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Price Path Variability and the Disposition Effect: Do Volatile Paths Affect the Decision to Sell?

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Abstract

This study investigates whether price path variability influences the disposition effect, the tendency of investors to sell winning assets too early and hold on to losing assets too long. Based on prospect theory and prior work on visual risk perception, the study uses a survey experiment in which 124 participants are randomly assigned to one of three volatility treatments (low, average, or high). Each participant evaluates four price charts (two gain, two loss scenarios), generated using a Geometric Brownian Motion model, with visual volatility manipulated while holding trend, starting price, final price, and overall return constant across treatment groups. Willingness to sell is measured on a 7-point Likert scale, and the strength of the disposition effect is calculated as the difference between willingness to sell in gain versus loss scenarios. A one-way ANOVA reveals a statistically significant effect of volatility condition on disposition effect scores, with a Tukey HSD post-hoc test indicating that participants in the high-volatility condition exhibit a significantly stronger disposition effect than those in the low-volatility condition ($p = .012$). The findings suggest that higher visual volatility amplifies behavioral biases, highlighting the importance of graphical representation in financial decision-making.

Keywords: Price Paths, Disposition Effect, Investment Behavior, Behavioral Finance, Prospect Theory, Risk Perception, Volatility.

1 Introduction

Investors often exhibit a disposition effect - the tendency to keep losing investments too long while selling winners too early (Arora & Rajendran, 2023; Shefrin & Statman, 1985). This bias can be costly, as selling winners too quickly and holding losers too long can negatively impact portfolio returns. The bias has been widely documented in both empirical (Odean, 1998), and experimental settings (Weber & Camerer, 1998). Because the disposition effect can strongly influence investment decisions, it is important to understand what kind of information might trigger or amplify it. Given how often financial information is now displayed in simple visuals such as price charts, this is becoming increasingly relevant.

The main explanation for the disposition effect to date stems from prospect theory (Kahneman & Tversky, 1979), which describes how individuals evaluate gains and losses relative to a subjective reference point. Once investors experience a gain, they tend to become risk-averse, preferring to lock in their profits. In contrast, when they suffer a loss, they become risk-seeking, holding on to losing assets in the hope of a recovery (Shiv et al., 2005). This behavior is reinforced by the notion that losses generally hurt more than equivalent gains can generate joy. In other words, losing €100 feels worse than the joy of gaining €100. The prospect theory value function reflects this asymmetry because it is steeper for losses than for gains. Additionally, the function is convex in the loss domain and concave in the gain domain, implying that the sensitivity to gains and losses diminishes the further away an outcome is from the reference point. For example, it feels like a bigger gain to go from €100 to €200 rather than from €1,100 to €1,200 (Kahneman & Tversky, 1979).

Prospect theory is also related to how investors and laypeople evaluate how the value of an asset has changed over time (Borsboom & Zeisberger, 2020; Cordes et al., 2024; Grosshans & Zeisberger, 2018; Gulen & Woeppel, 2022; Nolte & Schneider, 2018). Price paths show how the value of an asset has developed over time. They give users important information because they are typically the only visual representation of financial assets. Individuals either consciously or unconsciously form an opinion about the price path based on certain characteristics. Based on their expectations about the future performance of these assets, they may decide to buy, sell, or hold the security. The academic literature so far has investigated only a handful of aspects related to price

paths. For example, studies show that the past volatility of an asset leads investors to perceive this asset as riskier when making an investment decision (Borsboom & Zeisberger, 2020).

Furthermore, an increased probability that an asset will decline in value leads investors to form a more pessimistic belief about the asset. According to Zeisberger (2023), loss probability is an even stronger indicator of perceived risk than the commonly used standard deviation of returns. Other studies have also examined which risk measures, such as standard deviation and expected loss, investors and laypeople believe to be most appropriate (e.g., Holzmeister et al. (2019)). This is relevant in the context of the disposition effect, as higher perceived risk, in the form of loss probability, may affect investors' selling decisions. The reluctance to realize losses can lead them to hold on to losing positions for too long. In sum, various psychological mechanisms and perceptions of risk contribute to the existence of the disposition effect.

Yet, research has mainly focused on particular price path characteristics and their relationship with investors' satisfaction and willingness to buy (Borsboom & Zeisberger, 2020). The current research aims to investigate the effect of price path variability on the disposition effect, thereby combining two strands of literature. Borsboom and Zeisberger (2020) call for a study that analyses selling decisions when faced with price paths, thereby extending Nolte and Schneider (2018) and Grosshans and Zeisberger (2018). The research question can thus be formulated as follows: "*What is the effect of price path variability on the disposition effect?*"

Price path variability in this study is the visual volatility that can be observed when evaluating the price chart of an asset. It refers to the up-and-down movements in the value of the asset, or price level, over time. It will likely correlate with the standard deviation of returns, but it is important to note that it is primarily a behavioral measure of volatility. It concerns the perception of volatility by investors. This can therefore vary per investor. Chapter 3 will delve deeper into the operationalization of the concept.

