significance. Therefore, it can be concluded that demographic characteristics do not lead to any significant risk perception differences. When it comes to education level, the literature is inconclusive in regard to whether this factor significantly affects risk perception. Studies show that there is certainly an inverse relationship between highest educational level attained and risk perception. For example, Gutter and Fontes (2006) found that being more educated significantly increases the likelihood of possessing risky assets. Likewise, research by Brown and Taylor (2007) showed that risk tolerance increases with the highest attained educational level. Similarly, the studies that found no significant effect of educational level on risk perception concluded that there is a negative (positive) effect of highest completed educational level on risk perception (risk tolerance) (Hallahan et al., 2003; Yao et al., 2011). In line with Hallahan et al. (2003) and Yao et al. (2011), it was found that risk perception decreases with the highest attained education level, but the highest attained education level does not have a significant impact on the risk perception of an individual. In contrast, the descriptive statistics showed (Table 4) that there is significant difference in the mean values of the risk perception between groups of different completed education levels. Thus, there is some degree of correlation between the highest attained education level and risk perception, but this effect is not significant.

Moreover, the vast majority of studies found a significant effect of gender on risk tolerance or risk perception. The literature demonstrates that males have, on average, a significantly higher (lower) risk tolerance (risk perception) than females (Grable, 2000; Hallahan et al., 2003; Charness & Gneezy, 2012; Yao et al., 2011). Even when studies conclude that there is no significant effect of gender on risk perception (risk tolerance), it still appears that males are, on average, more risk-tolerant than females (Cohn et al., 1975). Hence, the result in this model partly contradict previous findings. This model shows, first, that gender does not significantly alter the risk perception of individuals; and second, that, on average, females perceive lower risk when it comes to investment decisions than males do. However, the finding of this model confirms the descriptive statistics presented in Table 4, that the difference in mean values of perceived risk are not significantly different between males and females. Hence, there is some degree of correlation between gender and risk perception, but this effect is not significant.

For the last two characteristics, age and status, similar conclusions can be drawn. Status has no significant effect on the risk perception of an individual. Similarly, age does not significantly change the risk perception of an individual. Only for the age-category 0-17 years old, it appears that individuals should perceive much higher risk compared to the other age groups. However, it should be noted that only one individual between 0-17 years participated in the experiment. In general, these results are in contradiction to numerous studies that have been relatively consistent in finding that age is an important factor in risk-taking behavior (Cohn et al., 1975; Riley & Chow, 1992; Hallahan et al., 2003; Yao et al., 2011). However, there is ongoing debate over whether there is a linear (Cohn et al., 1975 or Yao et al., 2011) or non-linear pattern (Hallahan et al., 2003 or Riley & Chow, 1992) between age and risk tolerance.

A similar result can be drawn for the personal questions regarding owning financial products, willingness to take financial risks, and statistical skills. All of these control variables prove to have no significant influence on risk perception. However, this model (Model 3) indicates that financial knowledge is an important factor for risk perception. The effect of financial knowledge is positive and significant, implying that individuals with higher financial knowledge perceive, on average, a higher risk than less financially sophisticated individuals. This is in line with Borsboom and Zeisberger (2020), who found the risk perception to change depended on the financial literacy of individuals.

<u>Result 10</u>: demographic characteristics such as gender, age, highest attained education level, and status, have no significant effect on the risk perception of a retail financial investor.

Model 4 provides the same results as those discussed in Model 2 and Model 3. Again, the price path characteristics are significant on the same significance levels while the magnitude of these explanatory variables have changed for all these effects. Model 4 explains that the findings of Model 2 are consistent when controlling for personal characteristics. Unfortunately, the significance of the interaction term *bars*positive* does not change, confirming the previous outcome that the provision of the return bar chart with the price chart does not significantly increase the difference in risk perception between the price paths with positive and negative ending points by retail financial investor. In line with Model 2, other interaction variables did not become significant, supporting the robustness of previous results. In this case, too, financial knowledge significantly affects perceived risk by retail financial investors.

The interaction effects changed in magnitude, but they are still insignificant. A more striking result in these two robustness models (Model 3 and Model 4) is that, due to the inclusion of control variables, the variable *bars* seems to be significant on a 5% significance level. This result implies that the provision of the additional return information alongside the price charts leads individuals to perceive higher risk than when only price charts are displayed to them. Therefore, when controlling for the financial knowledge, the provision of the return bar chart alongside the price chart of the underlying asset leads to significant difference in risk perception compared to the situation when only the price chart of the underlying asset is displayed to a retail financial investor.

<u>Result 11</u>: owning financial products, willingness to take financial risk, and statistical skills do no significantly affect the financial risk perception of a retail financial investor.

<u>Result 12</u>: financial knowledge has significant effect on the risk perception of a retail financial investor.

<u>Result 13</u>: when controlling for the financial knowledge, the simultaneous provision of the return bar chart alongside the price chart of the underlying asset significantly increases perceived risk by the retail financial investors compared to when only the price chart of the underlying asset is provided.

The last model provides a further robustness check of the findings with respect to price path characteristics by controlling for unobserved characteristics of the respondents by means of a fixed effects regression model. The outcome of this analysis is presented in Model 5. The variable *bars* has been excluded from analysis as it does not vary within an individual respondent, i.e., an individual received a survey either with or without return bar charts. This model implies that, even after controlling for individual fixed effects, the influence of the price path characteristics on risk perception remains significant. The magnitude of the effects has slightly increased for explanatory variables *Positive, Up-Down,* and *Peak*, while has decreased for the variable *Late*. This is also the only variable whose significance has decreased from a significance level of 1% to one of 5%. Moreover, the sign of these explanatory variables is not influenced by unobserved individual characteristics, confirming the previous conclusions of this study. Overall, this model gives even stronger evidence that the price path characteristics are of significant influence on the perceived risk perception of retail financial investors. Therefore, the previous conclusions of this chapter, i.e., Result 1 to Result 4, regarding the price path characteristics cannot be refuted.

5 DISCUSSION & CONCLUSION

Traditional financial economics assumes the rational behavior of financial investors as they base their investment decisions on all information available to them. However, abundant literature provides evidence that the financial behavior of investors is far from rational. One irrationality is the way in which individuals use price charts in financial investment decisions. Seemingly, price and return charts are the most extensively used information source by financial investors for investment decisions. Moreover, different scholars have shown that price path development significantly influences the perceived attractiveness of financial investments, perceived riskiness of financial investments, and perceived investment satisfaction.

Previous research has studied how different presentation formats and their elements influence the risk perception of financial investors. However, studies exploring how risk perception changes as soon as a retail financial investor receives additional return information about an investment are lacking. To fill this gap, this study did not merely replicate previous research on this topic but aimed to answer the following question:

"To what extent do price charts in conjunction with return bar charts influence the risk perception of a retail financial investor compared to price charts alone?"

To answer this question, an incentivized online experiment was conducted in which participants were divided in two groups and shown either price charts in conjunction with return bar charts or only the price charts of the underlying asset. In total, 16 price charts with underlying returns were created containing different combinations of four dichotomous characteristics. In line with previous studies, this experimental study shows that individuals are prone to the different price path developments. First of all, investors perceive higher risk when the price path of an underlying asset offers a negative return over its observation horizon than when a price path with the same characteristics yields a positive return. Furthermore, it was found that investors prefer price paths that first fall and then rise (down-up) to those which first rise and then fall (up-down) as the former results in a significantly lower risk perception. It also appeared that subjects perceived price paths with a more gradual price trend to be less risky than those with salient peaks or troughs. Although previous studies have demonstrated the tendency of individuals to exaggerate recent trends, this study concluded the opposite. Apparently, individuals perceive price paths with an early turning point to be less risky than price paths with a late turning point. Similarly, this study finds that the provision of return bar charts alongside price charts leads to the equalization of perceived riskiness across various price path characteristics. It has been shown that, for characteristics such as down-up versus up-down trend, peak (trough) versus no peak (trough), and early versus late turning point, there was no significant difference in the risk perception for the given dichotomous characteristic if individuals received the additional return information. However, the same was concluded for the price paths with positive and negative returns, which appears a very unrealistic proposition.

In this study, different regression models were constructed to measure the significance of different effects. In two models, it appeared that the inclusion of return bar charts alongside price charts leads to any or marginal risk perception differences when compared to displaying only the price charts of the underlying asset. However, after controlling for financial knowledge, it appeared that return bar charts could indeed lead to a deviation in risk perception. In general, it can be concluded that, after controlling for financial knowledge, the provision of a return bar chart next to a price chart increases the risk perceived by a retail financial investor compared to the situation in which only a price chart of the underlying asset is displayed to them.

The findings in this study contribute to the current literature on price paths and risk perception. Principally, however, this study tried to provide an experiment that mimics the real-world setting in which retail financial investors base their investment decisions on various information sources, namely price charts and return bar charts. This approach extends current studies on risk perception by showing how risk perception changes when financial investors consult different information sources simultaneously as opposed to only one information source. From a practical point of view, this study has various applications for both businesses and policy makers. It has been shown that individuals can be manipulated very easily, depending on how information is presented to them, which demonstrates the importance of financial risk commutations, such as the KIDD. These types of investor programs are important to protect (retail) investors from detrimental financial investments and greedy institutional investors or financial markets.

There are, of course, limitations to this study which should be addressed and improved on in the future. The literature review showed that there are at least four types of price path characteristic that could be of significant influence on risk perception. Future research should extend this list with additional characteristics, such as different starting points or difference in highest and lowest values reached over the observation horizon. It should also be considered whether the amount of time that a price path is above or below its starting point has a significant influence on risk perception. Another limitation of this study is that the return bar charts were assumed to be the only information source that financial investors can use to evaluate investment decisions. However, investors can consult other measures as well in the investment decision process from simple price changes to more complex measures such as, loss probability, reward profile, or the volatility of the assets in consideration.

Further, each of the price path characteristics was tested in isolation. This implies that, in this study, the fact that different characteristics could reinforce their effect on each other was not taken into account. For example, in contradiction to the literature review, this study showed that individuals do not necessarily overweight more recent information or more recent trends as they perceived the price paths with an early turning point to be less risky than those with a late turning point. It could, however, be the case that differentiating between the turning points in down-up and up-down price paths would provide entirely different results, as in Grosshans and Zeisberger (2018). Additionally, an attempt was made to mimic real-world conditions as well as possible but further steps could be taken in this regard as well. For example, instead of an internet survey, a real-world experiment could be conducted, based on real stock market data, as this could improve the external validity of the findings. Moreover, the experiment took place in one period of time, while financial investments is a process that spans multiple periods. Therefore, undertaking an experiment over multiple periods of time could provide even stronger and world-applicable results.

REFERENCES

Al Mamun, M., Syeed, M. A., & Yasmeen, F. (2015). Are investors rational, irrational or normal? *Journal of Economic & Financial Studies*, *3*(04), 1–15. https://doi.org/10.18533/jefs.v3i04.161

Bailey, W., Kumar, A., & Ng, D. (2011). Behavioral biases of mutual fund investors. *Journal of Financial Economics*, *102*(1), 1–27. https://doi.org/10.1016/j.jfineco.2011.05.002

Bazley, W. J., Cronqvist, H., & Mormann, M. (2021). Visual Finance: The Pervasive Effects of Red on Investor Behavior. *Management Science*, 1–26. https://doi.org/10.1287/mnsc.2020.3747

Benartzi, S., & Thaler, R. H. (1995). Myopic Loss Aversion and the Equity Premium Puzzle. *The Quarterly Journal of Economics*, *110*(1), 73–92. https://doi.org/10.2307/2118511

Bose, D., Cordes, H., Nolte, S., Schneider, J. C., & Camerer, C. F. (2020, 19 August). Decision Weights for Experimental Asset Prices Based on Visual Salience. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3654021

Borsboom, C., Janssen, D. J., Strucks, M., & Zeisberger, S. (2020, 30 november). *Short versus Long: The Influence of Price Chart Display Horizons on Investor Behavior. SSRN*. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3722819.

Borsboom, C., & Zeisberger, S. (2020). What makes an investment risky? An analysis of price path characteristics. *Journal of Economic Behavior & Organization*, *169*, 92–125. https://doi.org/10.1016/j.jebo.2019.11.002

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. https://ideas.repec.org/p/zbw/imbwps/88.html

Brown, S. E., & Taylor, K. (2007, January). Education, Risk Preference and Wages. Working Paper No. 2006002, *The University of Sheffield, Department of Economics*, 1-27. https://www.academia.edu/31016744/Education_Risk_Preference_and_Wages

Charness, G., & Gneezy, U. (2012). Strong Evidence for Gender Differences in Risk Taking. *Journal of Economic Behavior & Organization*, *83*(1), 50–58. https://doi.org/10.1016/j.jebo.2011.06.007

Cohn, R. A., Lewellen, W. G., Lease, R. C., & Schlarbaum, G. G. (1975). INDIVIDUAL INVESTOR RISK AVERSION AND INVESTMENT PORTFOLIO COMPOSITION. *The Journal of Finance*, *30*(2), 605–620. https://doi.org/10.1111/j.1540-6261.1975.tb01834.x

de Bondt, W. P. (1993). Betting on trends: Intuitive forecasts of financial risk and return. *International Journal of Forecasting*, *9*(3), 355–371. https://doi.org/10.1016/0169-2070(93)90030-q

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. https://doi.org/10.1016/j.joep.2006.01.003

Duxbury, D., & Summers, B. (2018). On perceptions of financial volatility in price sequences. *The European Journal of Finance*, *24*(7–8), 521–543. https://doi.org/10.1080/1351847x.2017.1282882

Fama, E. F. (1995). Random Walks in Stock Market Prices. *Financial Analysts Journal*, *51*(1), 75–80. https://doi.org/10.2469/faj.v51.n1.1861

Fama, E. F., & French, K. R. (2004). The Capital Asset Pricing Model: Theory and Evidence. *Journal of Economic Perspectives*, *18*(3), 25–46. https://doi.org/10.1257/0895330042162430

Fiske, S. T., & Taylor, S. E (1978). Salience, Attention, and Attribution: Top of the Head Phenomena. *Advances in Experimental Social Psychology*, *11*, 249–288. https://doi.org/10.1016/s0065-2601(08)60009-x

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. https://doi.org/10.1111/jofi.12835

Goodman, J. K., Cryder, C. E., & Cheema, A. (2012). Data Collection in a Flat World: The Strengths and Weaknesses of Mechanical Turk Samples. *Journal of Behavioral Decision Making*, *26*(3), 213–224. https://doi.org/10.1002/bdm.1753

Grable, J. E. (2000). Financial Risk Tolerance and Additional Factors That Affect Risk Taking in Everyday Money Matters. *Journal of Business and Psychology*, *14*(4), 625–630. https://doi.org/10.1023/A:1022994314982

Grosshans, D., & Zeisberger, S. (2018). All's well that ends well? On the importance of how returns are achieved. *Journal of Banking & Finance*, *87*, 397–410. https://doi.org/10.1016/j.jbankfin.2017.09.021

Gutter, M. S., & Fontes, A. (2006). Racial Differences in Risky Asset Ownership: A Two-Stage Model of the Investment Decision-Making Process. *Journal of Financial Counseling and Planning*, *17*(2), 64–78. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2232188

Hallahan, T., Faff, R., & McKenzie, M. (2003). An exploratory investigation of the relation between risk tolerance scores and demographic characteristics. *Journal of Multinational Financial Management*, *13*(4–5), 483–502. https://doi.org/10.1016/S1042-444X(03)00022-7

Huber, C., & Huber, J. (2019). Scale matters: risk perception, return expectations, and investment propensity under different scalings. *Experimental Economics*, *22*(1), 76–100. https://doi.org/10.1007/s10683-018-09598-4

Huddart, S. J., Lang, M. H., & Yetman, M. (2005, March). Psychological Factors, Stock Price Paths, and Trading Volume. *AFA 2006 Boston Meetings Paper*. https://doi.org/10.2139/ssrn.687065

Huddart, S., Lang, M., & Yetman, M. H. (2009). Volume and Price Patterns Around a Stock's 52-Week Highs and Lows: Theory and Evidence. *Management Science*, *55*(1), 16–31. https://doi.org/10.1287/mnsc.1080.0920

Kahneman, D. (1973). *Attention and effort*. Prentice-Hall., Englewood Cliffs, New Jersey. https://scholar.princeton.edu/sites/default/files/kahneman/files/attention_hi_quality.pdf

Kahneman, D. (2003). Maps of Bounded Rationality: Psychology for Behavioral Economics. *American Economic Review*, *93*(5), 1449–1475. https://doi.org/10.1257/000282803322655392

Kahneman, D., & Tversky, A. (1979). Prospect Theory: An Analysis of Decision under Risk. *Econometrica*, *47*(2), 263–292. https://doi.org/10.2307/1914185

Kliger, D., & Gilad, D. (2012). Red light, green light: Color priming in financial decisions. *The Journal of Socio-Economics*, *41*(5), 738–745. https://doi.org/10.1016/j.socec.2012.07.003

Lawrence, M., & O'Connor, M. (1992). Exploring judgemental forecasting. *International Journal of Forecasting*, *8*(1), 15–26. https://doi.org/10.1016/0169-2070(92)90004-s

Levis, M. (1989). Stock market anomalies: A re-assessment based on the UK evidence. *Journal of Banking & Finance*, *13*(4–5), 675–696. https://doi.org/10.1016/0378-4266(89)90037-x

List, J. A., & Millimet, D. L. (2008). The Market: Catalyst for Rationality and Filter of Irrationality. *The B.E. Journal of Economic Analysis & Policy*, *8*(1), 1–53. https://doi.org/10.2202/1935-1682.2115

Loewenstein, G. F., & Prelec, D. (1993). Preferences for sequences of outcomes. *American Psychological Association, Inc.*, *100*(1), 91–108. https://doi.org/10.1037/0033-295x.100.1.91

Mcclure, B. (2020, 1 February). What Are Stock Fundamentals? *Investopedia*. https://www.investopedia.com/articles/fundamental/03/022603.asp#:%7E:text=Fundamental%20analysis%20involves%20looking%20at,on%20assets%2C%20and%20conservative%20gearing.