Regarding the disposition effect, it is important to understand that it captures the difference in willingness to sell between winning assets and losing assets. The disposition effect predicts that investors sell winning assets too quickly and hold losing assets too long. This study, thus, aims to examine whether this potential difference in willingness to sell between gains and losses is affected by the level of price path variability.

In terms of the practical relevance of this research, banks and other financial institutions might deliberately display their most attractive-looking financial products based on the price path (Huber

& Huber, 2019). In that manner, they hope to sell more of their products. According to Diacon and Hasseldine (2007), financial regulators are concerned that financial institutions will cherry-pick past performance information and present this selectively in their promotional materials. This could mislead potential investors. The selective presentation of financial information could lead investors to make decisions based on misleading or overly optimistic graphics. As a result, they may be more prone to cognitive biases such as the disposition effect. In the long run, this could negatively impact the level of trust in financial institutions.

By studying how price path variability affects selling intention, this research sheds light on which visual representations might steer investors' decisions in biased ways. If price path features like volatility are shown to significantly increase the likelihood of selling winners too early (or holding on to losers too long), this may indicate to regulators that, in addition to the data itself, the visual representation of financial data is also important. Understanding the underlying causes of biases in financial decision-making contributes to bias control. Moreover, it should help data providers in presenting financial information and inform regulators about how market data should be presented during panics and crashes (Raghubir & Das, 2009).

In addition to this, financial graphs often contain measurement distortion, suggesting a more favourable view of financial performance than realized. Graphical devices such as a non-zero axis[1] or a broken axis[2] are examples of measurement distortion, causing trends to appear more positively (Diacon & Hasseldine, 2007). Huber and Huber (2019) emphasize the increasing importance of better understanding how people's risk perception and investment propensity are influenced by various graphical representations of past returns. They mention the emergence of robot-advisors, online brokers, and new products like cryptocurrencies as possible causes for this.

The research question will be investigated using a survey experiment. The main question the paper is interested in is about participants' willingness to sell the assets they are told to hold. The survey design will include price paths with varying levels of volatility. Specifically, it will distinguish low, average, and high volatility.

The remainder of this study is structured as follows. Chapter 2 provides a literature review, discussing key theories and previous findings on price path characteristics, investor behavior, and

[1] A non-zero axis occurs when the y-axis of a graph doesn't start at zero. This magnifies small price changes, making an asset appear to have a more favourable trend than it has.

[2] A broken axis has a gap (often market with a zigzag) in the scale of the y-axis. It therefore 'skips' a portion of the scale. Sharp drops may be hidden because of this.

the disposition effect. Chapter 3 outlines the methodology, including the research design, operationalization of variables, data collection, and analysis method. Chapter 4 presents the results of the survey experiment. Chapter 5 provides a discussion of the findings, considers their implications, and reflects on the study's limitations and directions for future research.

2 Literature review

Price paths influence the perceived attractiveness of an asset by highlighting specific asset characteristics (Nolte & Schneider, 2018). If the price path is labeled as historical, this creates a different decision context than if it is labeled as simulated (i.e., potential future price path). An upward-sloping price path that is labeled as historical may be perceived as much more bullish by investors than an upward-sloping price path that is labeled as simulated. Investors may place more value on realized returns than on expectations from experts. This demonstrates how price path features may influence the perceived attractiveness of an asset.

2.1 Price path characteristics

Even though this study focuses on volatility as the main characteristic of interest, it is important to first look at some other price path features as well. In practice, investors perceive volatility within a broader framework, where other price path characteristics, such as trend and amplitude, can also affect the perception of volatility. In other words, they take in the entire shape of the price path. All these features can affect how volatile a price path looks or feels to an investor. For example, a price path with a lot of sharp turns (i.e., 'trend reversals') might be perceived as riskier than one that gradually moves up or down, even if both have the same overall return. Therefore, discussing some of these characteristics is necessary for theoretical completeness.

2.1.1 Trend

First of all, investors find the recent trend an important part of price paths. When making an investment decision, investors tend to focus on more recent outcomes (Barberis et al., 1998; De Bondt, 1993). In other words, investors particularly pay attention to the most recent price developments. They believe that the most recent price developments are more important in determining the future direction of the asset than earlier parts of the price path. Bailey et al. (2011) found that investors tend to buy mutual funds with more positive recent returns. These investors are extrapolating the current trend into the future. It shows that investors often rely too much on recent movements when forming expectations. An increase or decrease near the end of a price path might heavily influence their view, even if the overall trend is stable. In this way, trend extrapolation can shape perceived risk.

Jegadeesh and Titman (1993) showed that a trading strategy based on selecting equities with high past 6-month returns and holding them for the subsequent 6 months yields an average compounded excess return of approximately 12% per year. This finding provides evidence for short-term momentum in financial equity markets (i.e., < 1 year). From this perspective, extrapolating the recent trend could be profitable to investors. However, it is important to note that such momentum strategies do not need to rely on price paths. They can be based on numerical return data or other price-based indicators.

According to Nolte and Schneider (2018), negative trends lead to lower investments when price paths are labeled as historical. This is intuitive, as investors are likely to extrapolate this negative trend into the future, as shown by Bailey et al. (2011). They expect the asset will decline even more in value. Hence, they are reluctant to invest in these assets. Nonetheless, they could decide to short-sell these assets if they anticipate a continued downward trend.

2.1.2 Amplitude

According to Raghubir and Das (2009), financial decisions are primarily made based on trade-offs between risk and return. The decisions are often based on recommendations or information about the risk and return of financial assets that consumers get from companies, brokers, and third parties. However, they also acknowledge that risk perception is dependent on how financial information is presented graphically. As market information is being increasingly visually displayed, this is becoming more and more important.

As stated by Raghubir and Das (2009), there are two major summary elements of a series of financial data. First, consider the trend, which might be either increasing or decreasing, linear or exponential, or cyclical. Second, the noise that surrounds this trend is captured through its variance and higher-order moments[3]. They propose that people simplify their financial analysis by selecting points from the price path of an asset to determine trend and noise. For example, the amplitude is constructed from the extreme points of the distribution – the local maxima and minima across the path. The local maximum is the highest value, and the local minimum is the lowest value across the path. On a graph, the local maximum looks like a peak, whereas the local minimum looks like

[3] Higher-order moments provide insights into the shape and characteristics of probability distributions beyond just its mean and variance. Skewness shows if gains or losses are more extreme, while kurtosis captures how sharp or smooth the ups and downs are.

a valley. The authors discovered that people primarily use these data points to estimate risk. That is, they use the amplitude (width of the price path on the y-axis) to assess risk.

These findings suggest that investors use visual cues, such as peaks and valleys, to estimate risk. This supports the design of the current study, which adopts a visual approach to study investor behavior and selling intention. It reinforces the idea that visual characteristics might meaningfully affect selling decisions and thereby possibly affect behavioral biases such as the disposition effect.

2.1.3 Convex versus concave shape

Cordes et al. (2024) found that convex price paths, those that initially decline and subsequently rise, lead to higher investment levels and more positive emotions compared to concave shapes. This aligns with earlier findings by Grosshans and Zeisberger (2018), who show that investors report greater satisfaction for assets that first decrease and then rise ("down-up"), compared to assets that first rise and subsequently decrease ("up-down"). According to these results, the order of gains and losses has a big impact on how people feel and behave while making investment decisions.

In the experiment, this study will therefore show price paths that instantly start their way up or down, independent of the volatility condition, but also price paths that first increase before they begin to move down, and price paths that first decrease before they begin to move up (see 3.1).

2.2 Risk

In traditional finance, risk is typically defined as the standard deviation of returns, a statistical measure of how much returns deviate from the mean (Markowitz, 1952). This definition forms the basis of models like modern portfolio theory and remains widely used in practice. However, it has increasingly been questioned whether this formal definition reflects how people actually perceive risk (Zeisberger, 2023).

Recent studies suggest that investors rarely think in terms of standard deviation in the context of risk. Instead, they rely on more intuitive, visual cues. Risk is often judged based on what stands out in a price chart: the general shape, sudden drops, and the distance between highs and lows. Borsboom and Zeisberger (2020) find that price charts with more ups and downs are interpreted as riskier, even when the standard deviation of returns is held constant. Similar findings from Raghubir and Das (2009) show that investors often use amplitude to estimate risk.

Other visual features also play a role. According to Borsboom and Zeisberger (2020), salient features such as highs, lows, and crashes are the most influential drivers of perceived risk in price paths. He and Liang (2024) expand on this by showing that investors rely on three visual features when interpreting price paths: recency, cluster, and sign. These features not only shape perceived risk but also influence the confidence investors have in their expectations. Recency captures the unevenness in the distribution of fluctuations, i.e., whether volatility is concentrated at the beginning or the end of a chart. Cluster captures the extent to which consecutive returns have the same sign, making trends appear smoother or more fragmented. Sign represents the average direction of returns across the period.

In short, while standard deviation remains a common risk measure, actual risk perception appears to be driven by more than just statistical measures. Visual cues, salient events, and patterns shape how investors interpret and respond to risk, especially when information is presented in graphical form.

2.3 Reference points

The relevance of price paths becomes particularly evident when considering that individuals derive utility not from their absolute level of wealth, but from changes in wealth relative to a subjective reference point (Baucells et al., 2011; Camerer, 1998). In behavioral finance, reference prices are assumed to be determined by the past purchase prices of the financial asset (Shefrin & Statman, 1985). More precisely, investors tend to rely on the average price at which they purchased an asset. In the absence of that, they may use recent prices or historical peaks. A reference price can thus be defined as the price at which individuals would feel “neither happy nor unhappy about the sale” (Baucells et al., 2011). Prices above this level are generally perceived positively, while prices below it may elicit negative emotions.

Theoretically, the disposition effect is driven by the reference point (Nolte & Schneider, 2018). Assets that have declined in value compared to the reference point are often kept because individuals become risk-seeking in the loss domain, while winning assets are often sold because individuals become risk-averse in the gain domain (Shiv et al., 2005).