Mussweiler, T., & Schneller, K. (2003). "What Goes Up Must Come Down"-How Charts Influence Decisions to Buy and Sell Stocks. *Journal of Behavioral Finance*, *4*(3), 121–130. https://doi.org/10.1207/s15427579jpfm0403_2

Nolte, S., & Schneider, J. C. (2018). How price path characteristics shape investment behavior. *Journal of Economic Behavior & Organization*, *154*, 33–59. https://doi.org/10.1016/j.jebo.2018.07.018

Pincus, S., & Kalman, R. E. (2004). Irregularity, volatility, risk, and financial market time series. *Proceedings of the National Academy of Sciences*, *101*(38), 13709–13714. https://doi.org/10.1073/pnas.0405168101

Read, D. (2005). Monetary incentives, what are they good for? *Journal of Economic Methodology*, *12*(2), 265–276. https://doi.org/10.1080/1350178050008618O

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. https://doi.org/10.1086/644762

Riley, W. B., & Chow, K. V. (1992). Asset Allocation and Individual Risk Aversion. *Financial Analysts Journal*, *48*(6), 32–37. https://doi.org/10.2469/faj.v48.n6.32

Shaton, M. (2017). The Display of Information and Household Investment Behavior. *Finance and Economics Discussion Series*, *2017*(043). https://doi.org/10.17016/feds.2017.043

Sobolev, D., & Harvey, N. (2016). Assessing Risk in Graphically Presented Financial Series. *Assessing Risk in Graphically Presented Financial Series*, *36*(12), 2216–2232. https://doi.org/10.1111/risa.12595

Statman, M. (2014). Behavioral finance: Finance with normal people. *Borsa Istanbul Review*, *14*(2), 65–73. https://doi.org/10.1016/j.bir.2014.03.001

Verma, E. (2021, 23 March). *Financial Risk and Its Types*. Simplilearn.Com. https://www.simplilearn.com/financial-risk-and-types-rar131-article

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 Analysis*, *25*(3), 597–609. https://doi.org/10.1111/j.1539-6924.2005.00627.x

Yao, R., Sharpe, D. L., & Wang, F. (2011). Decomposing the age effect on risk tolerance. *The Journal of Socio-Economics*, *40*(6), 879–887. https://doi.org/10.1016/j.socec.2011.08.023

APPENDIX A: Personal Questions & Survey

Personal Questions

AGE **What is your age?**

- ◯ 0 - 17 years (1)
- ◯ 18 - 25 years (2)
- ◯ 26 - 35 years (3)
- ◯ 35 - 45 years (4)
- ◯ 46 - 55 years (5)
- ◯ 56 - 65 years (6)
- ◯ 66 years and older (7)

GENDER **What is your gender?**

- ◯ Male (1)
- ◯ Female (2)

DEGREE **What is the highest degree of education that you have completed?**

- ◯ Primary education (1)
- ◯ Secondary education (2)
- ◯ High school (3)
- ◯ Bachelor degree (4)
- ◯ Master degree (5)
- ◯ PhD and higher (6)

EMPLOYMENT **What is your current employment status?**

- Employed (1)
- Unemployed (2)
- Student (3)
- Retired (4)

FINANCIAL PRODUCTS **Do you own financial products (like stocks, bonds, etc.)?**

- Yes (1)
- No (2)

KNOWLEDGE **How much do you know about financial investments?**

- 0 (0)
- 1 (1)
- 2 (2)
- 3 (3)
- 4 (4)
- 5 (5)
- 6 (6)
- 7 (7)
- 8 (8)
- 9 (9)
- 10 (10)

FINANCIAL RISKS **How willing are you to take financial risks?**

- ○ 0 (0)
- ○ 1 (1)
- ○ 2 (2)
- ○ 3 (3)
- ○ 4 (4)
- ○ 5 (5)
- ○ 6 (6)
- ○ 7 (7)
- ○ 8 (8)
- ○ 9 (9)
- ○ 10 (10)

STATISTICAL SKILLS **How would you rate your statistical skills?**

- ○ 0 (0)
- ○ 1 (1)
- ○ 2 (2)
- ○ 3 (3)
- ○ 4 (4)
- ○ 5 (5)
- ○ 6 (6)
- ○ 7 (7)
- ○ 8 (8)
- ○ 9 (9)
- ○ 10 (10)

Survey

note: *this is one of the versions of the survey that has been displayed to the participants. The participants were randomly displayed 8 out of 16 price paths (and return bar charts) in randomized order. In this case an individual was displayed both price charts and return bar charts.*

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IN DEI NOMINE FELICITER

INTRODUCTION

Dear participant,

Thank you for your participation in this survey. This survey will take approximately 4 minutes of your time. I appreciate your time and feedback.

In this survey you will see a number of graphs showing the evolution of the price and return of a share over the past 12 months. Your task is to rate how risky a particular stock investment is on a scale from 0 (not risky at all) to 10 (extremely risky).

In the beginning you will be asked to answer some demographic questions before proceeding to the actual task.

Please take your time and remember that there are no right or wrong answers.

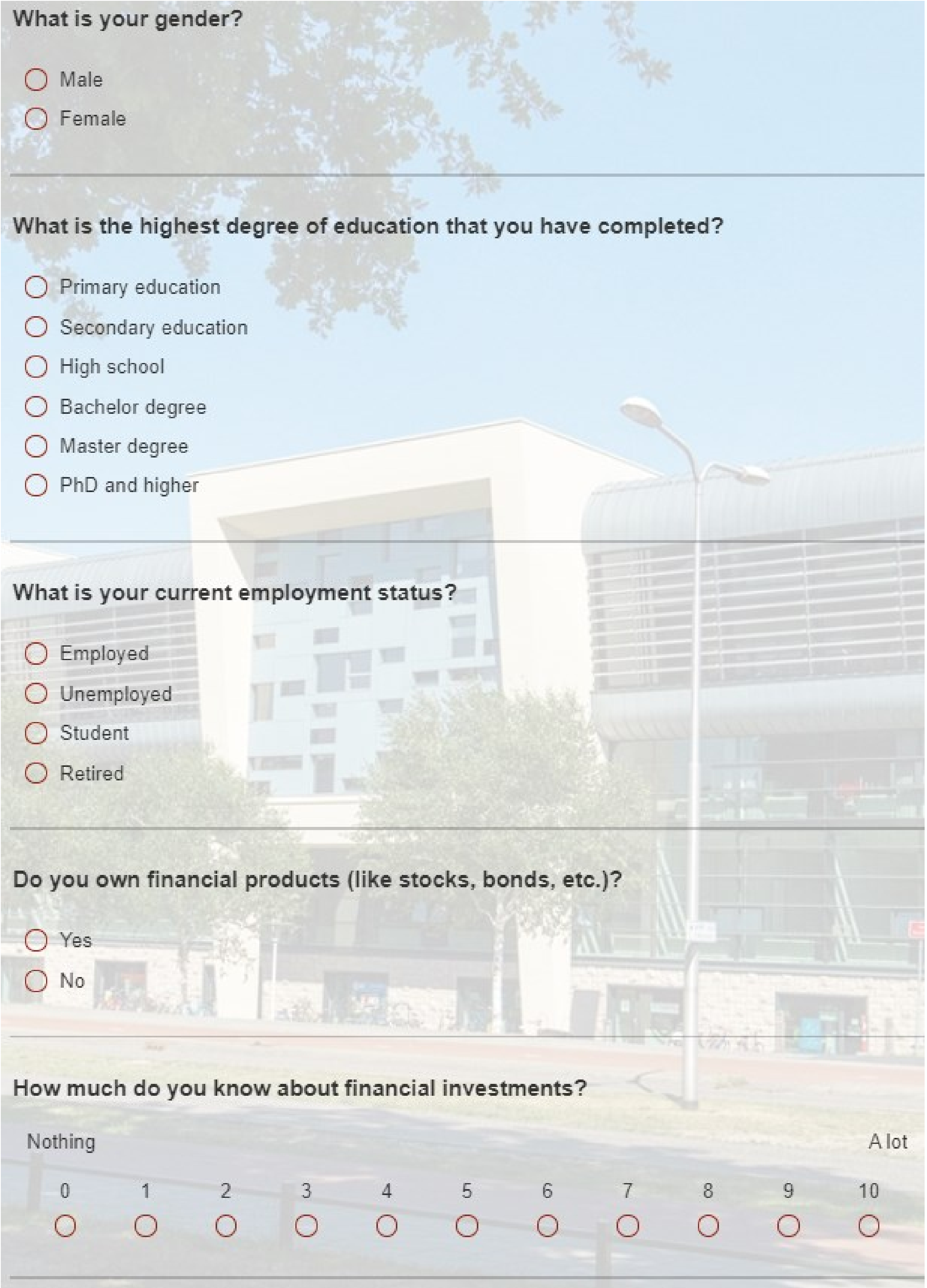
At the end of survey-collection I will randomly draw three participants that will receive € 50 each.

In case of any questions you can contact me at: b.lisowski@student.ru.nl

---

What is your age?

- ○ 0 - 17 years
- ○ 18 - 25 years
- ○ 26 - 35 years
- ○ 35 - 45 years
- ○ 46 - 55 years
- ○ 56 - 65 years
- ○ 66 years and older



What is your gender?

- ○ Male
- ○ Female

What is the highest degree of education that you have completed?

- ○ Primary education
- ○ Secondary education
- ○ High school
- ○ Bachelor degree
- ○ Master degree
- ○ PhD and higher

What is your current employment status?

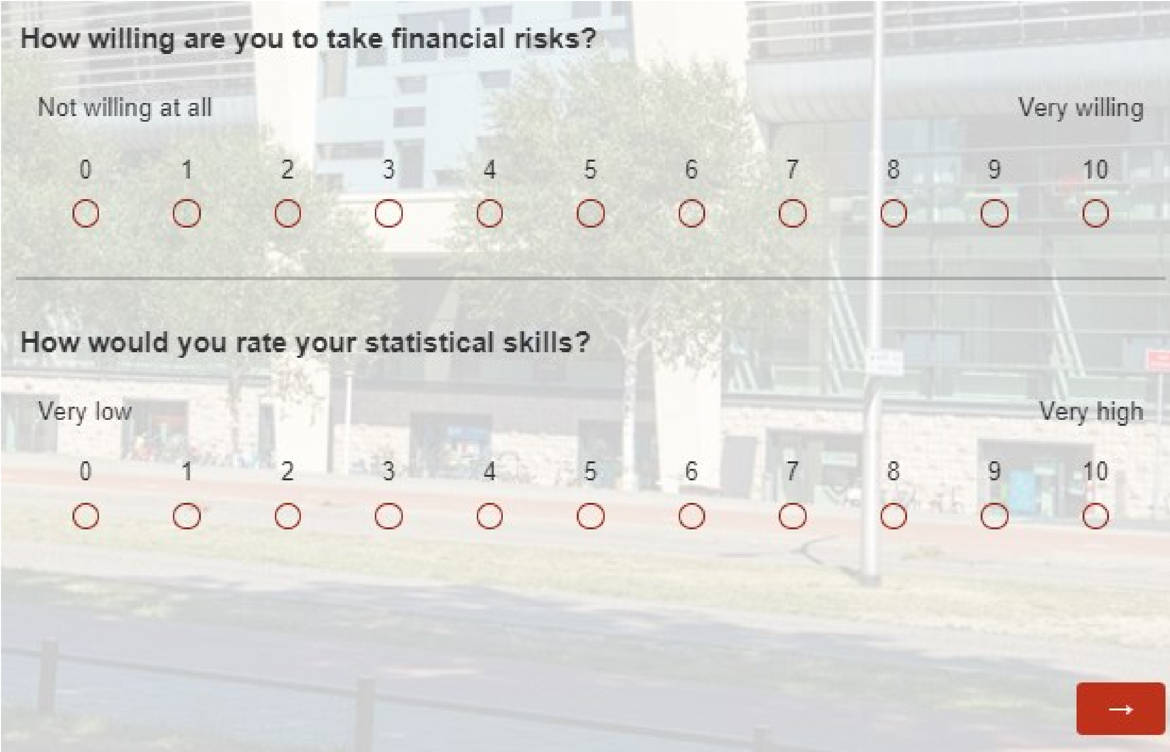
- ○ Employed
- ○ Unemployed
- ○ Student
- ○ Retired

Do you own financial products (like stocks, bonds, etc.)?

- ○ Yes
- ○ No

How much do you know about financial investments?

Nothing										A lot
0	1	2	3	4	5	6	7	8	9	10
○	○	○	○	○	○	○	○	○	○	○


How willing are you to take financial risks?

Not willing at all | Very willing

0 1 2 3 4 5 6 7 8 9 10

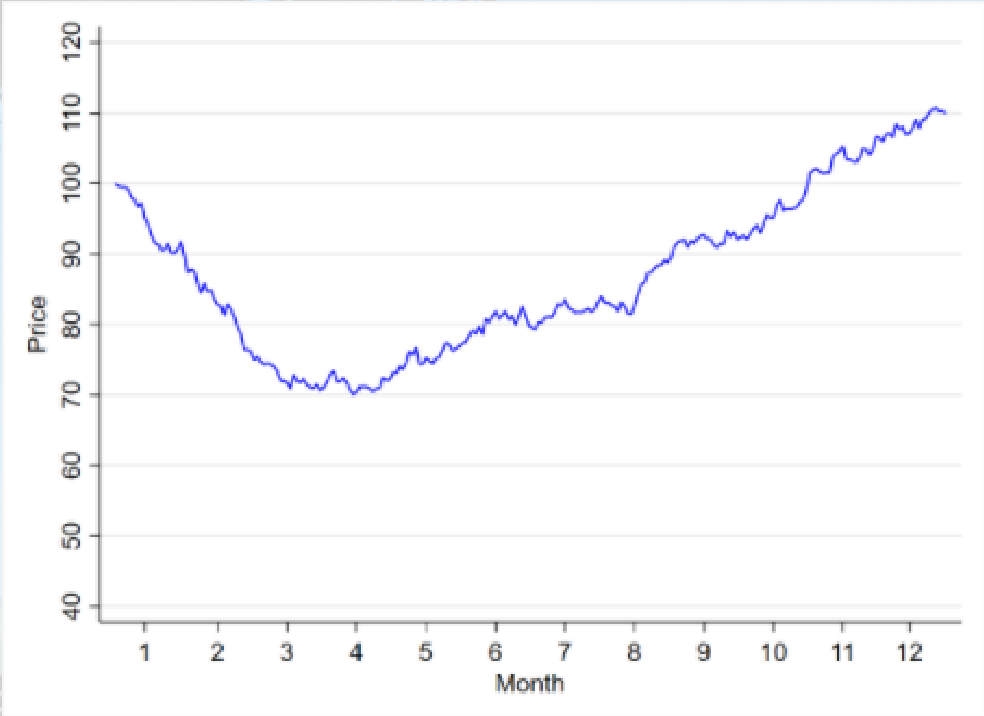
How would you rate your statistical skills?

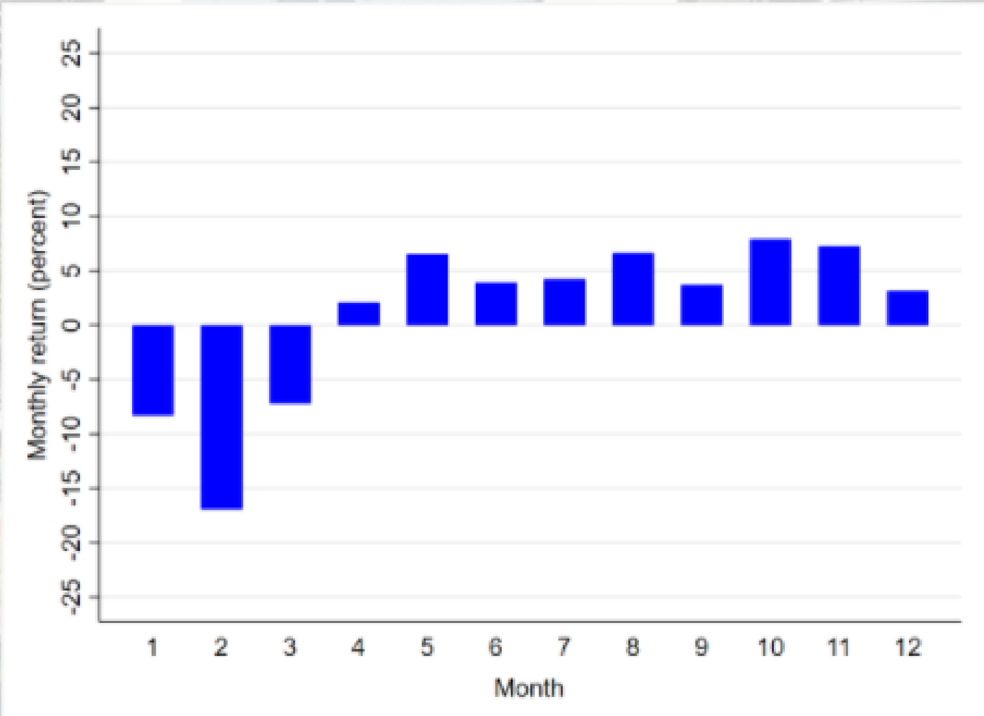
Very low | Very high

0 1 2 3 4 5 6 7 8 9 10

→

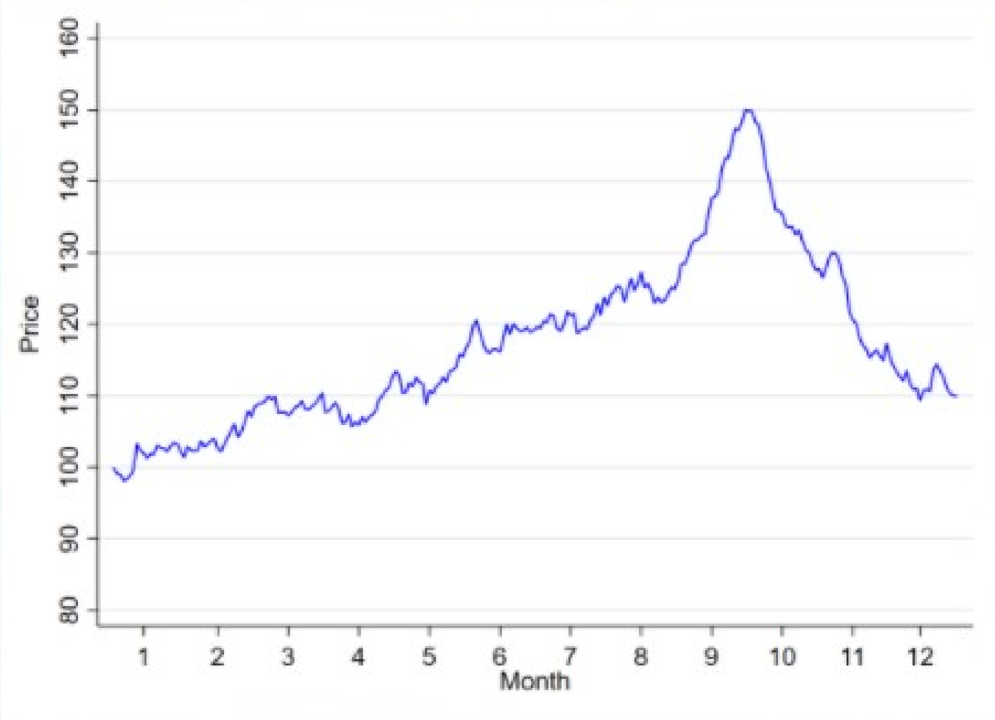
Look at the graphs below. How risky do you perceive this stock?

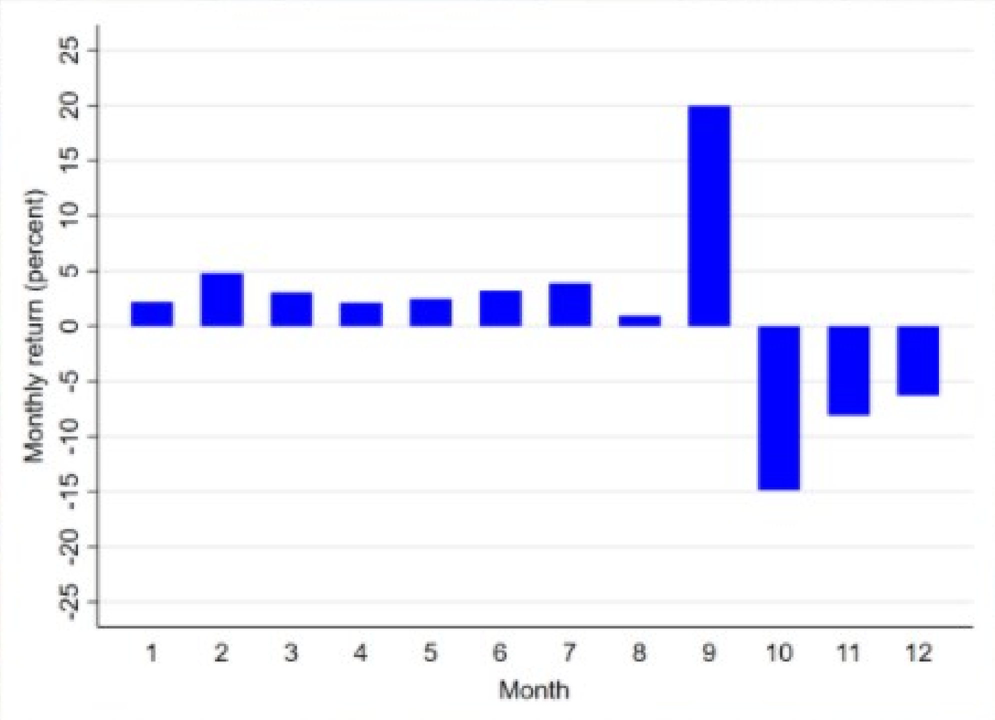




Not risky at all										Extremely risky
0	1	2	3	4	5	6	7	8	9	10

Look at the graphs below. How risky do you perceive this stock?