2.4 Disposition effect

The disposition effect, thus, refers to the tendency of investors to sell winning assets too early and hold on to losing assets for too long (Shefrin & Statman, 1985). It is considered one of the most robust anomalies in individual investor behavior and has been documented across both experimental settings and real-world trading data (Barberis & Xiong, 2009; Weber & Camerer, 1998). The effect is often explained using prospect theory (Kahneman & Tversky, 1979), which states that individuals are risk-averse in the domain of gains and risk-seeking in the domain of losses. As a result, investors tend to realize gains to secure a positive outcome while postponing the realization of losses in the hope of a recovery.

While much of the literature focuses on psychological drivers such as loss aversion or regret avoidance, more recent studies suggest that how information is presented may also play a role. It has been shown that risk perception can be influenced by the graphical presentation of financial data (Borsboom & Zeisberger, 2020; Cordes et al., 2024; Diacon & Hasseldine, 2007). Huber and Huber (2019) further demonstrate that identical return distributions can lead to different decisions depending on how the information is visualized.

Since most retail investors rely on simplified price charts, the visual shape of the price chart may be more important than its final value (Grosshans & Zeisberger, 2018). Features such as trend, amplitude, trend reversals, and visual volatility may influence risk perception and trigger behavioral responses. While earlier studies have primarily focused on how trend and amplitude affect decision-making, the potential role of volatility as a visual cue in shaping selling behavior remains unclear.

2.5 Hypothesis

The previous sections showed that investors do not only care about the final return of an asset, but also how this return was achieved (Grosshans & Zeisberger, 2018). The price path of an asset can influence how risky the asset is perceived and whether the investor decides to buy, sell, or hold the asset. So far, academic studies have mostly focused on specific price path features such as trend and amplitude, but the role of volatility in selling decisions - also in relation to the disposition effect - has not yet been researched.

A foundational experimental study by Weber and Camerer (1998) provided early evidence for the disposition effect in a laboratory setting. In their design, participants traded stocks over multiple periods and showed a clear pattern of welling winning stocks too early and holding onto losing stocks too long. Participants sold fewer of their shares when the price was falling and when it was below the purchase price. This suggests that multiple reference points – both the purchase price and previous prices – can steer investment choices.

Building on this behavioral foundation, recent research has begun to explore how the visual features of price paths might further shape investment behavior. Prior literature has consistently shown that individuals perceive volatile assets as more risky (Borsboom & Zeisberger, 2020; He & Liang, 2024), and that high volatility can trigger strong emotional reactions such as fear and hope (Loewenstein et al., 2001). Investors may therefore react differently when faced with a volatile price path compared to a more stable one, even if the overall return is exactly similar.

One potential mechanism is that volatile price paths with an overall gain might contribute to uncertainty and the perceived riskiness of the asset, prompting investors to sell the asset early to 'lock in' what was initially only a paper gain. Conversely, volatile price paths with an overall loss might contribute to belief and hope that the asset will rebound, therefore holding on to these assets longer (Weber & Camerer, 1998). In both cases, volatility may amplify the disposition effect.

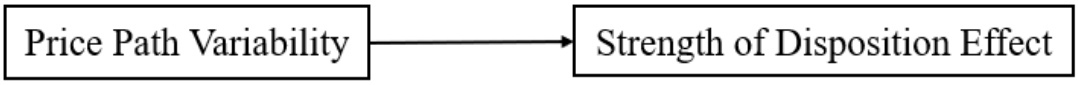
Stable, low-volatility price paths, on the other hand, may have the opposite psychological effect. In the gain domain, a smooth and stable upward trend could signal reliability and safe returns, thereby reducing the perceived urgency to sell these profitable investments early. Investors may feel more confident that the asset will continue to perform well, making them more inclined to hold the asset rather than to realize the gain already. In the loss domain, however, a low-volatility downward trend may reduce hope for a rebound, making the asset seem more predictably poor-performing. This could stimulate earlier realization of losses, leading to a smaller disposition effect.

Earlier work by Arora and Rajendran (2023) suggests that the disposition effect is stronger in volatile markets. However, this was based on overall market volatility. This research adds to that by looking at individual price paths with different levels of volatility and how they influence selling decisions. Based on the aforementioned, the main hypothesis of the study can be formulated as follows:

H1: The strength of the disposition effect increases with the level of price path variability.

The conceptual model corresponding to this hypothesis is presented in Figure 1.

FIGURE 1. CONCEPTUAL MODEL



3 Methodology

3.1 Research design

This study uses a survey experiment to examine whether different levels of price path variability affect the strength of the disposition effect. Participants are randomly assigned to one of the three treatment conditions: low, average, or high volatility. Each participant is asked to evaluate four price charts: two in the gain domain (final price above purchase price) and two in the loss domain (final price below purchase price). The order in which the four different price charts are shown is random to prevent anchoring effects. This setup strikes a balance between gathering sufficient data and preventing respondent fatigue.

In order to improve the external validity of the price charts and isolate the effect of visual volatility, the study varied the beginning and ending price of each price path within the treatment groups. This was done to reduce artificiality and better reflect the diversity found in actual price data. We could have chosen to fix the starting prices at €100, but this may have looked too artificial to the participants. To ensure balance and reduce potential anchoring effects, the starting prices varied proportionally around €100, while maintaining the overall percentage return. In the gain domain, one path started at €97.50 and ended at €117.00 (+20%), incorporating an interim loss. An interim loss means that the price decreased compared to the starting price, but eventually will be profitable (since it is the gain domain). The other one started at €102.50 and ended at €123.00 (+20%), without an interim loss. In the loss domain, one path started at €95.50 and ended at €76.40 (-20%), including an interim gain. An interim gain means that the price increased compared to the starting price, but eventually, it will not be profitable (since it is in the loss domain). The other one started at €104.50 and ended at €83.60 (-20%), without an interim gain. Table 1 provides an overview, also incorporating information about the percentage size of the interim gains/losses compared to the starting prices.

Volatility was the only factor that changed because the price variations remained consistent across the three volatility treatments. The implementation of interim gains and losses in the same price path types ensured consistency across the treatment groups. Furthermore, each price path has a fixed time horizon of one year (252 trading days). This aligns with conventions in both the academic literature and online platforms (Benartzi & Thaler, 1995; Grosshans & Zeisberger, 2018).

The vertical axis was fixed between €75 and €135 on all charts, regardless of whether the asset ended in a gain or a loss, to ensure a consistent presentation of all price paths. Although the loss scenarios result in relatively more empty space above the price trajectory compared to the gain scenarios, this fixed scaling is necessary to avoid introducing framing biases that could affect participants' risk perceptions (Huber & Huber, 2019). Using a standardized axis range is consistent with prior experimental research in this field (Borsboom & Zeisberger, 2020; Grosshans & Zeisberger, 2018)

Additionally, instead of using the default red and green colors typically associated with losses and gains (e.g., as seen in platforms like Google), this study uses a neutral blue tone. This choice follows Borsboom and Zeisberger (2020) and helps to avoid any unintended influence of color on investor behavior. In the experiment, we use a total of twelve different price paths (four per treatment group). We used the neutral term "assets" instead of "stocks" to label the financial products shown to participants. All twelve price paths employed are displayed in Appendix B: Price Paths Overview.

TABLE 1
PRICE PATH CHARACTERISTICS ACROSS ALL TREATMENTS

Volatility condition	Interim Percentage	Start Price	End Price	Return
Low				
Gain with interim loss	1.32%	97.50	117.00	20%
Gain no interim loss	-	102.50	123.00	20%
Loss with interim gain	1.74%	95.50	76.40	-20%
Loss no interim gain	-	104.50	83.60	-20%
Average				
Gain with interim loss	4.82%	97.50	117.00	20%
Gain no interim loss	-	102.50	123.00	20%
Loss with interim gain	4.21%	95.50	76.40	-20%
Loss no interim gain	-	104.50	83.60	-20%
High				
Gain with interim loss	3.51%	97.50	117.00	20%
Gain no interim loss	-	102.50	123.00	20%
Loss with interim gain	5.66%	95.50	76.40	-20%
Loss no interim gain	-	104.50	83.60	-20%

3.2 Experimental procedure and ethics

Participants were given standardized instructions explaining the goal and design of the study at the start of the survey. They were told that there were no right or wrong answers and that the goal of the research was to better understand how people make investment decisions. Participation was completely voluntary, anonymous, and took approximately 8 minutes. Additionally, participants were told that they could withdraw at any moment without explanation. Before beginning, explicit agreement was needed following ethical guidelines.

In the next screen, participants were asked to imagine they had invested in four financial assets exactly one year ago and were now reviewing their performance. They were told that they would be shown a total of four price charts, each representing the historical price development of one asset over the past year. After each chart, they were asked whether they would prefer to sell or continue holding the asset.

Participants were instructed to evaluate each chart independently and base their decision solely on the information presented in the specific chart. They were explicitly told not to compare any chart to earlier or upcoming ones. This was done to prevent anchoring effects. To prevent priming effects, volatility was not mentioned in the survey.

Consistent with Grosshans and Zeisberger (2018), participants were not allowed to return to previous screens once a new price chart was shown. This made sure that every choice was based on an immediate evaluation rather than a retrospective one.. After completing the investment decision tasks, participants answered a set of psychological control and socio-demographic questions, including age, gender, investment experience, and risk preference (see Appendix A: Survey Questions Format).

3.3 Sample and data collection

Before conducting the statistical analyses, the raw survey data were cleaned. First, incomplete and invalid responses (e.g., surveys with missing outcomes or answers from bots) were excluded from the dataset. Only participants who fully completed the investment decision tasks and other questions were included in the analysis.

Next, key variables were computed based on participants' responses to the Likert scale items.

For each participant, the willingness to sell score was averaged for gain and loss scenarios, resulting in a gain and loss score. The disposition effect score was then calculated by subtracting the average loss score from the average gain score. A higher disposition effect score thus indicates a greater inclination toward selling winners and holding losers.

The final dataset consisted of 124 complete observations, with an approximately equal distribution across the three volatility groups: low (n = 44), average (n = 40), and high (n = 40). The sample was obtained through convenience sampling, using personal networks, social media, and relevant online platforms. This non-probability sampling may have reduced external validity, but it was an acceptable method to recruit individuals within the study period.