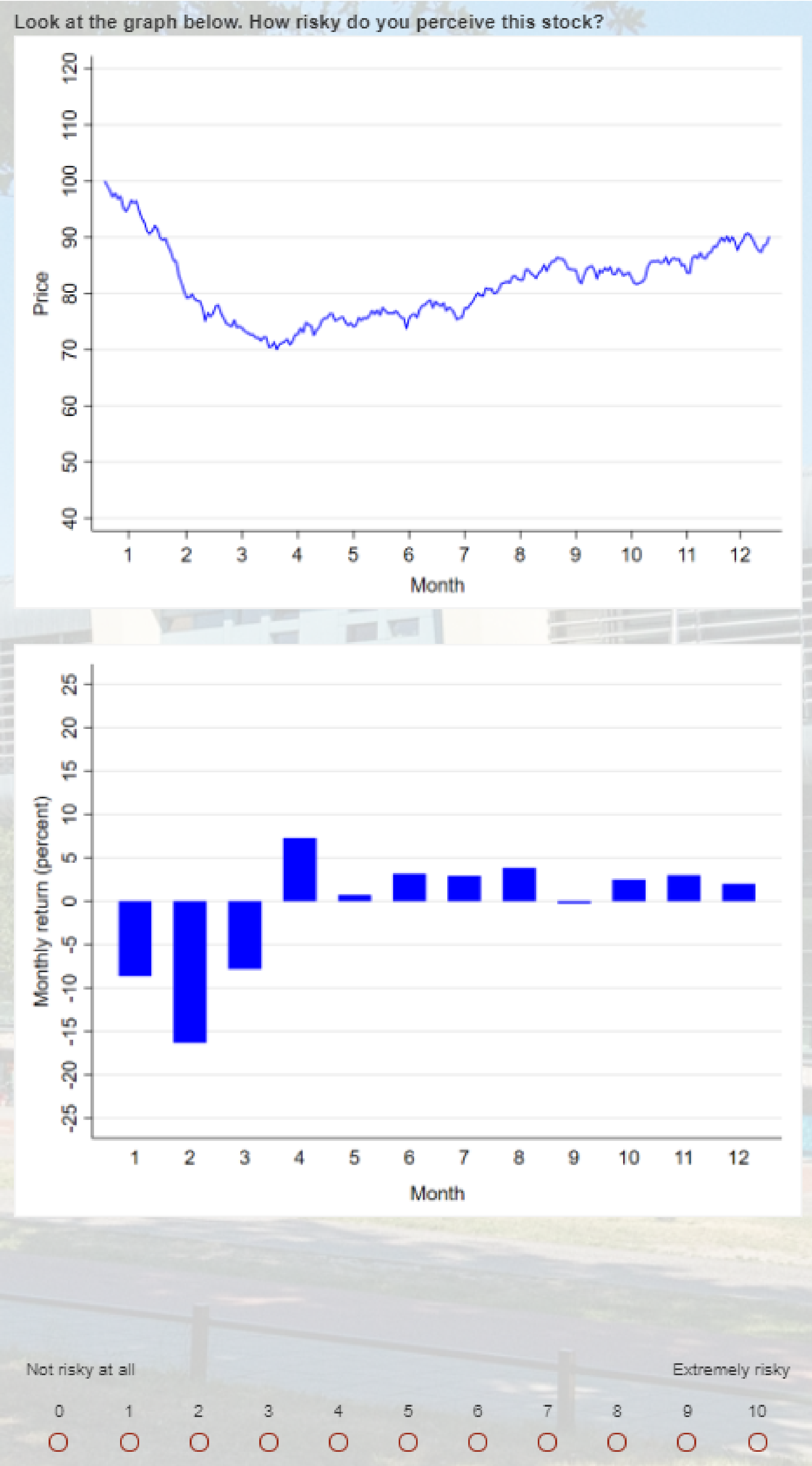




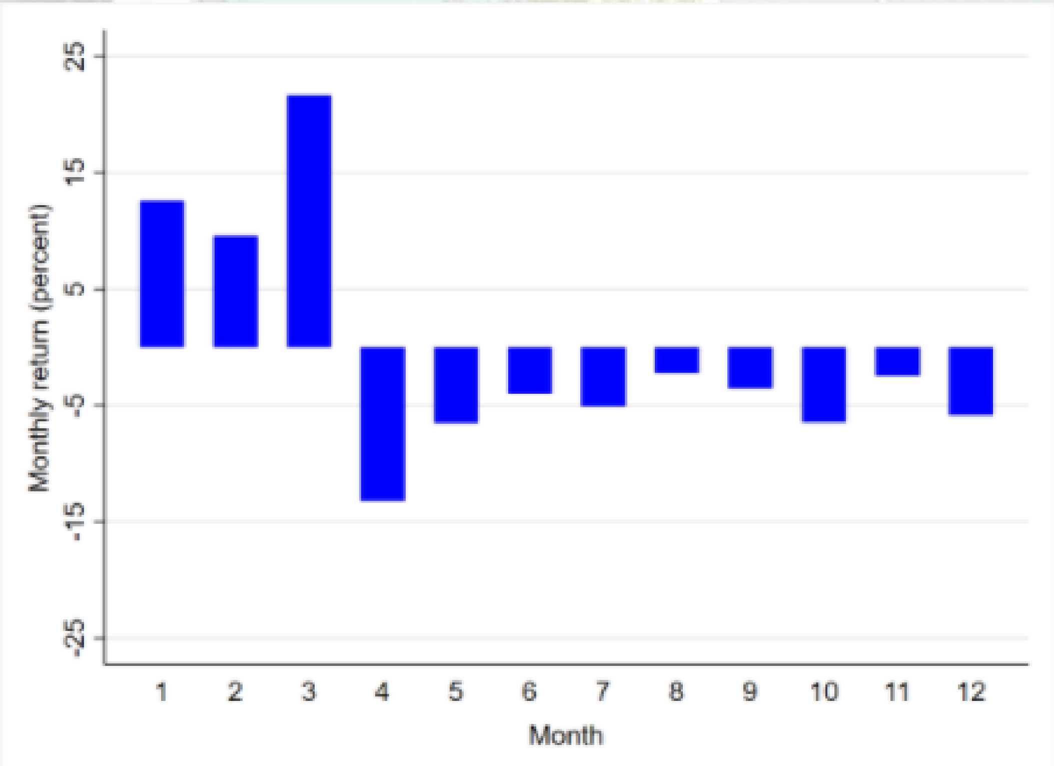
Not risky at all

Extremely risky

0 1 2 3 4 5 6 7 8 9 10


Look at the graph below. How risky do you perceive this stock?
Price
Month
Monthly return (percent)
Month
Not risky at all
Extremely risky
0 1 2 3 4 5 6 7 8 9 10

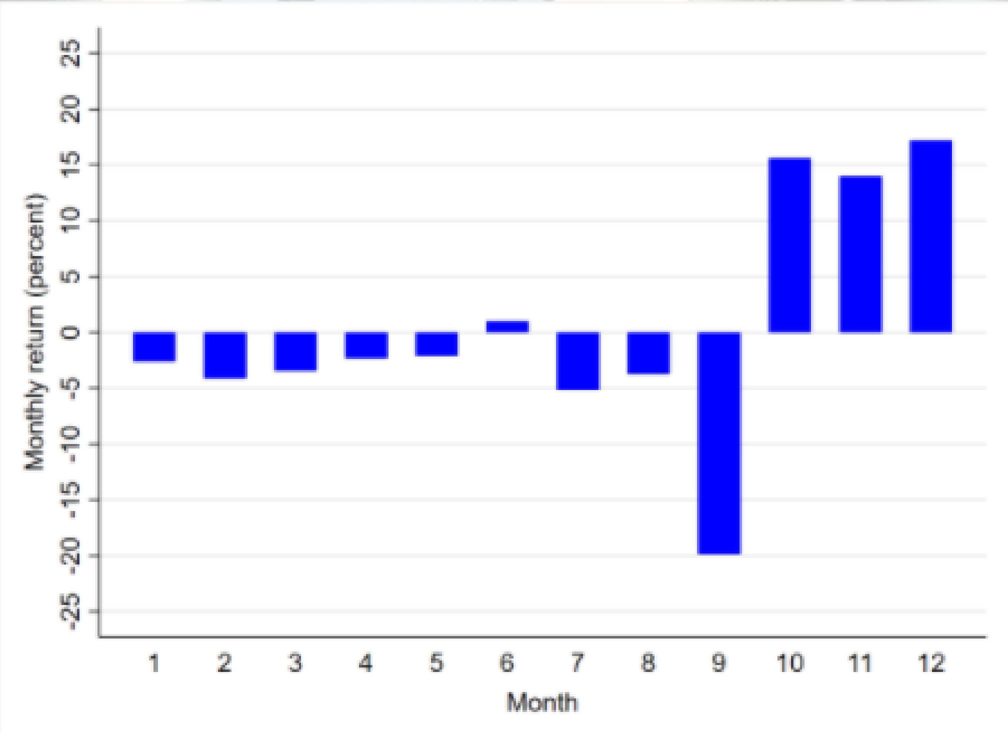
Look at the graphs below. How risky do you perceive this stock?



Not risky at all | Extremely risky

0 1 2 3 4 5 6 7 8 9 10

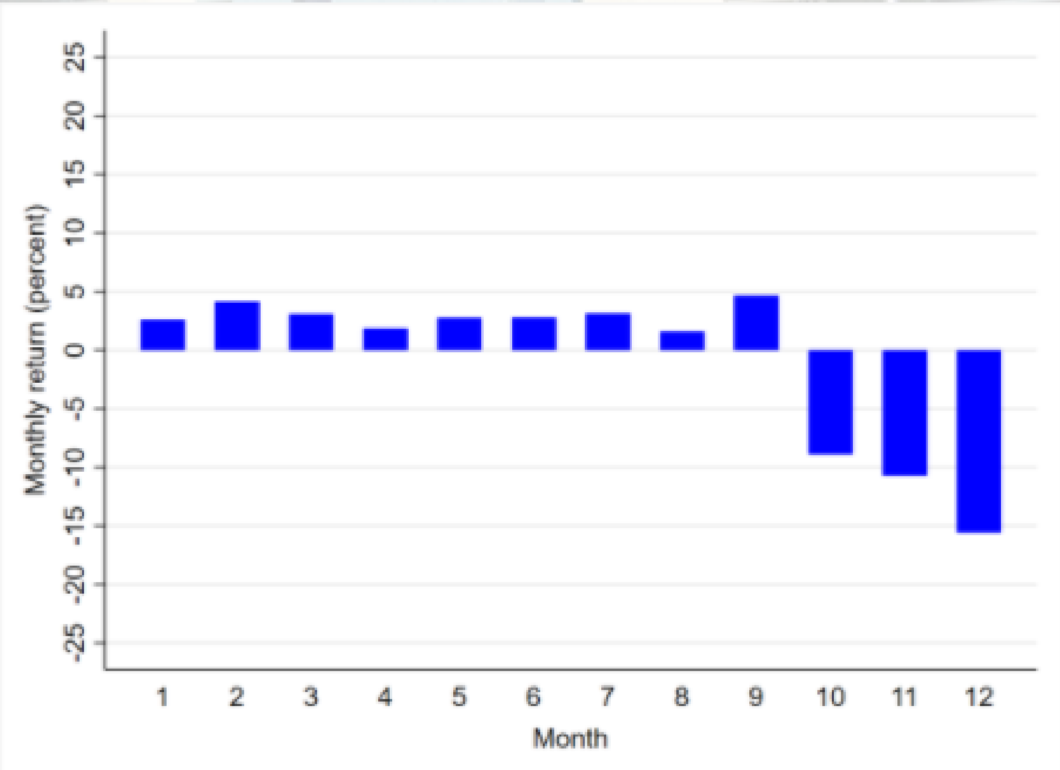
Look at the graphs below. How risky do you perceive this stock?



Not risky at all — Extremely risky

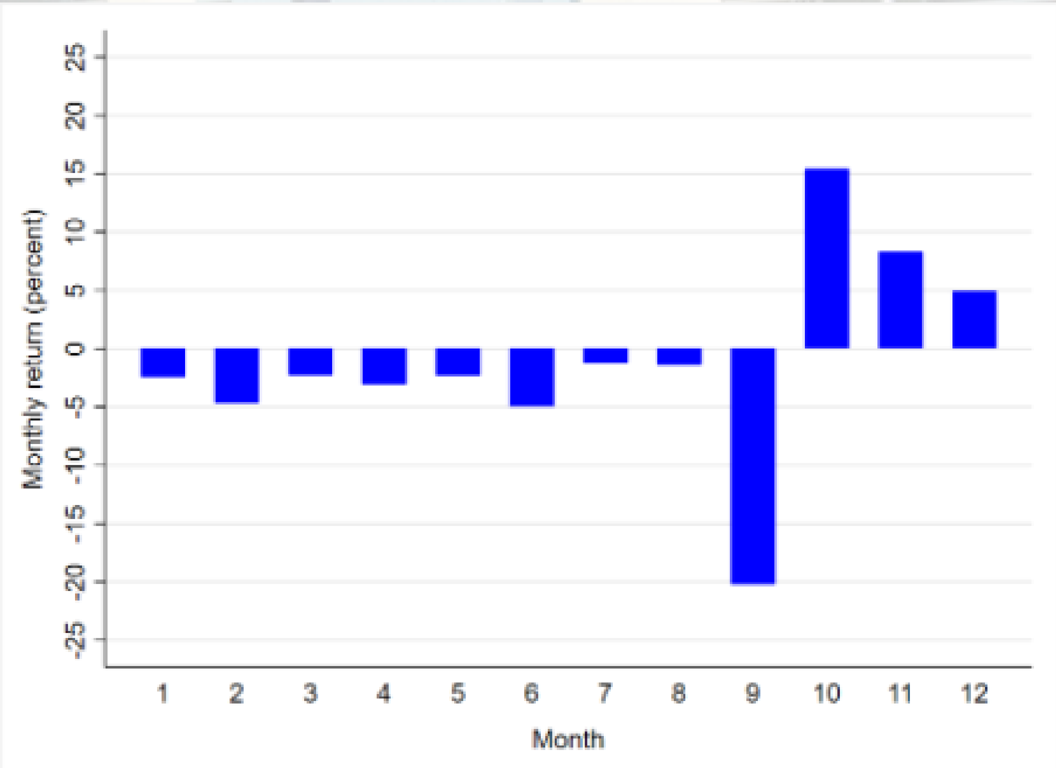
0 1 2 3 4 5 6 7 8 9 10

Look at the graphs below. How risky do you perceive this stock?



Not risky at all										Extremely risky
0	1	2	3	4	5	6	7	8	9	10
○	○	○	○	○	○	○	○	○	○	○

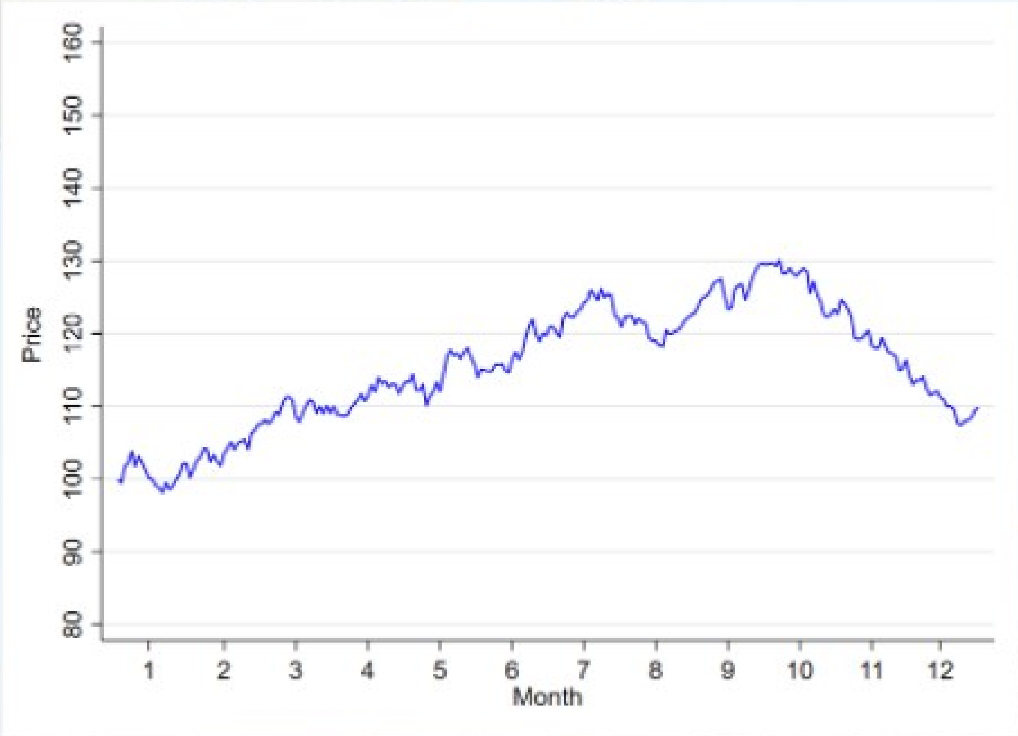
Look at the graphs below. How risky do you perceive this stock?

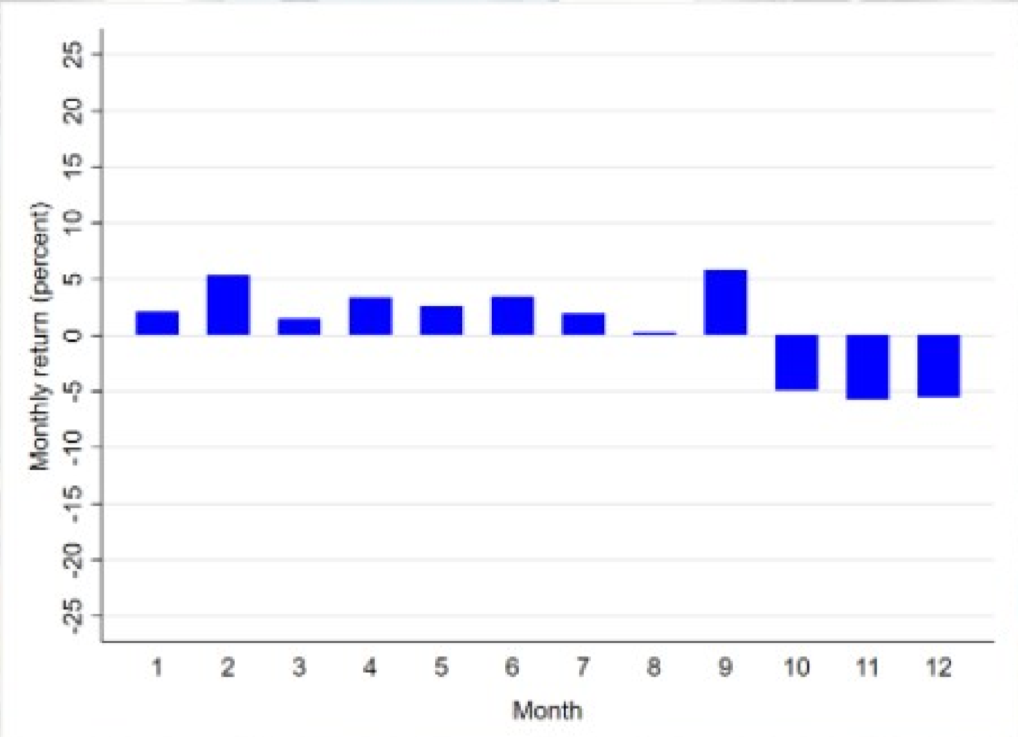


Not risky at all — Extremely risky

0	1	2	3	4	5	6	7	8	9	10
○	○	○	○	○	○	○	○	○	○	○

Look at the graphs below. How risky do you perceive this stock?





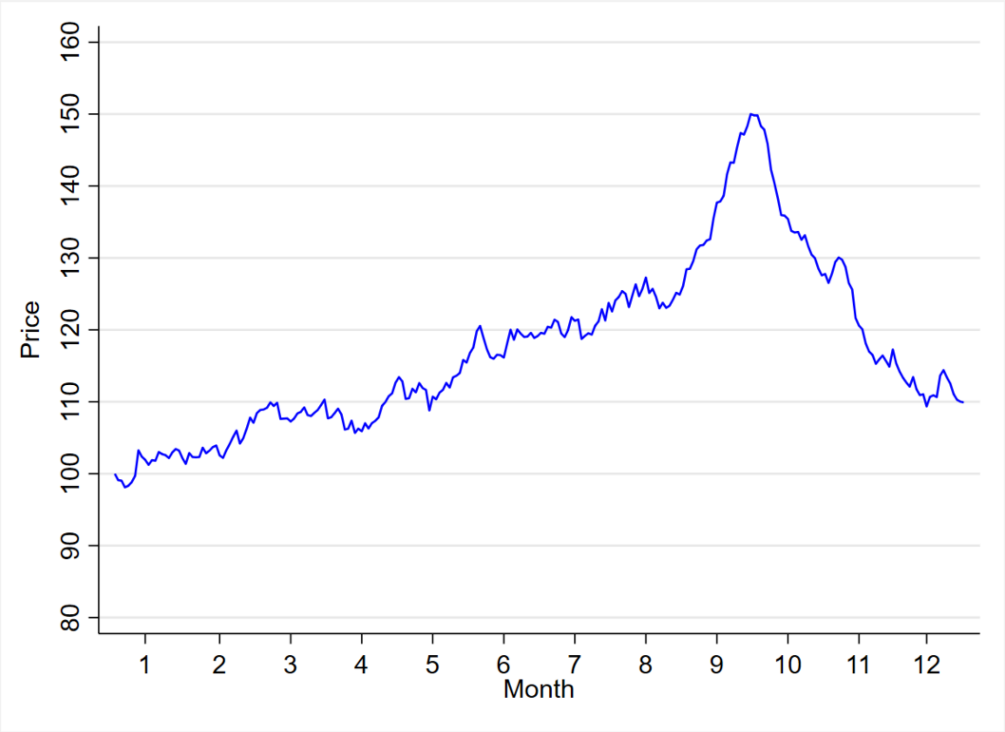
Not risky at all | Extremely risky

0	1	2	3	4	5	6	7	8	9	10
○	○	○	○	○	○	○	○	○	○	○

APPENDIX B: Price Charts & Return Bar Charts

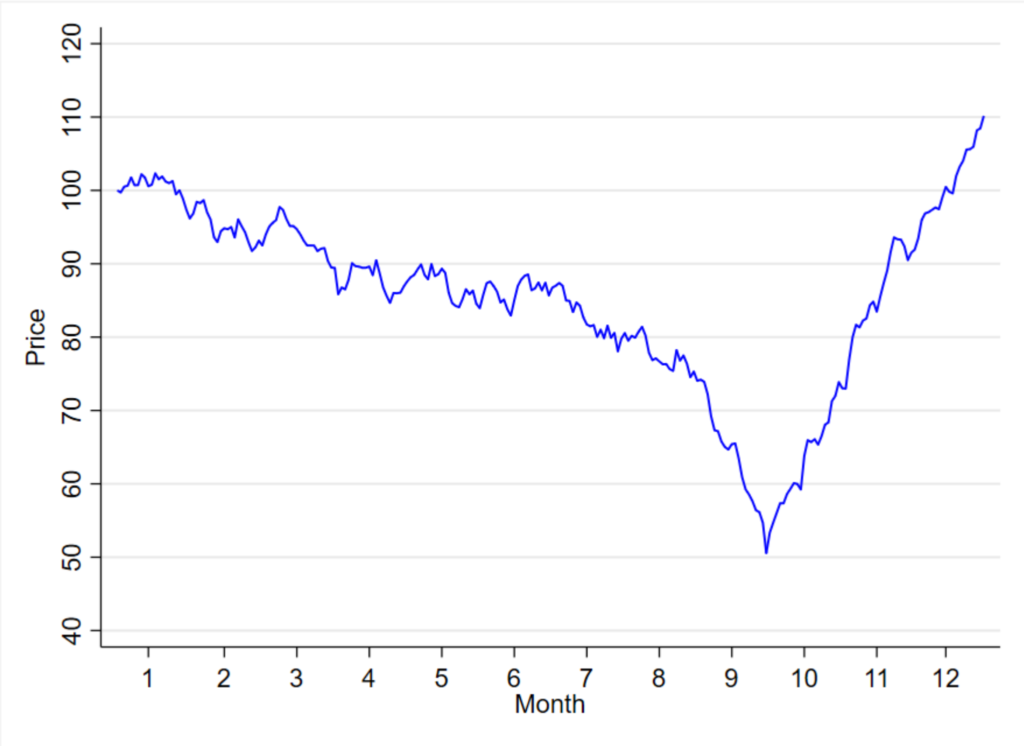
Price Charts

Price Chart 1

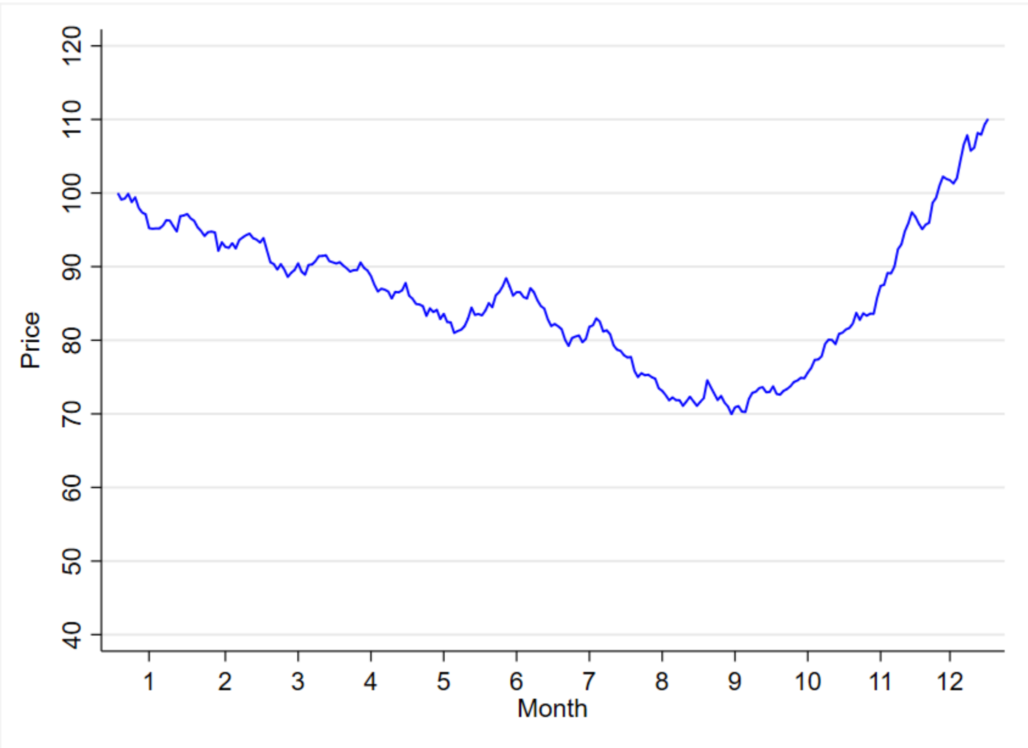


Price Chart 2

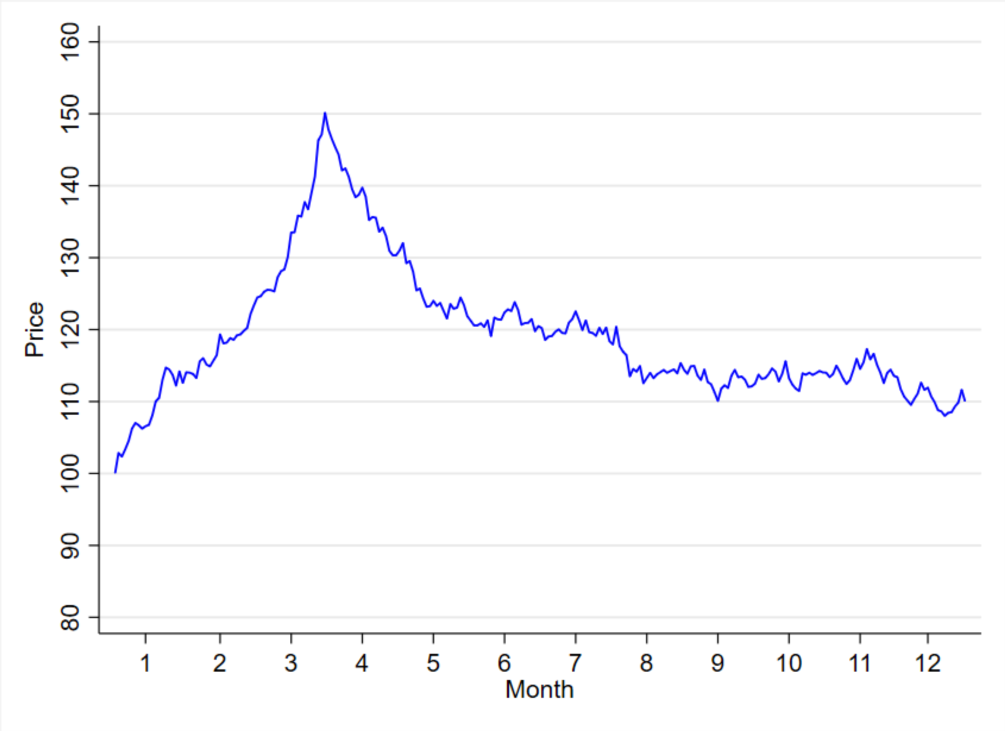
Price Chart 3



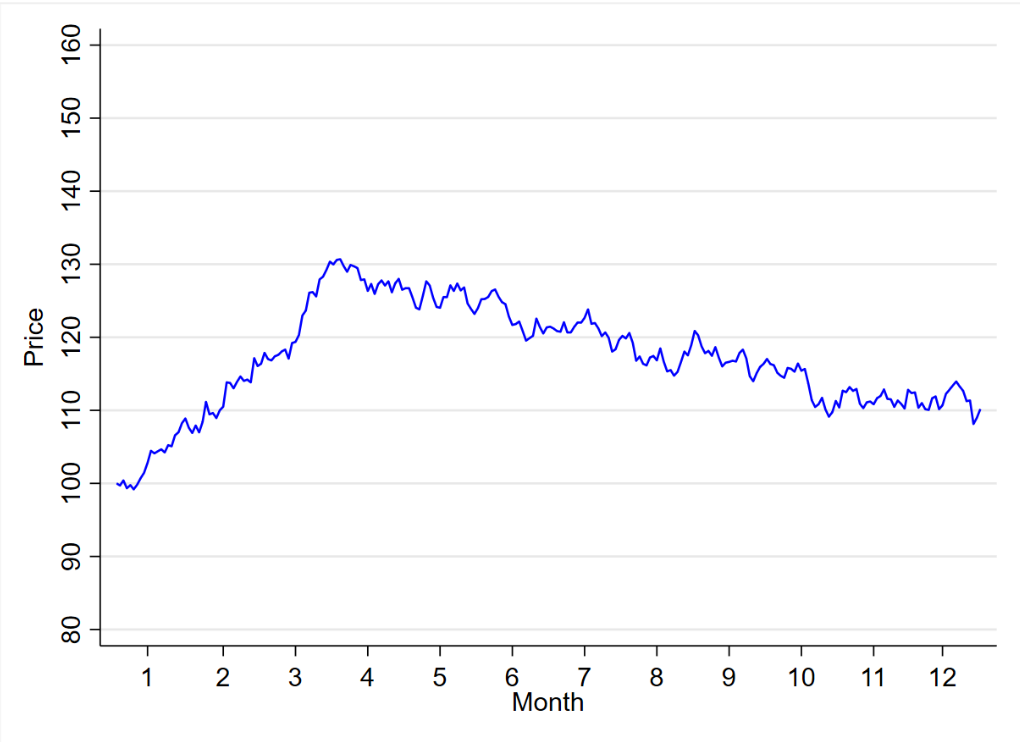
Price Chart 4



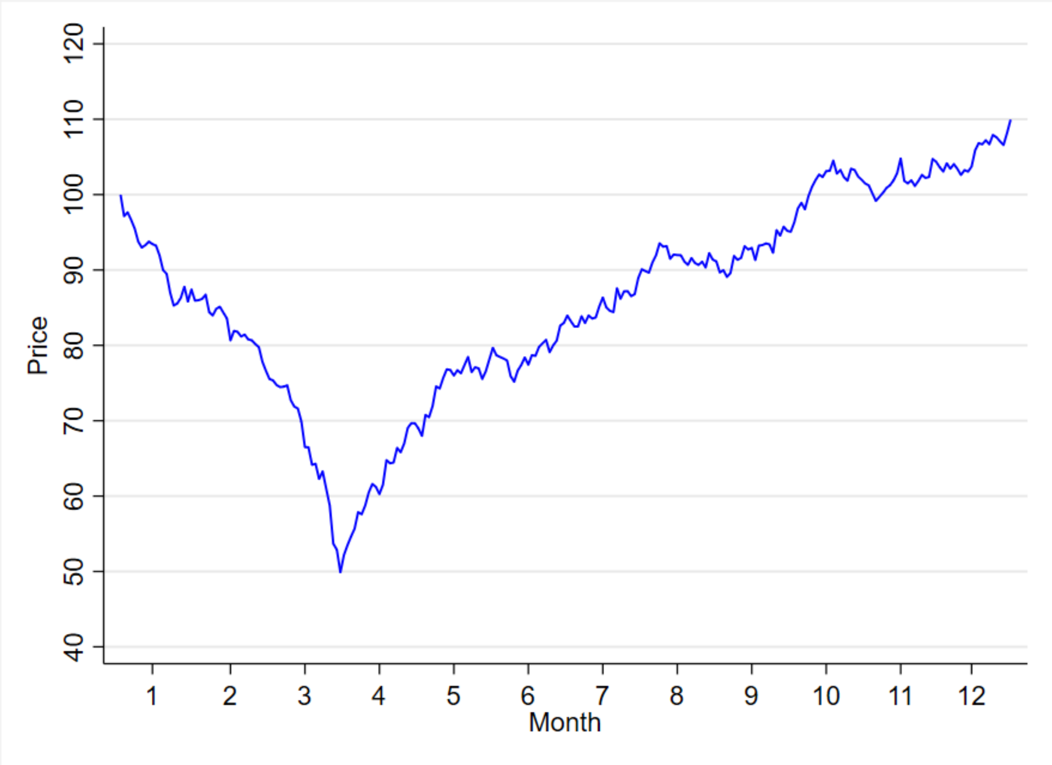
Price Chart 5



Price Chart 6

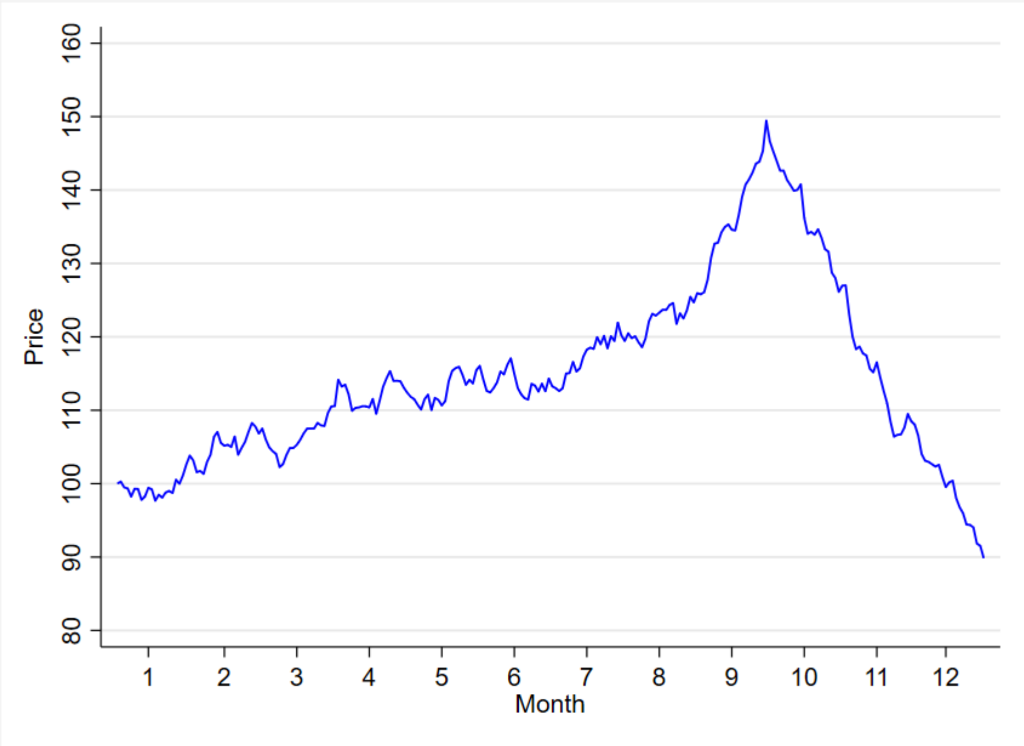


Price Chart 7



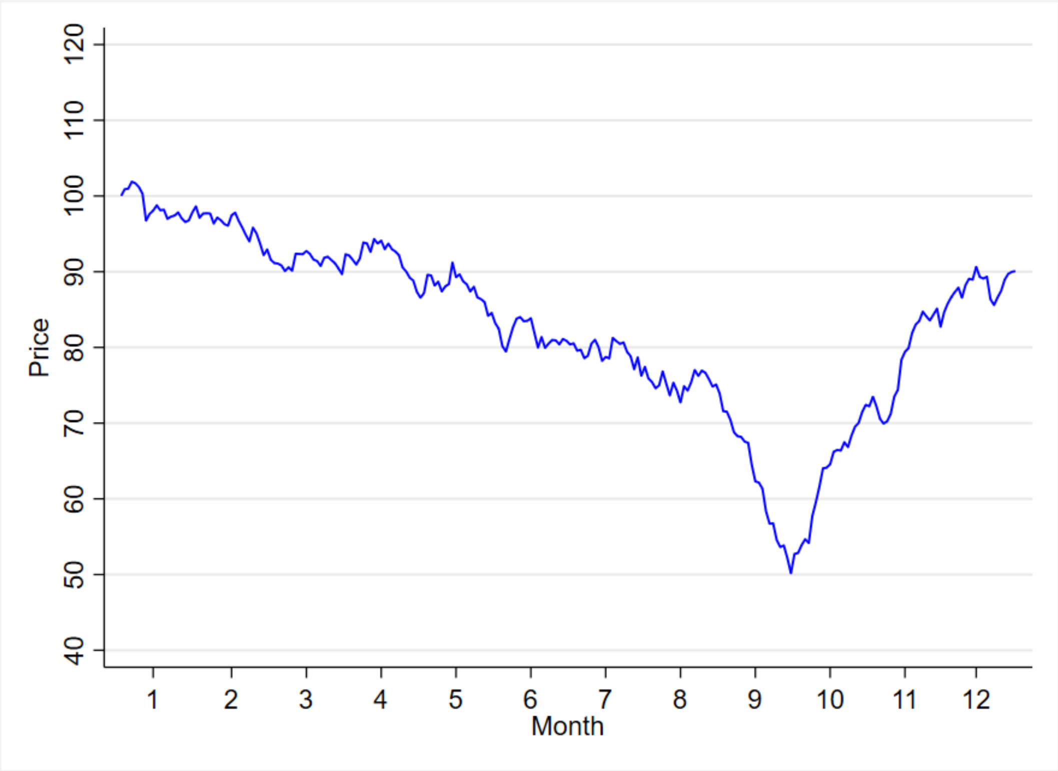
Price Chart 8

Price Chart 9

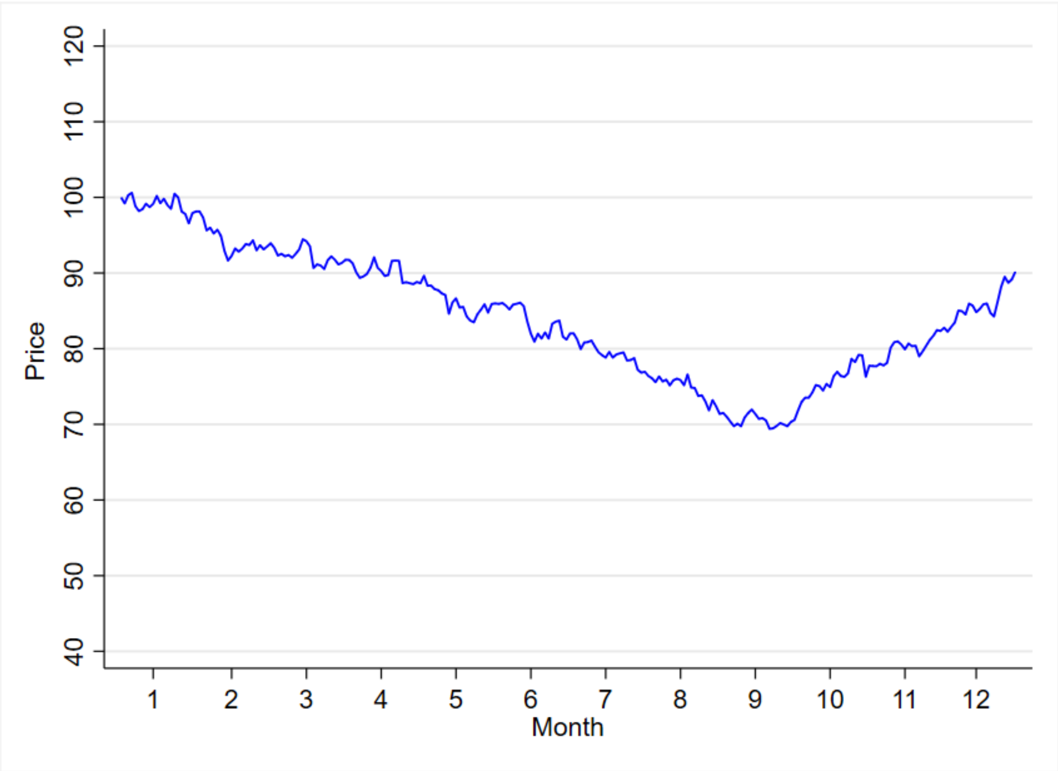


Price Chart 10

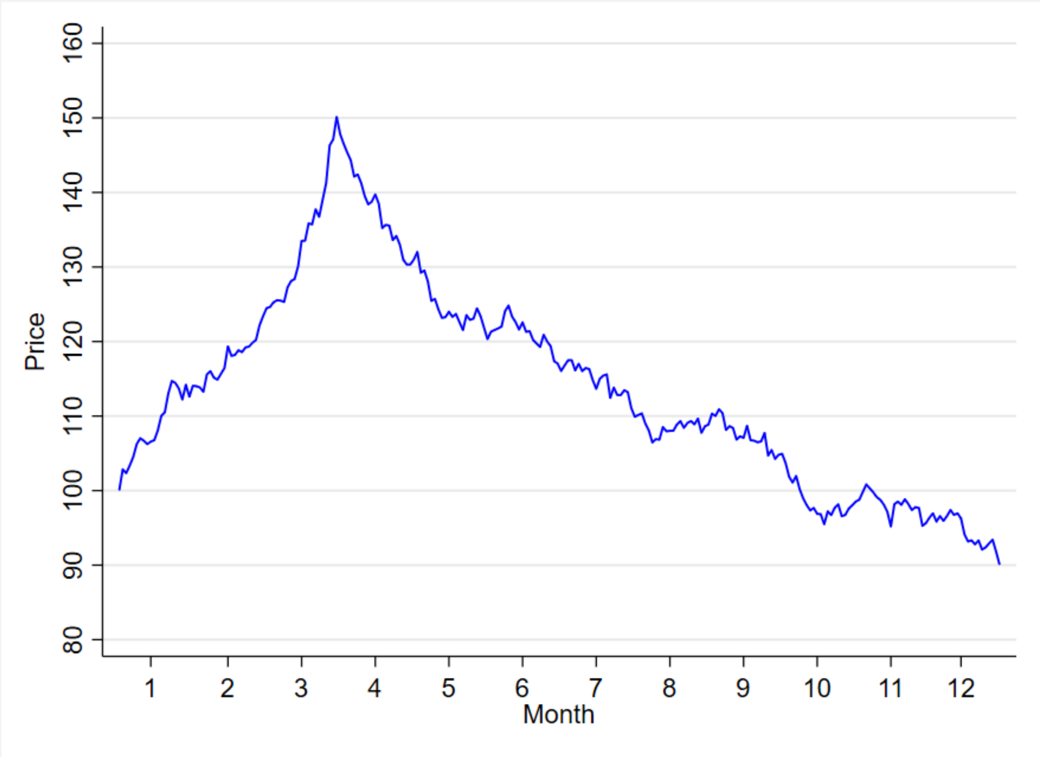
Price Chart 11



Price Chart 12

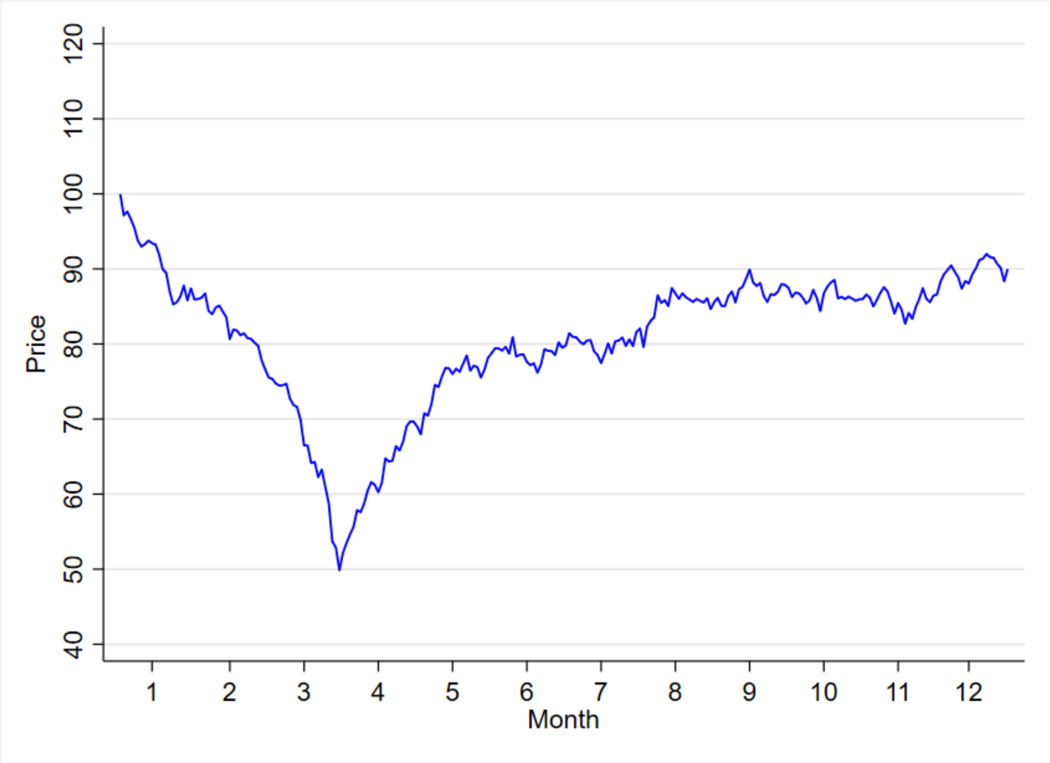


Price Chart 13

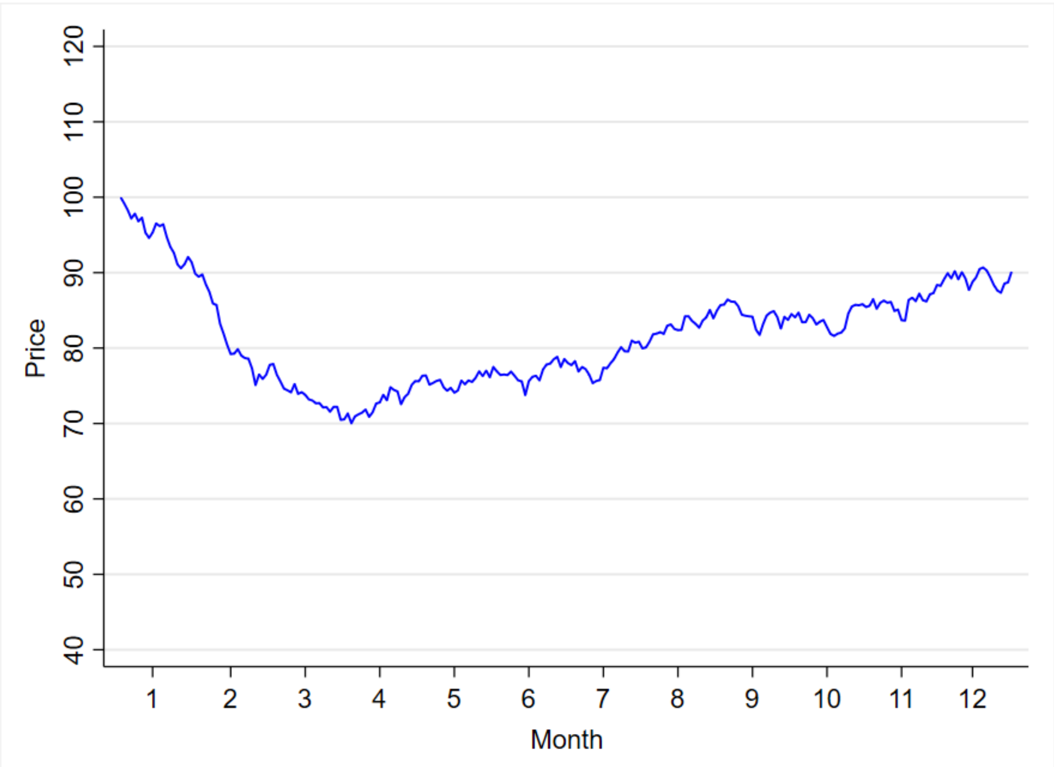


Price Chart 14

Price Chart 15

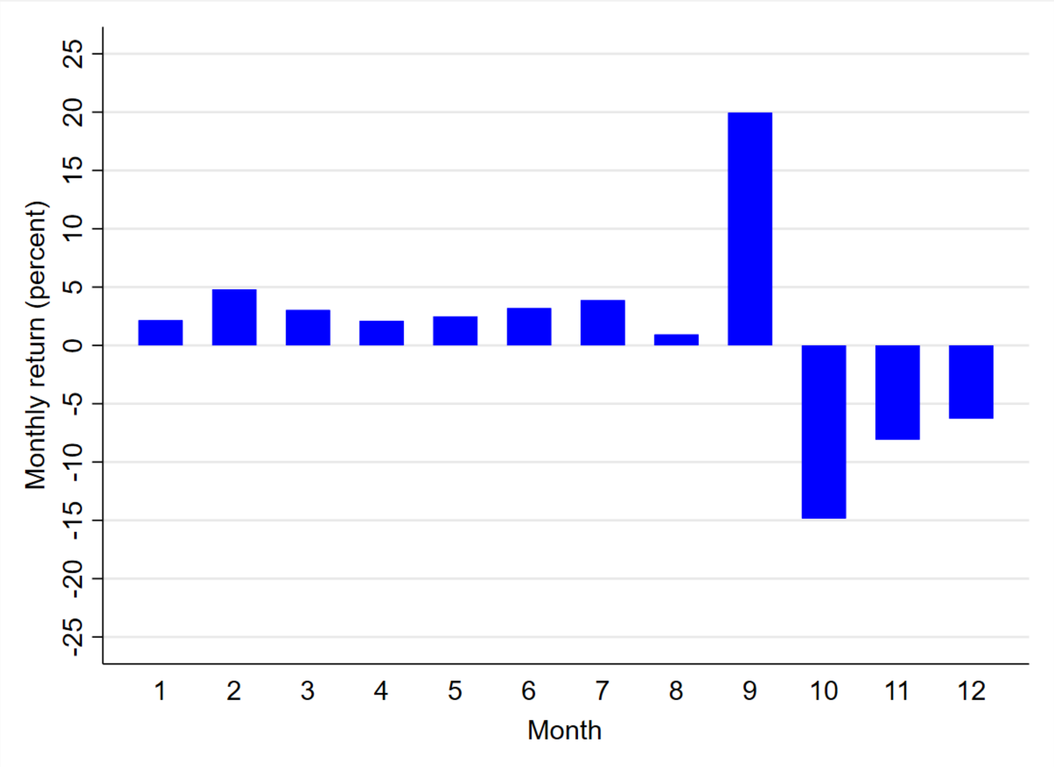


Price Chart 16

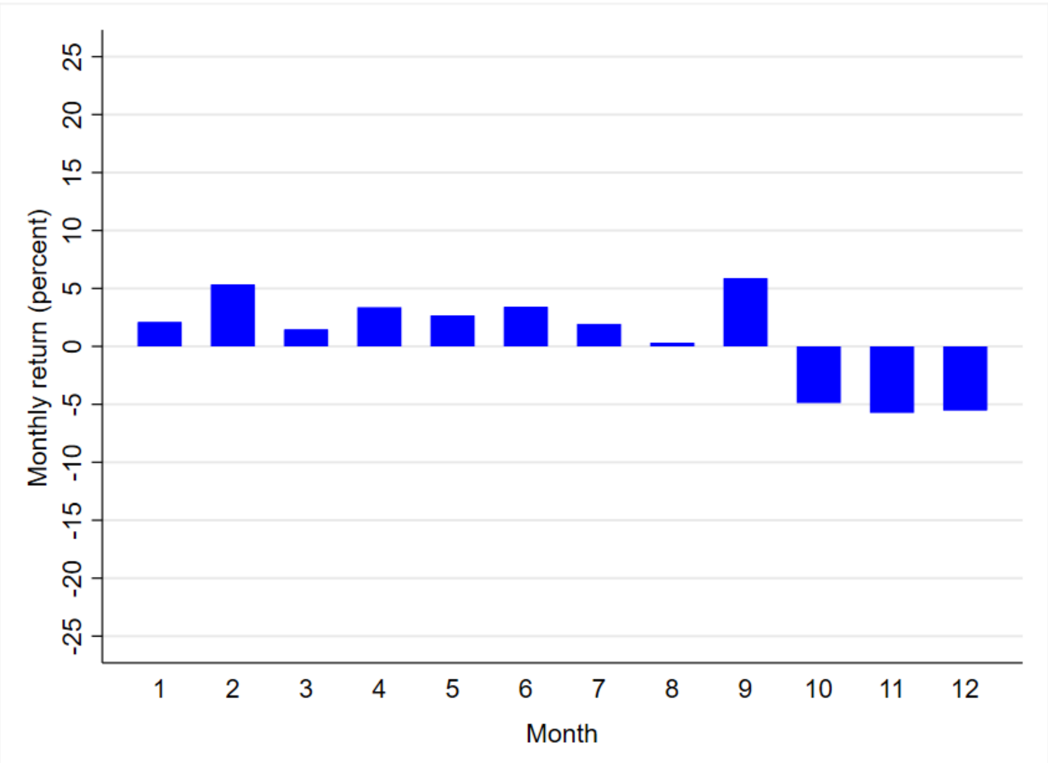


Return Bar Charts

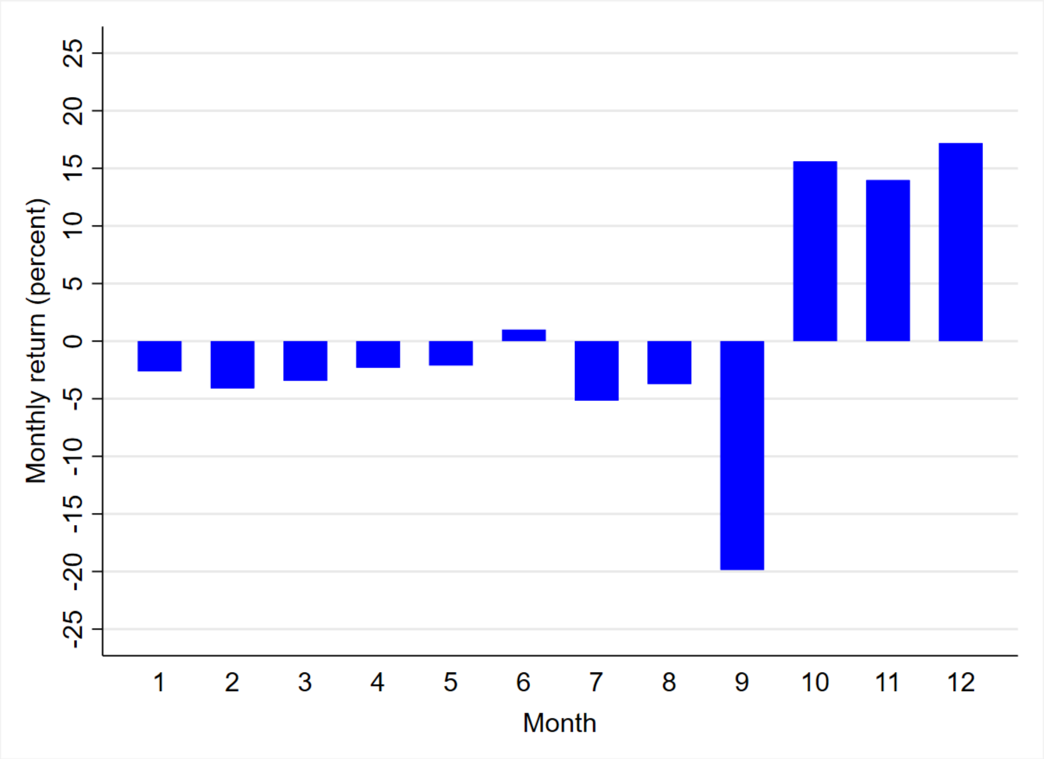
Return Bar Chart 1



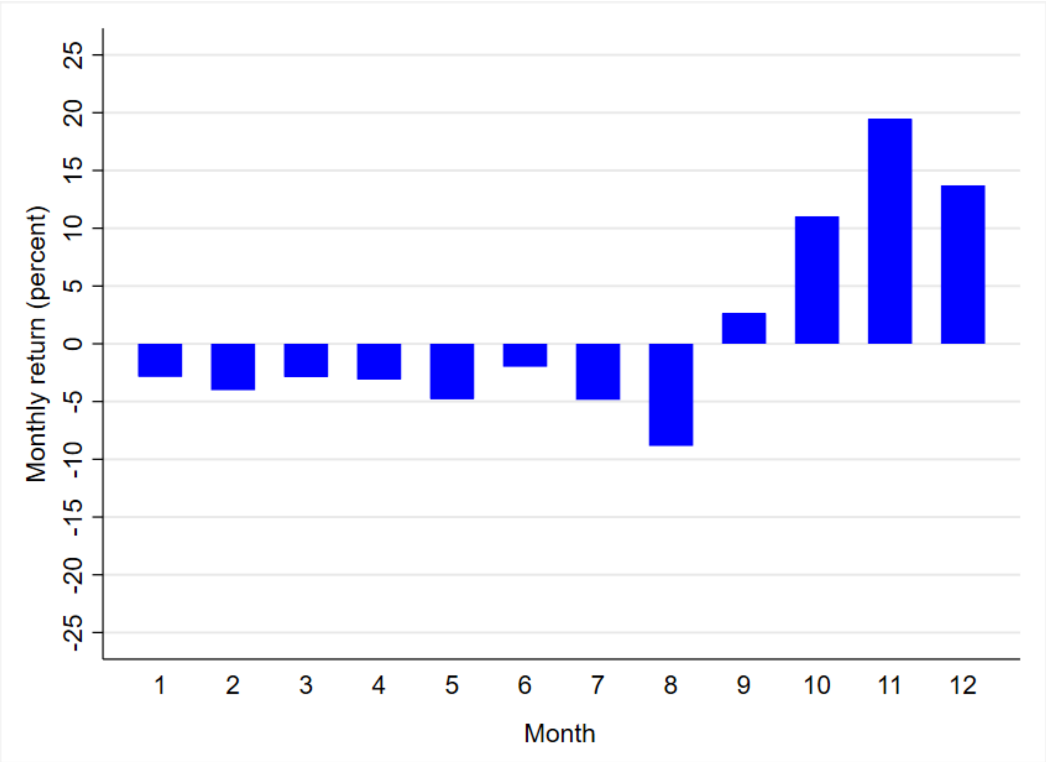
Return Bar Chart 2



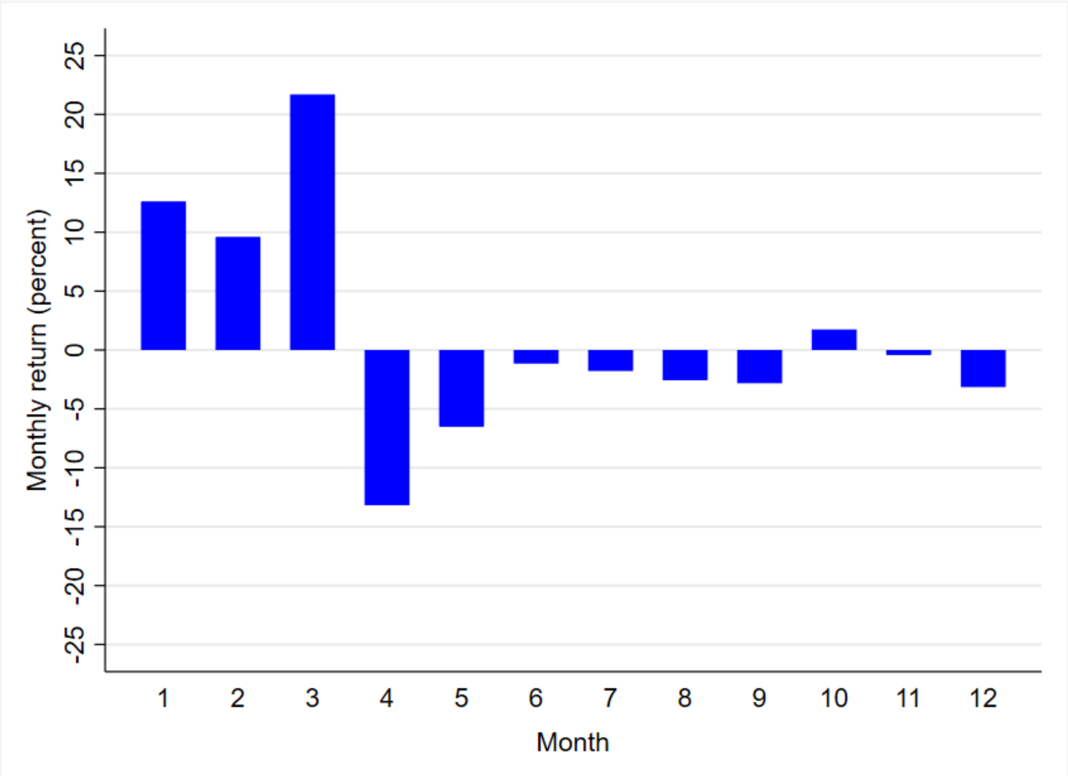
Return Bar Chart 3



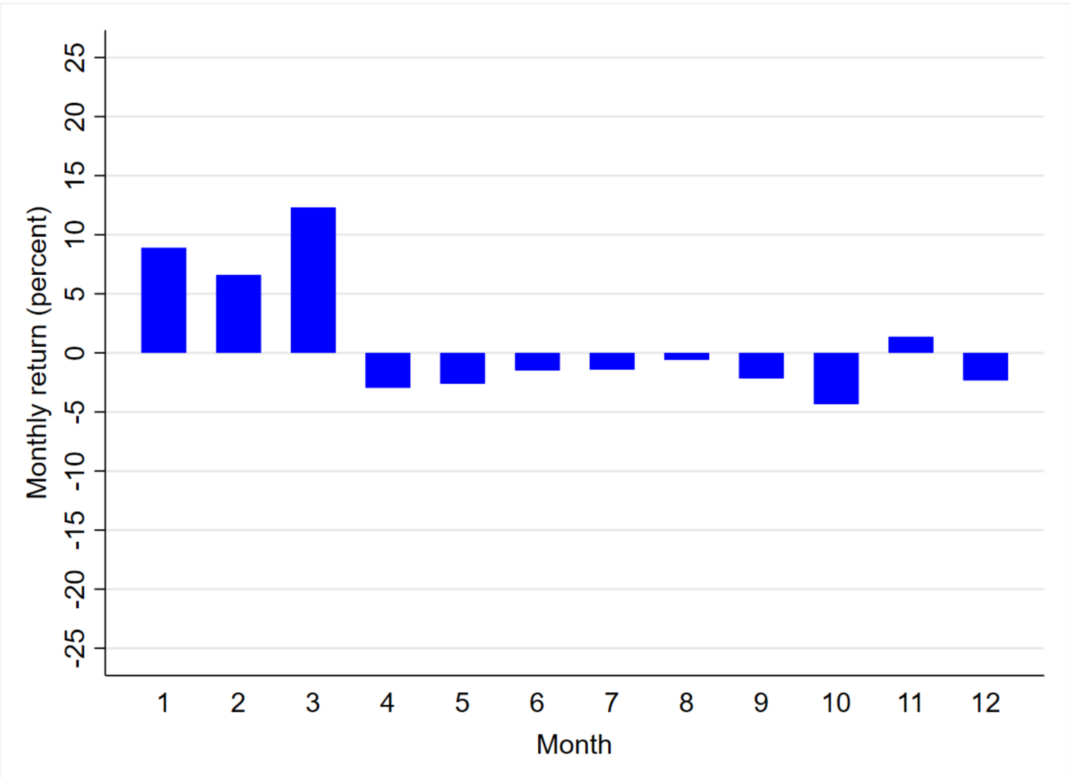
Return Bar Chart 4



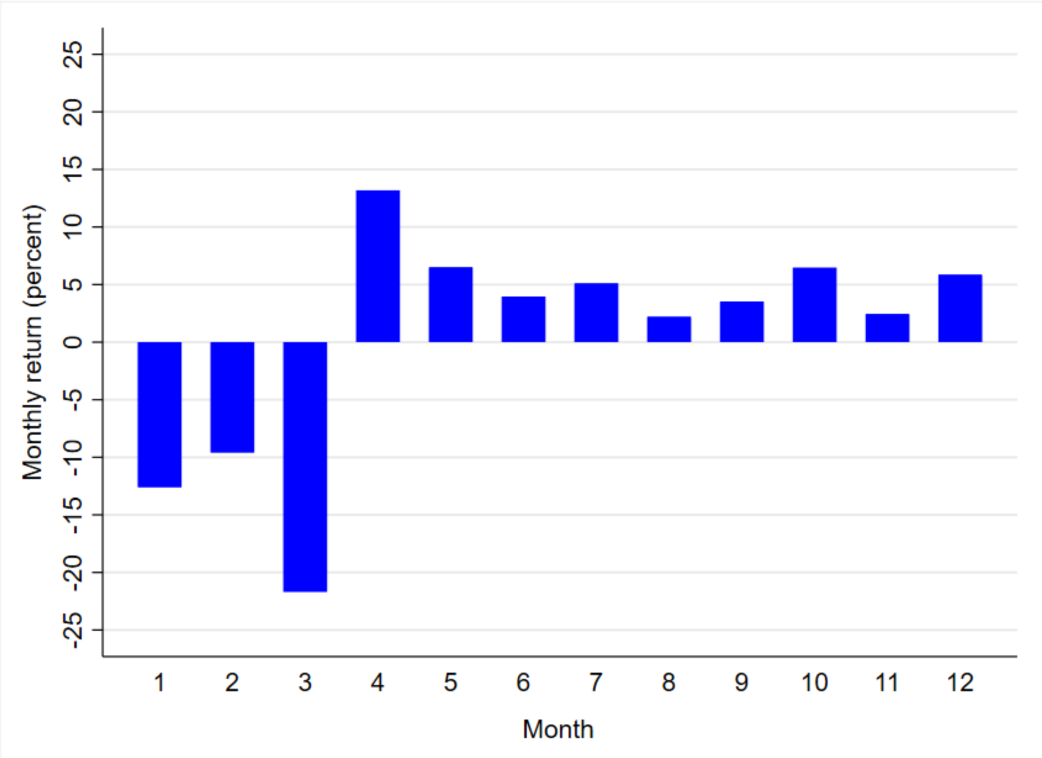
Return Bar Chart 5



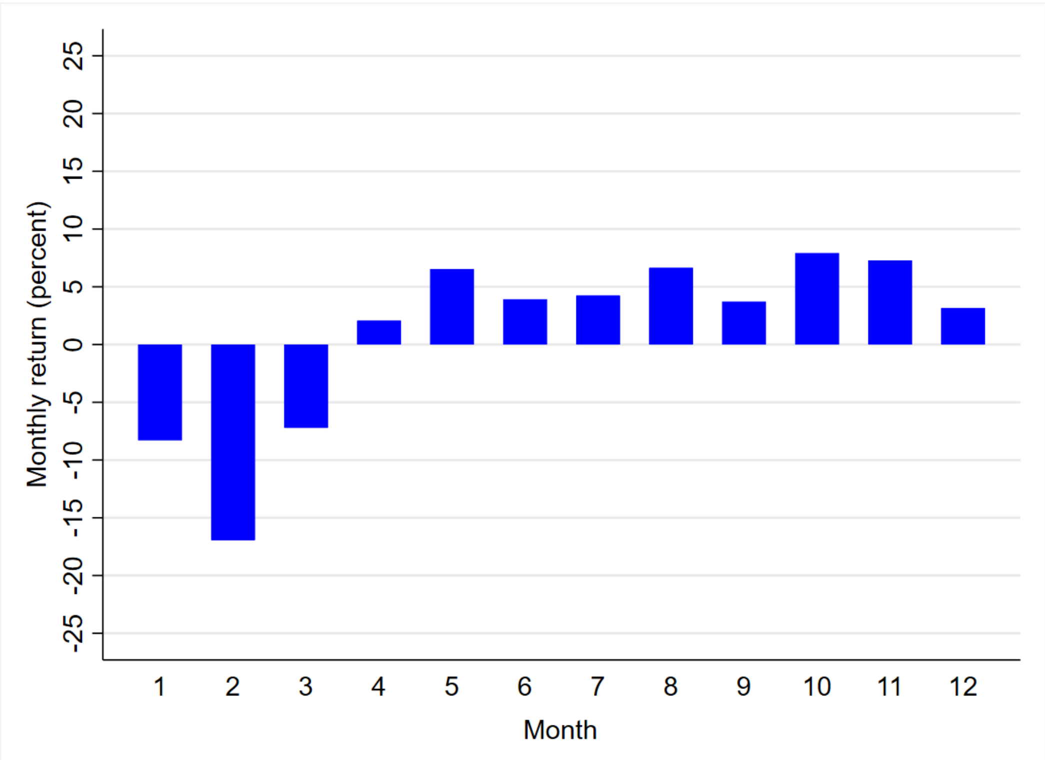
Return Bar Chart 6



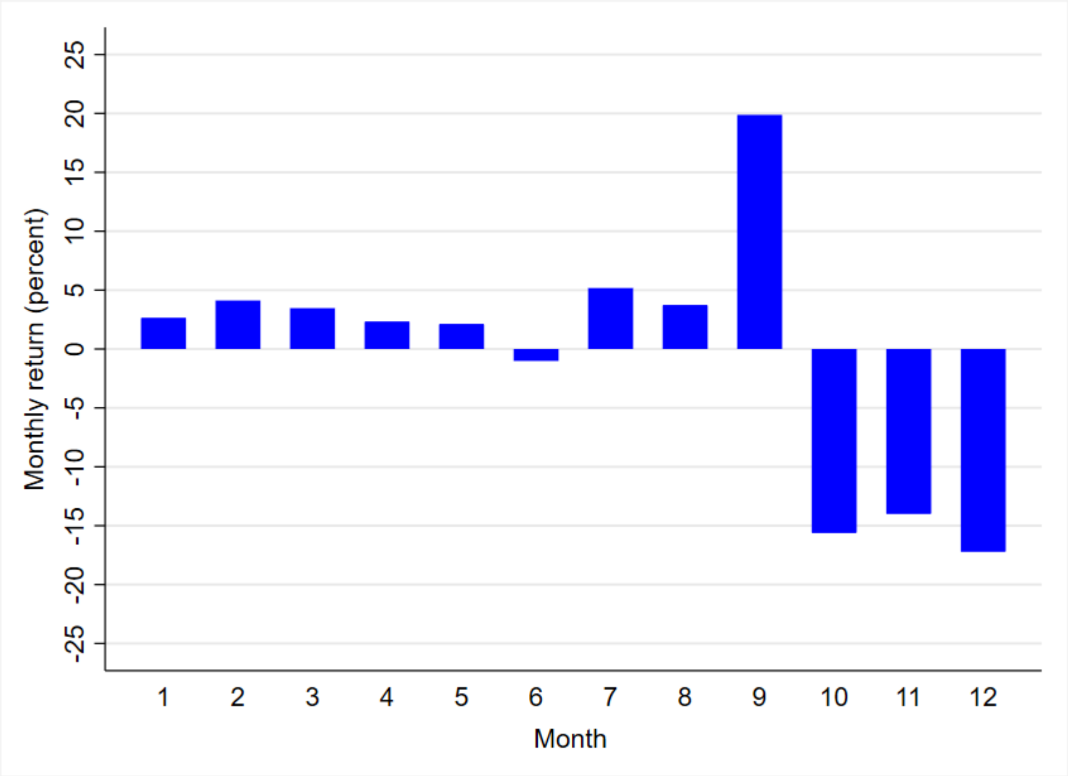