3.4 Operationalization

3.4.1 Independent variable

Volatility in this study is defined as visual volatility: the magnitude and frequency of price fluctuations in the chart within a given timeframe. Instead of focusing on a statistical measure of volatility, such as the standard deviation of returns, this research uses a visual approach, in which volatility is represented through the shape of the price paths presented to participants. This approach aligns with prior experimental studies investigating the effects of price path characteristics on investor behavior (Borsboom & Zeisberger, 2020; Grosshans & Zeisberger, 2018; Nolte & Schneider, 2018).

Price paths are generated in Python using a Geometric Brownian Motion (GBM) model[4]. The GBM parameters include the initial price (s0), target end price (st), trend component (mu), volatility component (sigma), and a stochastic component derived from a Wiener process. Additionally, one can specify how many paths need to be simulated and the time steps to be used, which is one day in this study. However, since GBM simulations can differ substantially visually despite having the same sigma value, a large number of price paths are simulated, and we manually select those that best match the desired volatility levels.

Specifically, volatility is operationalized by distinguishing three different volatility conditions: (1) a low-volatility price path is characterized by small and infrequent price movements over time and has the lowest sigma value (0.03); (2) an average-volatility price path shows moderate and

[4] https://www.pyquantnews.com/the-pyquant-newsletter/how-to-simulate-stock-prices-with-python

occasional fluctuations and its sigma value lies between the low and high-volatility condition (0.06); and (3) a high-volatility price path displays large and frequent price movements and has the highest sigma value (0.09).

3.4.2 Dependent variable

The dependent variable in this study is the strength of the disposition effect. In the context of this experiment, the strength of the disposition effect is measured through participants' willingness to sell the asset in each scenario.

Participants are asked whether they would like to hold or sell the respective asset at its current price, using a 7-point Likert scale ranging from 1 ("very likely hold") to 7 ("very likely sell"). This approach builds on previous research using visual price path manipulations (Grosshans & Zeisberger, 2018), but extends their 4-point scale to a 7-point scale to allow for greater variation in the dependent variable. The scale can be used to measure the propensity of individuals to realize gains or avoid realizing losses.

For each participant, the willingness to sell score for the two gain scenarios is averaged to form one gain score, and the willingness to sell score for the two loss scenarios is averaged to form one loss score. The disposition effect score is then calculated as:

$$Disposition\ Effect\ Score = Average\ Willingness\ to\ Sell\ (Winners) - Average\ Willingness\ to\ Sell\ (Losers)$$

A higher score indicates a stronger disposition effect, reflecting a greater tendency to sell winners and hold losers. Appendix A: Survey Questions Format shows the questions as they are asked to participants.

3.5 Data analysis method

The average disposition effect scores for each of the three volatility conditions will be compared using a one-way analysis of variance (ANOVA) in order to evaluate the hypothesis. This statistical method is appropriate given that we use one independent variable with three categorical levels and a continuous dependent variable measured on an interval scale (Verma, 2013). The ANOVA will test whether the average disposition effect score differs significantly between at least two of the three volatility conditions.

The null hypothesis states that there are no significant differences in the average disposition effect scores across the three conditions. The alternative hypothesis states that at least one group differs significantly from the overall mean. Since an ANOVA only indicates whether a statistically significant difference exists somewhere among the groups, a post-hoc analysis will be performed to identify the specific group differences. For this purpose, a Tukey's Honest Significant Difference (HSD) test will be used.

In addition to this, secondary analyses will be conducted to further explore the robustness of the findings. A multiple linear regression will be used to determine whether individual characteristics, such as risk preference and confidence level, influence the strength of the disposition effect. Furthermore, the survey includes an additional quantitative question to provide an alternate operationalization of the dependent variable (see Appendix A: Survey Questions Format). Instead of asking participants to indicate their willingness to sell on a Likert scale, this question asks them to state the actual amount of their investment they would sell in each scenario. This gives additional information about their actual selling intention and supports the main measure used in the analysis.

4 Results

4.1 Descriptive results

Table 2 summarizes the demographic characteristics of the final sample (N = 124). The mean age of respondents was 27.3 years (SD = 10.0), with ages ranging from 18 to 67, indicating a relatively young and diverse group in terms of age. The sample was predominantly male (70.97%), which is typical in investment-related research, where men tend to be overrepresented due to higher self-reported interest and activity in financial markets (Almenberg & Dreber, 2015; Fisher & Yao, 2017).

In terms of marital status, the majority of participants reported being single (77.42%), followed by 17.74% who were married or in a civil partnership. This reflects a sample that largely consists of young individuals, which could affect investment behavior due to lower disposable income and higher willingness to take risks. However, since this study focuses on behavioral responses to visual price paths under controlled experimental conditions, these demographic factors are not expected to systematically bias the results.

Educational attainment was relatively high. Nearly half of all respondents had completed a field of study at the university: 29.84% held a university bachelor's degree, and 20.97% had obtained a university master's degree. An additional 24.19% completed higher professional education (hbo). These numbers suggest a well-educated sample, consistent with similar experimental research using convenience sampling and online recruitment (Bethlehem, 2010). Only a small fraction of the sample reported having completed a PhD (1.61%), which amounts to 2 participants.