Return Bar Chart 7



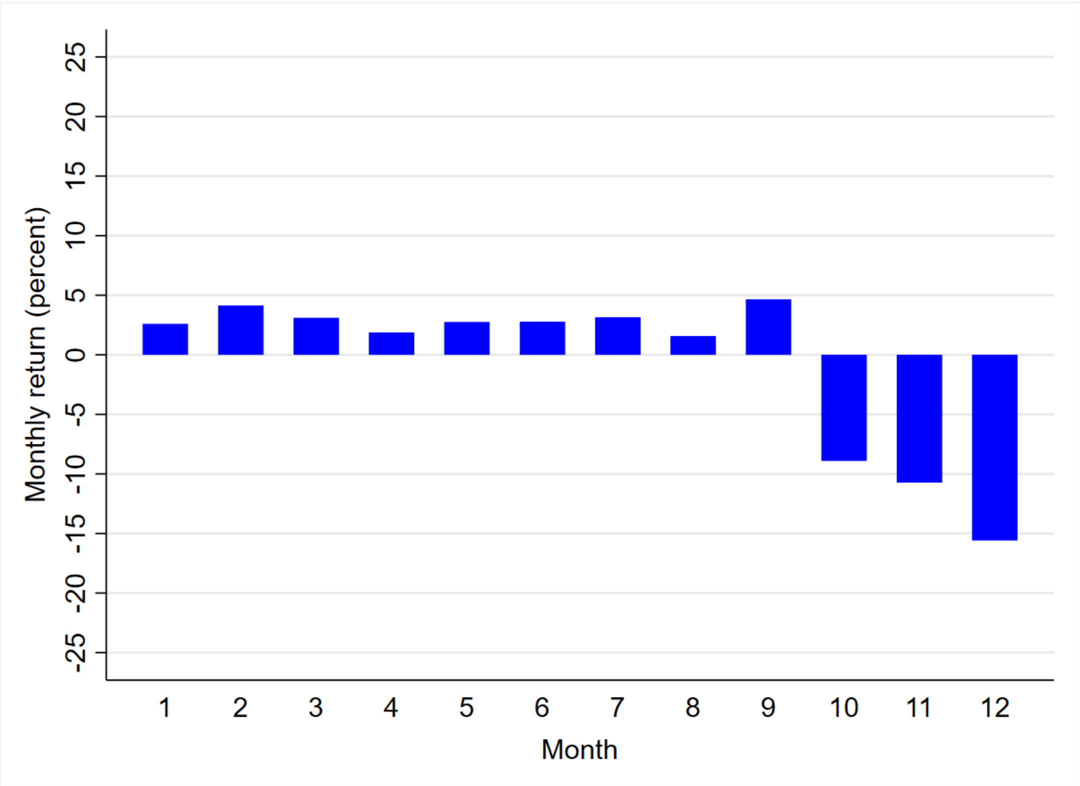
Return Bar Chart 8



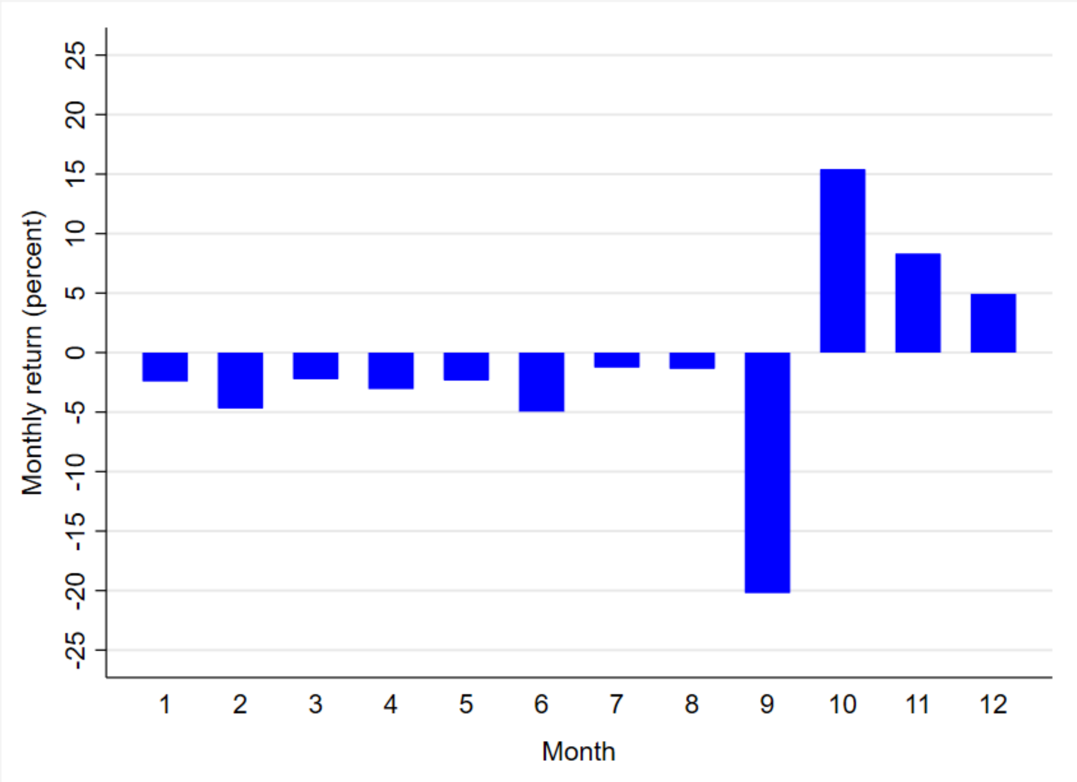
Return Bar Chart 9



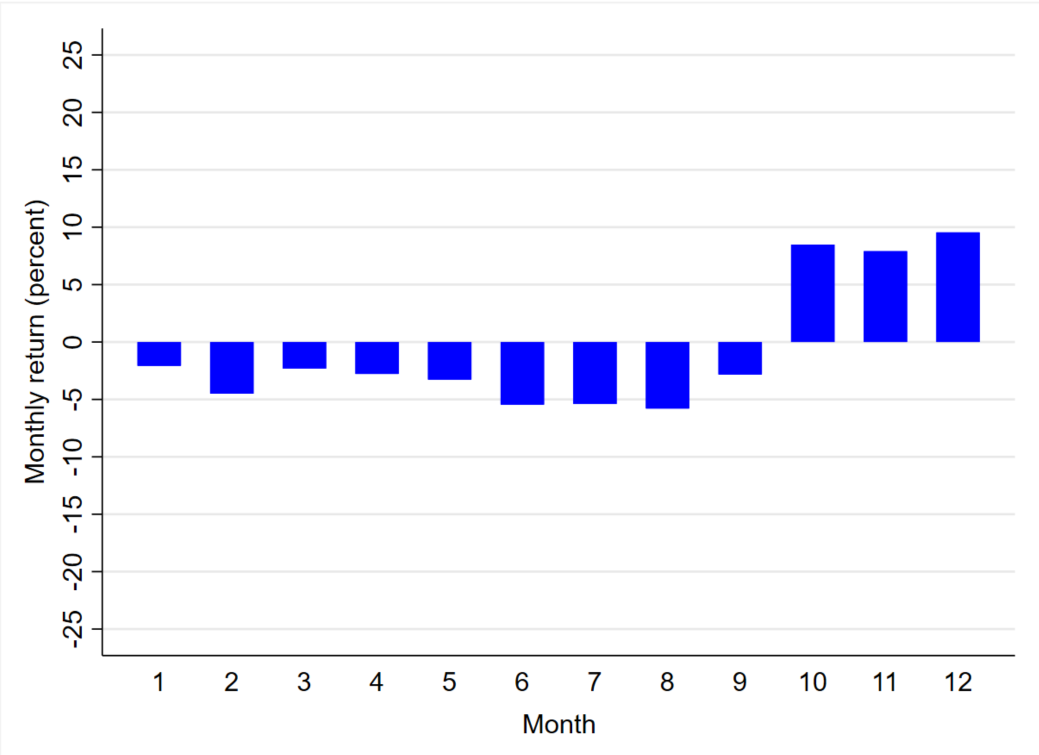
Return Bar Chart 10



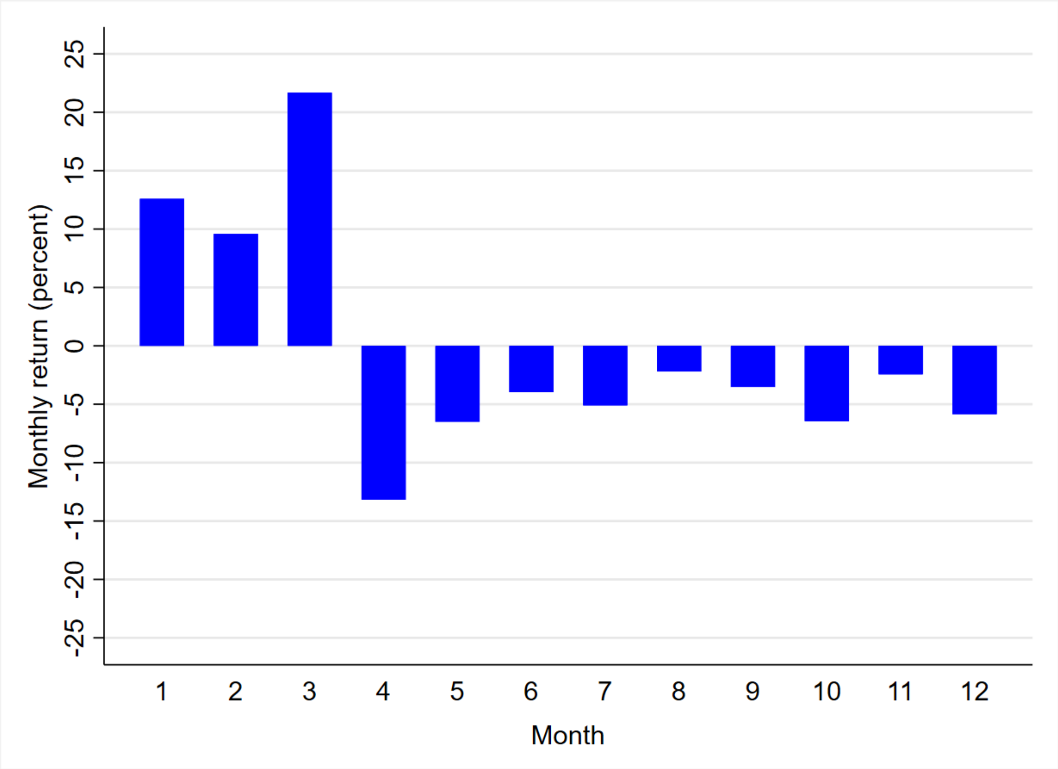
Return Bar Chart 11



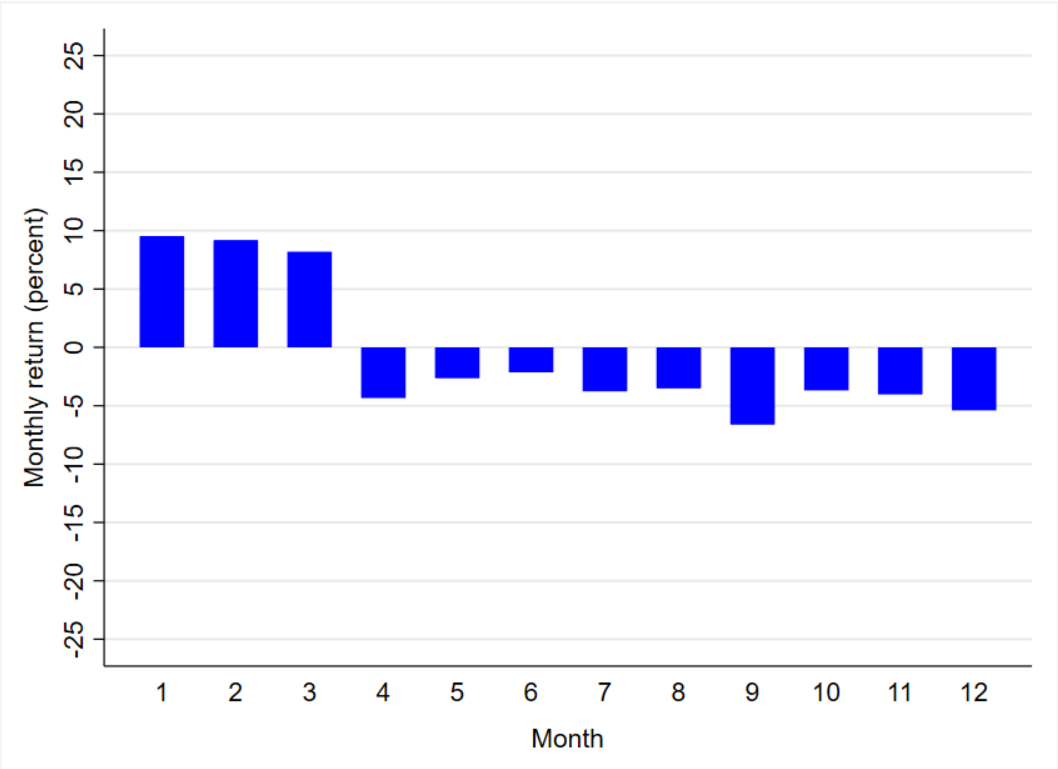
Return Bar Chart 12



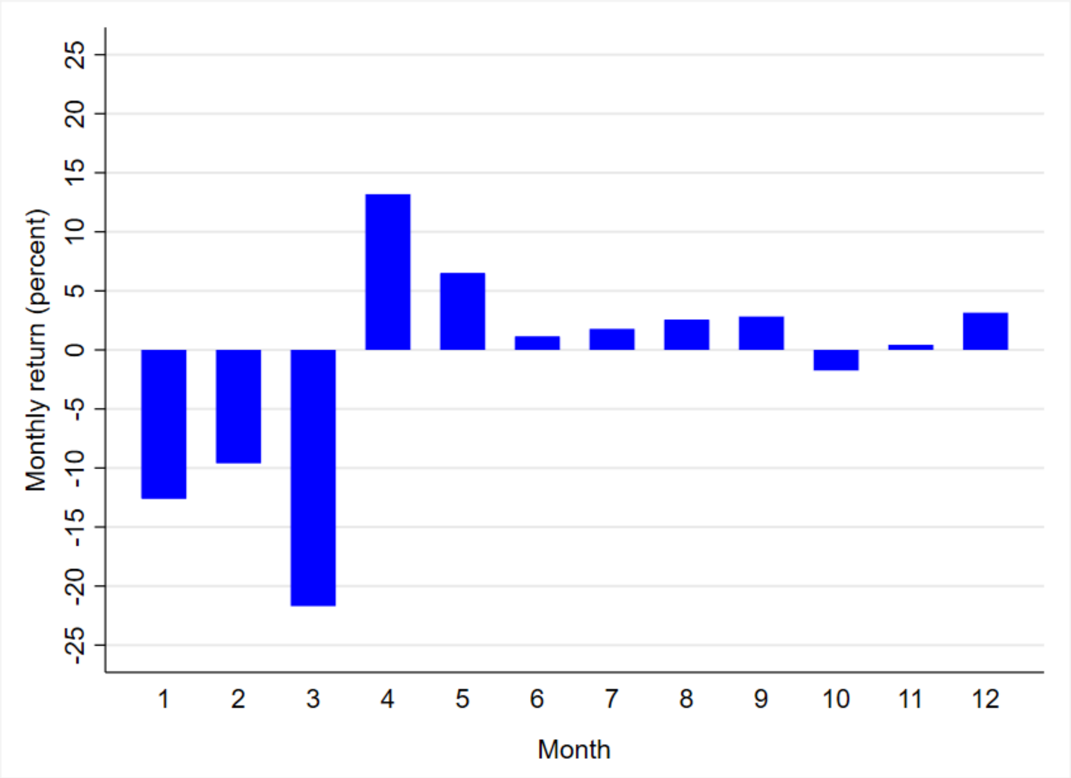
Return Bar Chart 13



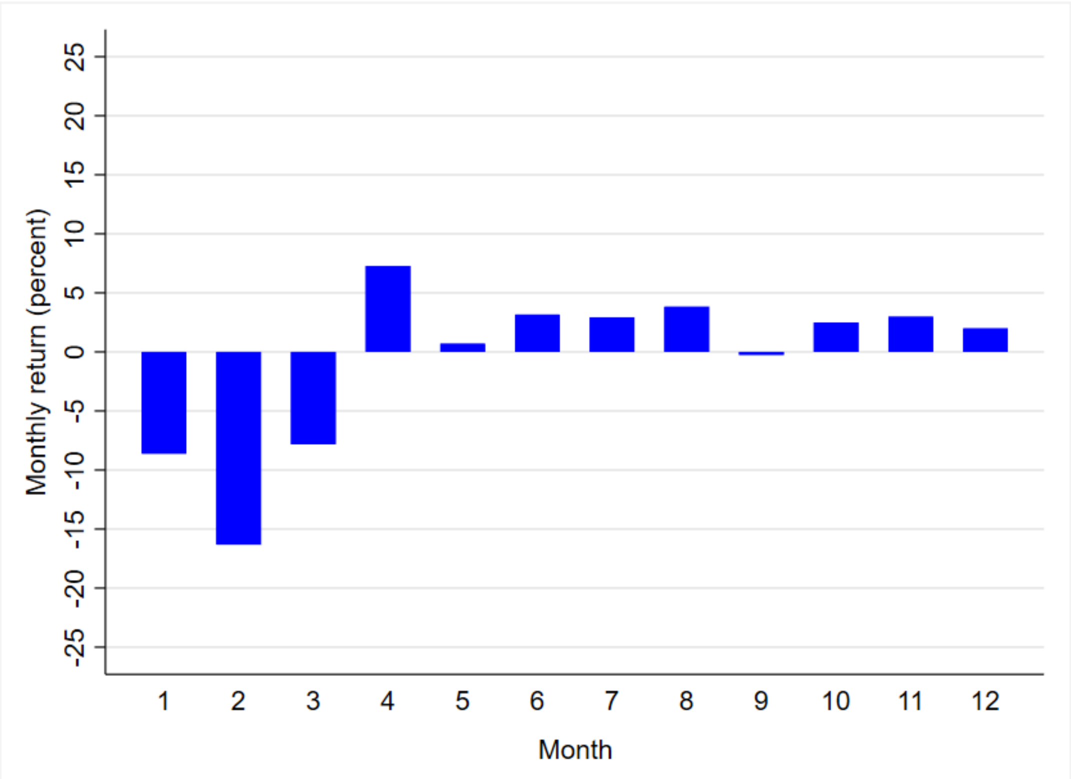
Return Bar Chart 14



Return Bar Chart 15



Return Bar Chart 16



APPENDIX C: STATA Syntax

Syntax Price Charts and Return Bar Charts

note: this syntax file is an example of commands that were used for creation of the price paths, i.e., price charts, and return bar charts. This particular do-file describes commands for the simulation of *Price Chart 1 and Return Bar Chart 1*. The final version of the price charts and the return bar charts as displayed in the survey were adjusted for the scaling of vertical and horizontal axes.

```
*** PRICE CHARTS
clear
set obs 252

generate day = _n
generate month = floor((day-1)/21)+1

forvalues i=1/10 {

        scalar mu = 0.0001
        scalar sigma = 0.01

        generate p=100 in 1

        scalar teller = 0 // counts the number of price paths created in the loop

        quietly while abs(p[21] - 103)>1 {
                generate epsilon = rnormal() in 2/21
                replace p = p[_n-1] + p[_n-1]*mu + p[_n-1]*sigma*epsilon in 2/21