Gross income levels were broadly distributed, though skewed toward the lower end. Over a quarter of participants (26.61%) earned less than €10,000 annually, which aligns with the relatively large proportion of students in the sample (33.87%). Another 17.74% earned between €30,000 and €39,999, while only 1.62% earned above €80,000. Finally, 10.48% of respondents preferred not to disclose their income.

The sample showed a wide range in terms of investment experience. While 41.13% of respondents reported having no investment experience, the remaining participants were spread across various experience levels: 14.52% reported less than one year, 22.58% had between 1 and 3 years, and 6.45% had over six years of experience. These numbers indicate that a substantial

portion of the sample consisted of relatively inexperienced investors, defined as having fewer than four years of experience.

Employment status was divided mainly between full-time employment (39.52%) and student status (33.87%), followed by part-time employment (18.55%). Only a very small part of the sample reported being unemployed (0.81%) or retired (0.81%). The high percentage of students and full-time workers is consistent with the age and income profile discussed earlier.

Taken together, these figures imply that the sample is relatively young, well-educated, and inexperienced in investing. These characteristics should be considered when interpreting the generalizability of the findings.

TABLE 2
DEMOGRAPHIC CHARACTERISTICS FINAL SAMPLE

Variable	Category	% of Sample
Age	Mean (SD)	27,3 (10,0)
	Range	18 - 67
Gender	Male	70,97%
	Female	29,03%
Marital status	Single	77,42%
	Married/Civil Partnership	17,74%
	Divorced	1,61%
	Prefer not to say	3,23%
Education level	High school	12,90%
	Vocational education	8,87%
	Higher professional education	24,19%
	University bachelor's degree	29,84%
	University master's degree	20,97%
	PhD	1,61%
Gross income	< €10,000	26,61%
	€10,000 - €19,999	14,52%
	€20,000 - €29,999	4,03%
	€30,000 - €39,999	17,74%
	€40,000 - €49,999	14,52%
	€50,000 - €59,999	7,26%
	€60,000 - €79,999	3,23%
	€80,000 - €99,999	0,81%
	> €100,000	0,81%
	Prefer not to say	10,48%
Investment experience	No experience	41,13%
	< 1 year	14,52%
	1-3 years	22,58%
	4-6 years	15,32%
	> 6 years	6,45%
Employment status	Employed full-time	39,52%
	Employed part-time	18,55%
	Student	33,87%
	Unemployed	0,81%
	Retired	0,81%

Table 3 shows the demographic characteristics of participants across the three treatment groups. The distribution appears to be relatively balanced, with only minor differences. The average age ranged from 26.6 in the low-volatility group to 28.3 in the average-volatility group, indicating that all three conditions consisted of relatively young participants. The distribution of gender differed slightly, with the proportion of male respondents being highest in the low-volatility group (79.55%), and lowest in the high-volatility group (62.50%). The percentage of respondents being single is comparable across treatments, and ranged from 75.00% in the average- and high-volatility groups to 81.82% in the low-volatility group.

To report on educational background, a dummy variable was created. Respondents who selected primary school, high school, or vocational education were classified as "low educated", while the others (hbo and higher) were classified as "highly educated". Based on this classification, 84.09% of participants in the low-volatility group had a high level of education, compared to 80% in the average-volatility group and 70% in the high-volatility group.

Similarly, for income, a dummy variable was created using a median split. Respondents who earned less than €30,000 annually were categorized as "low income", while those earning €30,000 or more were classified as "high" income. Based on this classification, 54.84% of respondents in the low-volatility condition had a high income, compared to 59.09% in the average-volatility condition and 62.50% in the high-volatility condition. This suggests that the three treatment groups are roughly balanced in terms of income level.

TABLE 3
DEMOGRAPHIC CHARACTERISTICS ACROSS TREATMENT GROUPS

Variable	Low Volatility	Average Volatility	High Volatility
N	44	40	40
Mean Age (SD)	26,6 (8,58)	28,3 (11,19)	27,1 (10,28)
% Male	79,55%	70,00%	62,50%
% Female	20,45%	30,00%	37,50%
% Single	81,82%	75,00%	75,00%
% Married	11,36%	22,50%	20,00%
% Low educated	15,91%	20,00%	30,00%
% Highly educated	84,09%	80,00%	70,00%
% Low income	45,16%	40,91%	37,50%
% High income	54,84%	59,09%	62,50%

Table 4 provides summary statistics for the psychological control variables that were included in the survey to capture individual differences in risk preference, confidence, and investment behavior. These variables will be used as control variables in the secondary analysis (robustness check) to test if they are significant predictors of individuals exhibiting the disposition effect.

The average score for general risk preference was 3.59 (SD = 1.43), measured on a 7-point scale ranging from 1 (highly risk-averse) to 7 (highly risk-seeking). This indicates that participants were, on average, somewhat risk-averse to risk-neutral. Financial risk preference showed a similar pattern, with a somewhat lower average score of 3.46 (SD = 1.54). These findings are consistent with other survey-based studies showing that self-reported risk preference tends to cluster around the midpoint in non-professional investor samples (Dohmen et al., 2011).