                drop epsilon
                scalar teller = teller + 1
                }

        quietly while abs(p[42] - 107)>1 {
                generate epsilon = rnormal() in 22/42
                replace p = p[_n-1] + p[_n-1]*mu + p[_n-1]*sigma*epsilon in 22/42
                drop epsilon
                scalar teller = teller + 1
                }

        quietly while abs(p[63] - 110)>1 {
                generate epsilon = rnormal() in 43/63
                replace p = p[_n-1] + p[_n-1]*mu + p[_n-1]*sigma*epsilon in 43/63
                drop epsilon
                scalar teller = teller + 1
                }

        quietly while abs(p[84] - 113)>1 {
                generate epsilon = rnormal() in 64/84
                replace p = p[_n-1] + p[_n-1]*mu + p[_n-1]*sigma*epsilon in 64/84
                drop epsilon
                scalar teller = teller + 1
                }
```

```
quietly while abs(p[105] - 116)>2 {
	generate epsilon = rnormal() in 85/105
	replace p = p[_n-1] + p[_n-1]*mu + p[_n-1]*sigma*epsilon in 85/105
	drop epsilon
	scalar teller = teller + 1
	}

qui while abs(p[126] - 119)>5 {
	generate epsilon = rnormal() in 106/126
	replace p = p[_n-1] + p[_n-1]*mu + p[_n-1]*sigma*epsilon in 106/126
	drop epsilon
	scalar teller = teller + 1
	}

quietly while abs(p[147] - 122)>2 {
	generate epsilon = rnormal() in 127/147
	replace p = p[_n-1] + p[_n-1]*mu + p[_n-1]*sigma*epsilon in 127/147
	drop epsilon
	scalar teller = teller + 1
	}

quietly while abs(p[168] - 125)>1 {
	generate epsilon = rnormal() in 148/168
	replace p = p[_n-1] + p[_n-1]*mu + p[_n-1]*sigma*epsilon in 148/168
	drop epsilon
	scalar teller = teller + 1
	}

quietly while abs(p[189] - 150)>1 {
	generate epsilon = rnormal() in 169/189
	replace p = p[_n-1] + p[_n-1]*mu + p[_n-1]*sigma*epsilon in 169/189
	drop epsilon
	scalar teller = teller + 1
	}

quietly while abs(p[210] - 125)>3 {
	generate epsilon = rnormal() in 190/210
	replace p = p[_n-1] + p[_n-1]*mu + p[_n-1]*sigma*epsilon in 190/210
	drop epsilon
	scalar teller = teller + 1
	}

quietly while abs(p[231] - 117)>1 {
	generate epsilon = rnormal() in 211/231
	replace p = p[_n-1] + p[_n-1]*mu + p[_n-1]*sigma*epsilon in 211/231
	drop epsilon
	scalar teller = teller + 1
	}

quietly while abs(p[252] - 110)>0.3 {
	generate epsilon = rnormal() in 232/252
	replace p = p[_n-1] + p[_n-1]*mu + p[_n-1]*sigma*epsilon in 232/252
	drop epsilon
	scalar teller = teller + 1
	}
```

```
	display "Price path : " `i'
	display "Number of iterations = " teller
	display "mu = " mu
	display "sigma = " sigma
	display ""

	generate p_`i'=p

	drop p
}

tsset day

twoway tsline p_10, ytitle(price) xtitle("Month") scheme(s2mono) plotregion(fcolor(white)) graphregion(fcolor(white)) lcolor(blue) tlabel(10 "1" 32 "2" 53 "3" 74 "4" 95 "5" 116 "6" 137 "7" 158 "8" 179 "9" 200 "10" 221 "11" 241 "12")
```

***** RETURN BAR CHARTS**

```
bysort month: generate day_of_month = _n // variable that numbers days within a month
keep if day_of_month==21 | (day_of_month==1 & month==1) // this part retains only the data of last day of each month + starting value of day 1 (price=100)

forvalues i=1/10 {
	generate return_p_`i' = (p_`i'[_n]-p_`i'[_n-1])/p_`i'[_n-1] * 100 // calculating the change of a price in percent as difference between price at end of each month compared to the previous month
	format %5.1f return_p_`i'
}

graph bar (mean) return_p_10, over(month) ytitle("Monthly return (percent)") b1title("Month") scheme(s2mono) plotregion(fcolor(white)) graphregion(fcolor(white)) bar(1, color(blue))
```

Syntax Analysis

```
********
* Import and clean data
********
clear all

import excel "C:\Users\Barto\OneDrive\Bureaublad\Thesis (final)\Survey - Results (numeric).xlsx",
sheet("Sheet0") firstrow case(lower) clear

foreach v of varlist * {
	replace `v' = subinstr(`v',"Look at the graph below. ","",.)
	replace `v' = subinstr(`v',"Look at the graphs below. ","",.)
	label var `v' "`=`v'[1]'"
}

drop in 1
destring _all, replace

drop if distributionchannel=="preview"
drop if progress==79 // drop 2 case for incomplete answers
drop if duration<15 // drop 1 case who took only 12sec

generate id=_n
order id, first

label define labelage 1 "0-17" 2 "18-25" 3 "26-35" 4 "36-45" 5 "46-55" 6 "56-65"
label values age labelage

generate female = 1 if gender==2
replace female = 0  if gender==1
label define labelgender 0 "men" 1 "women"
label values female labelgender

generate education = 1 if degree <=3
replace education = 2 if degree ==4
replace education = 3 if degree >=5
label define labeleduc 1 "high school or lower" 2 "bachelor" 3 "master or higher"
label values education labeleduc

drop status
rename employment status
label define labelstatus 1 "employed" 2 "unemployed/inactive" 3 "student" 4 "retired"
label values status labelstatus

generate ownfinancial = 1 if financialproducts==1
replace ownfinancial = 0 if financialproducts==2
```

drop recipientlastname recipientfirstname recipientemail externalreference distributionchannel userlanguage lottery ipaddress recordeddate responseid enddate *_nps_group gender degree financialproducts
order id female age education status ownfinancial knowledge financialrisks statisticalskills, first

****
*** Table 2: descriptive statistics**
****

summarize female i.age i.education i.status ownfinancial knowledge financialrisks statisticalskills

****
*** Reshape to id-path file**
****

reshape long pricepath rb, i(id) j(path)

generate bars = 1 if rb!=.
replace bars = 0 if pricepath!=.

generate riskiness = pricepath if pricepath!=.
replace riskiness = rb if rb!=.

recode path (1/8=1) (9/16=0), gen(positive)
recode path (1/4=1) (5/8=0) (9/12=1) (13/16=0), gen(late)
recode path (1/2=1) (3/4=0) (5/6=1) (7/8=0) (9/10=1) (11/12=0) (13/14=1) (15/16=0), gen(down)
recode path (1=1) (2=0) (3=1) (4=0) (5=1) (6=0) (7=1) (8=0) (9=1) (10=0) (11=1) (12=0) (13=1) (14=0) (15=1) (16=0), gen(peak)

drop pricepath rb
drop if riskiness==.
order id path riskiness positive late down peak bars

****
*Figure 1: mean risk per price path
****

generate risk_bars = riskiness if bars==1
generate risk_nobars = riskiness if bars==0
collapse (mean) risk_*, by(path)

graph bar (mean) risk_nobars (mean) risk_bars, over(path) scheme(s2mono) plotregion(fcolor(white)) graphregion(fcolor(white)) b1title("Price path") ytitle("Average perceived risk") legend(order(1 "Without return bars" 2 "With return bars"))
*/

```
********
* Table 3: mean perceived risk for personal questions
********

egen cat_knowledge=cut(knowledge), group(2) label
egen cat_financialrisks=cut(financialrisks), group(2) label
egen cat_statisticalskills=cut(statisticalskills), group(2) label

oneway riskiness ownfinancial, mean
oneway riskiness cat_knowledge, mean
oneway riskiness cat_financialrisks, mean
oneway riskiness cat_statisticalskills, mean

********
* Table 4: mean perceived risk for demographic characteristics
********

oneway riskiness female, mean
oneway riskiness age, mean
oneway riskiness education, mean
oneway riskiness status, mean


********
* Table 6: regression analyses
********

* make interaction terms
generate bars_positive = bars*positive
generate bars_late = bars*late
generate bars_down = bars*down
generate bars_peak = bars*peak

* Missing values on the control variables: dummy variable adjustment:
generate m_female = female
replace m_female = 0 if female==.
generate m_age = age
replace m_age=0 if age==.
generate m_status = status
replace m_status = 0 if status==.
generate m_ownfinancial = ownfinancial
replace m_ownfinancial = 0 if ownfinancial==.
generate m_knowledge = knowledge
replace m_knowledge = 0 if knowledge==.
generate m_financialrisks = financialrisks
replace m_financialrisks = 0 if financialrisks==.
generate m_statisticalskills = statisticalskills
replace m_statisticalskills = 0 if statisticalskills==.
```

```
generate missing_f = 0
replace missing_f = 1 if female==.
generate missing_a = 0
replace missing_a = 1 if age==.
generate missing_s = 0
replace missing_s = 1 if status==.
generate missing_o = 0
replace missing_o = 1 if ownfinancial==.
generate missing_k = 0
replace missing_k = 1 if knowledge==.

* 5 regression models:
regress riskiness positive late down peak bars, vce(cluster id)

regress riskiness positive late down peak bars bars_positive bars_late bars_down bars_peak,
vce(cluster id)

regress riskiness positive late down peak bars missing_* m_female ib1.education ib3.m_age
ib1.m_status m_ownfinancial m_knowledge m_financialrisks m_statisticalskills, vce(cluster id)

regress riskiness positive late down peak bars bars_positive bars_late bars_down bars_peak missing_*
m_female ib1.education ib3.m_age ib1.m_status m_ownfinancial m_knowledge m_financialrisks
m_statisticalskills, vce(cluster id)

reg riskiness positive late down peak i.id, vce(cluster id)
```

****
*** Table 5. Randomization checks**
****

```
foreach var of varlist female age education status {
	levelsof `var', local(values)
	foreach i of local values {
		summarize positive if `var'==`i'
		bitest  positive =.5 if `var'==`i'

		summarize late if `var'==`i'
		bitest  late =.5 if `var'==`i'

		summarize down if `var'==`i'
		bitest  down =.5 if `var'==`i'

		summarize peak if `var'==`i'
		bitest  peak =.5 if `var'==`i'
}
}
```

****

*** Subsample regression (Table 8 and Table 9)**

****

*** Missing values on the control variables: dummy variable adjustment:**

```
generate m_female = female
replace m_female = 0 if female==.
generate m_age = age
replace m_age=0 if age==.
generate m_status = status
replace m_status = 0 if status==.
generate m_ownfinancial = ownfinancial
replace m_ownfinancial = 0 if ownfinancial==.
generate m_knowledge = knowledge
replace m_knowledge = 0 if knowledge==.
generate m_financialrisks = financialrisks
replace m_financialrisks = 0 if financialrisks==.
generate m_statisticalskills = statisticalskills
replace m_statisticalskills = 0 if statisticalskills==.

generate missing_f = 0
replace missing_f = 1 if female==.
generate missing_a = 0
replace missing_a = 1 if age==.
generate missing_s = 0
replace missing_s = 1 if status==.
generate missing_o = 0
replace missing_o = 1 if ownfinancial==.
generate missing_k = 0
replace missing_k = 1 if knowledge==.
```

****

***Table 8**

****

```
keep if bars==0

regress riskiness positive late down peak, vce(cluster id)

regress riskiness positive late down peak missing_* m_female ib1.education ib3.m_age ib1.m_status
m_ownfinancial m_knowledge m_financialrisks m_statisticalskills, vce(cluster id)

reg riskiness positive late down peak i.id, vce(cluster id)
```

```
********
*Table 9
********
keep if bars==1

regress riskiness positive late down peak, vce(cluster id)

regress riskiness positive late down peak missing_* m_female ib1.education ib3.m_age ib1.m_status
m_ownfinancial m_knowledge m_financialrisks m_statisticalskills, vce(cluster id)

reg riskiness positive late down peak i.id, vce(cluster id)
```

APPENDIX D: Pairwise Price Path Comparison

Table 7: price charts comparison pairs

CHARACTERISTIC	PRICE PATH PAIR	
POSITIVE/NEGATIVE		
	Price Path 1	Price Path 9
	Price Path 2	Price Path 10
	Price Path 3	Price Path 11
	Price Path 4	Price Path 12
	Price Path 5	Price Path 13
	Price Path 6	Price Path 14
	Price Path 7	Price Path 15
	Price Path 8	Price Path 16
PEAK (TROUGH)/NO PEAK (TROUGH)		
	Price Path 1	Price Path 2
	Price Path 3	Price Path 4
	Price Path 5	Price Path 6
	Price Path 7	Price Path 8
	Price Path 9	Price Path 10
	Price Path 11	Price Path 12
	Price Path 13	Price Path 14
	Price Path 15	Price Path 16
EARLY/LATE		
	Price Path 1	Price Path 5
	Price Path 2	Price Path 6
	Price Path 3	Price Path 7
	Price Path 4	Price Path 8
	Price Path 9	Price Path 13
	Price Path 10	Price Path 14
	Price Path 11	Price Path 15
	Price Path 12	Price Path 16
UP-DOWN/DOWN-UP		
	Price Path 1	Price Path 3
	Price Path 2	Price Path 4
	Price Path 5	Price Path 7
	Price Path 6	Price Path 8
	Price Path 9	Price Path 11
	Price Path 10	Price Path 12
	Price Path 13	Price Path 15
	Price Path 14	Price Path 16

Note: *this table shows on which characteristic different price paths are being compared while other are being held constant, i.e., for each comparison three characteristics are kept constant for given price path pair.*

APPENDIX E: Subsample Regression Models

Table 8: regression analysis for respondents <u>without</u> return bar charts

	Model 6	**Model 7**	**Model 8**
	b/se	b/se	b/se
Positive	-.688***	-.675***	-.710***
	(.180)	(.176)	(.174)
Late	.393**	.334*	.252*
	(.145)	(.131)	(.114)
Up-Down	.775***	.769***	.818***
	(.203)	(.194)	(.207)
Peak	.419**	.520***	.483**
	(.145)	(.144)	(.145)
Female		-.596	
		(.314)	
Bachelor		-.636	
		(.472)	
Master or higher		-.570	
		(.573)	
Age: 0-17		4.294***	
		(.641)	
Age: 18-25		.379	
		(.399)	
Age: 36-45		.912*	
		(.358)	
Age: 46-55		1.300***	
		(.322)	
Age: 56-65		.710	
		(1.020)	
Unemployed		1.438*	
		(.556)	
Student		-.270	
		(.522)	
Own Financial Product		-.179	
		(.410)	
Financial Knowledge		.070	
		(.090)	
Financial Risk Willingness		.144	
		(.093)	
Statistical Skills		.182*	
		(.081)	
Missing: Female		.402	
		(.325)	
Missing: Age		.342	
		(.241)	
Missing: Status		1.552*	
		(.640)	
Missing: Own Financial Product		1.042*	
		(.493)	
Missing: Financial Knowledge		-2.041**	
		(.740)	

Constant	5.812***	3.774***	5.115***
	(.253)	(.524)	(.149)
Individual fixed effects	No	No	Yes
R-squared	.06	.21	.51
N (price paths)	877	877	877

Note: * p<.05; ** p<.01; *** p<.001. Standard errors (in parentheses) are clustered at the individual respondents. The reference categories are male for gender, high school or lower for education, 26-35 years old for age and employed for status.

Table 9: regression analysis for respondents with return bar charts

	Model 9	**Model 10**	**Model 11**
	b/se	b/se	b/se
Positive	-.514***	-.537***	-.554***
	(.142)	(.138)	(.130)
Late	.212	.185	.187
	(.129)	(.130)	(.128)
Up-Down	.475**	.527**	.545**
	(.176)	(.172)	(.191)
Peak	.559***	.492***	.556***
	(.141)	(.139)	(.140)
Female		-.055	
		(.239)	
Bachelor		-.068	
		(.536)	
Master or higher		-.307	
		(.578)	
Age: 18-25		-.172	
		(.355)	
Age: 36-45		-.266	
		(.378)	
Age: 46-55		-.789*	
		(.312)	
Age: 56-65		-.685	
		(.371)	
Unemployed		.021	
		(.504)	
Student		-.259	
		(.471)	
Retired		1.351***	
		(.263)	
Own Financial Product		.162	
		(.362)	
Financial Knowledge		.247*	
		(.096)	
Financial Risk Willingness		.048	
		(.079)	
Statistical Skills		.007	
		(.107)	
Missing: Female		.989	
		(.580)	

Missing: Age		-1.323***	
		(.361)	
Missing: Status		.537	
		(1.158)	
Missing: Own Financial Product		-.137	
		(.640)	
Missing: Financial Knowledge		1.202	
		(2.018)	
Constant	6.285***	4.587***	6.360***
	(.179)	(.589)	(.153)
Individual fixed effects	No	No	Yes
R-squared	.05	.16	.43
N (price paths)	859	859	859

Note: * p<.05; ** p<.01; *** p<.001. Standard errors (in parentheses) are clustered at the individual respondents. The reference categories are male for gender, high school or lower for education, 26-35 years old for age and employed for status.

To provide more context in the effects of different price path characteristics, in this section the regression analysis was conducted on the subsamples of this experiment, i.e., the subjects that only received the price charts and the ones that received simultaneously the price charts and return bar charts of the underlying asset. Compared to Table 6, in both Table 8 and Table 9, variable *bars* disappeared, i.e., the separate regression analysis on the subsamples. This implies also that interaction effects between the return bar charts and price path characteristics that were presented in Model 2 and Model 4 (Table 6) are not included. Note, however, that difference in the effects for price path characteristics between Model 6 and Model 9 gives exactly the same values as the coefficients obtained for the interaction effects in Model 2 (Table 6). For example, the coefficient -0.300 for *bars*up-down* (Model 2) is the difference between coefficients *up-down* in Model 9 (0.475) and Model 6 (0.775).

The models in Table 8 examine the effect of four price path characteristics on the risk perception when the participants were only displayed the price charts of the underlying asset. Model 6 shows that each price path characteristic results in significant change in the risk perception of an individual. Compared to Model 1 (Table 6), this model (Model 6) shows that two characteristics are significant at 0.01% significance level (*positive* and *up-down*), while another two characteristics (*late* and *peak*) are significant at 1% significance level. Moreover, the price sequences (down-up versus up-down) and ending points (positive versus negative) result in the highest difference in the perceived risk followed by the salient peaks (trough) and turning points. Another difference between a pooled regression and separate regression is the size of effects between Model 1 and Model 6, i.e., the difference in the risk perception increased in absolute values within each dichotomous price path characteristic. However, note that the effects of price path characteristics are approximately equal between Model 1 and Model 2 on the one hand and Model 6 on the other hand.

To test the robustness of these results, two additional models were estimated. Model 7 controls for the observed characteristics of respondents in the experiment, i.e., demographics and personal questions. According to this model all explanatory variables, i.e., price path characteristics, keep their significant effect and direction but the significance level decreased for turning points and increased for salient peaks (trough). Earlier it has been argued that the inclusion of personal characteristics, i.e., demographics and personal questions, as control variables should rule out that the findings are significantly driven by them. At the same time, this study included individuals with some financial knowledge in order to mimic real-world retail financial investors. Hence, it was not surprising to find that financial knowledge in Model 3 (Table 6) has significant effect on the risk perception of a retail financial investor. However, Model 7 shows that in the treatment group where only the price charts were displayed, financial knowledge is of no significance on the risk perception. Moreover, in contradiction to Model 3, the demographic characteristics in Model 7, such as age and status appear to significantly affect the risk perception of an individual. For example, the individuals in age-categories 36 – 45 and 46 – 55 years old perceived, on average, significantly higher risk compared to the other age categories. Similarly, the unemployed respondents perceived, on average, significantly higher risk than employed individuals, but there was no significant difference in the risk perception between the students and employed individuals. Also, in the subsample where only the price charts were viewed, statistical skills have a significant effect on the risk perception of an individual.

Further, Model 8 controls for all unobserved characteristics of the respondents by means of fixed effects regression model. According to this model, the price path characteristics retain their significant influence on the perceived risk by a retail financial investor. Moreover, this model shows that the magnitude for all explanatory variables has changed, while the significance level for variable *late* decreased from 1% to 5%. This model offers similar outcome to Model 5 from Table 6. Based on the outcome in Table 8, the previously stated conclusions (Result 1 to Result 4) cannot be refuted. Meanwhile, it should be concluded that statistical skills have a significant effect on the risk perceived by retail financial investors when they are shown the price chart of the underlying asset.

Further, Table 9 provides comparable models to Table 8, but for the subsample that was simultaneously shown the price chart and return bar chart of the underlying asset. The simple linear regression (Model 9) shows that the sign of each explanatory variable is the same as in the treatment group where only the price charts of the underlying asset were displayed (Model 6). Moreover, the difference in the risk perception decreased between price paths with positive and negative ending points, early and late turning points, and up-down and down-up trends. Hence, the provision of additional return information leads to a smaller risk perception gap for these three price path characteristics compared to when only the price chart of the underlying asset is displayed to an individual. In the case of a salient peak (trough) versus no peak (trough), the difference in perceived risk increased compared to the situation when only the price chart of the underlying asset was displayed to an individual (Model 6). More important, however, is that the turning points do not lead to significant risk perception differences among individuals in this treatment group. Therefore, a retail financial investor will perceive a price path with an early and late turning point as equally risky when simultaneously confronted with the price chart and return bar chart of the underlying asset.

Again, the other two models in Table 9 test robustness of the findings in Model 9. In Model 10 control variables were included for the observed characteristics of respondents. At the same time Model 11, controls for all unobserved characteristics of the respondents by means of a fixed effects regression model. Model 10 and Model 11 show robustness of the main effects because they hold the same level of significance across all three models. Therefore, the price path characteristics, with exception of the turning points, have significant effect on the perceived risk by retail financial investors when simultaneously shown the price chart and return bar chart of the underlying asset.

Moreover, it appears that the demographic variables, such as the highest attained educational level and gender, have no significant effect on the perceived risk by a retail financial investor. In contradiction to the results in Model 7 (only price charts displayed), Model 10 shows that individuals in the age group of 46 – 55 years old, on average, perceived significantly lower risk perception than individuals in other age categories when provided with the price chart and return bar chart of the underlying asset. Further, this model (Model 10) shows that retirees, on average, perceived significantly higher risk perception than the other groups. In contradiction to the findings in Model 7, there is no significant difference in the risk perception between the unemployed and employed individuals (Model 10).

Apparently, when controlling for the personal characteristics (Model 10) only financial knowledge has a significant effect on the perceived risk of an individual while other characteristics are of no significance, i.e., owning financial product, willingness to take financial risks or statistical skills. Remarkably, financial knowledge appeared to have no significant effect in the separate regression Model 7, i.e., subjects that received only the price chart of the underlying asset. In comparison to Model 7, Model 10 shows that statistical skills have no significant effect on the perceived risk of an individual when simultaneously shown the price chart and return bar chart of the underlying asset.