Confidence in investment decisions was measured on a 5-point scale ranging from 1 (not confident at all) to 5 (extremely confident), with a mean of 2.34 (SD = 0.94). This relatively low level of self-reported confidence is consistent with the large percentage of respondents with limited investment experience. Prior research supports the idea that new investors typically have less confidence in their financial decisions. According to Glaser and Weber (2007), for example, new investors frequently have difficulties remembering their past performance, which could indicate a lack of perceived competence. Also, Dittrich et al. (2005) showed that overconfidence in investment decisions tends to increase with age, implying that confidence develops once an investor gains experience.

In addition to risk preference and confidence, participants were asked how frequently they evaluate their investments. Table 5 provides an overview of the reported investment evaluation frequencies, measured on a 7-point categorical scale ranging from “daily” to “never”, and a category for respondents without any investments. The most common response was “no investments” (43.55%), which aligns with the earlier finding that 42.13% of respondents reported having no investment experience. Among participants who systematically evaluated their investments, the most common evaluation patterns were weekly (15.32%), monthly (13.71%), and quarterly (10.48%). Daily evaluation was reported by only 8.87% of participants, indicating that a minority of the sample were very active investors. A small fraction of the sample evaluated investment yearly (6.45%) or never (1.61%).

These numbers indicate an average level of involvement among those who do invest, with most

individuals evaluating their portfolios on a non-daily basis. Previous literature suggests that higher evaluation frequency can increase sensitivity to short-term losses, referred to as myopic loss aversion (Benartzi & Thaler, 1995; Gneezy & Potters, 1997).

TABLE 4
SUMMARY STATISTICS OF PSYCHOLOGICAL CONTROL VARIABLES

Variable	Scale	Mean/Mode (SD)	Range	*N*
General risk preference	1 (Highly risk-averse) to 7 (Highly risk-seeking)	3,59 (1,43)	1-7	124
Financial risk preference	1 (Highly risk-averse) to 7 (Highly risk-seeking)	3,46 (1,54)	1-7	124
Confidence in investment decisions	1 (Not confident at all) to 5 (Extremely confident)	2,34 (0,94)	1-5	124
Investment evaluation frequency	Categorical (see note)	No investments	1-7	124

Note: Investment evaluation frequency was measured using categorical response options: 1 = Daily, 2 = Weekly, 3 = Monthly, 4 = Quarterly, 5 = Yearly, 6 = Never, 7 = No investments.

TABLE 5
FREQUENCY OF INVESTMENT EVALUATION

Frequency	Participants	% of Sample
Daily	11	8,87%
Weekly	19	15,32%
Montly	17	13,71%
Quarterly	13	10,48%
Yearly	8	6,45%
Never	2	1,61%
No investments	54	43,55%
Total	124	100%

TABLE 6
DISTRIBUTION MOST IMPORTANT PRICE TERM

Price term	Participants	% of Sample
First three months	2	1,61%
Second three months	0	0,00%
Third three months	2	1,61%
Last three months	35	28,23%
All parts were equally important	85	68,55%
Total	124	100%

Participants were also asked to indicate which segment of the price chart they found most important when deciding whether to sell or hold the asset, for which they could see last year's price development. As shown in Table 6, a clear majority of respondents (68.55%) indicated that all parts of the price chart were equally important. This suggests that most participants consider the whole price path, rather than focusing on short-term trends or the most recent price developments.

Nonetheless, among those who considered a particular price term most important, the last three months were answered most often (28.23%), consistent with previous findings that investors tend to overweight recent price movements when forming expectations (Bailey et al., 2011; Barberis et al., 1998). On the other hand, the earlier periods of the price path were not often selected: only 2 participants considered the first or third segments to be most important, and no one chose the second segment.

Additionally, participants were asked about how much the lowest and highest values in the price chart affected their perception of risk. The purpose of this question was to determine whether amplitude, the range between the minimum and maximum value of a price path, can serve as a proxy for risk, as shown by Raghubir and Das (2009). As displayed in Table 7, 30.65% of participants indicated that the extremes influenced their perception of risk moderately, while 28.23% answered strongly, and another 28.23% reported being slightly influenced. Only a small portion of the sample reported either a very strong influence (4.03%) or no influence at all (8.87%).

These results indicate that for most participants, extreme values had at least some influence on how risky they perceived the asset. This aligns with prior literature showing that investors rely on salient visual cues such as peaks and valleys when assessing risk (Borsboom & Zeisberger, 2020; Raghubir & Das, 2009).

TABLE 7
INFLUENCE HIGHEST/LOWEST VALUE IN GRAPH ON RISK PERCEPTION

Degree of influence	Participants	% of Sample
Not at all	11	8,87%
Slightly	35	28,23%
Moderately	38	30,65%
Strongly	35	28,23%
Very strongly	5	4,03%
Total	124	100%

4.2 Main analysis

Table 8 presents the mean disposition effect scores across the three volatility conditions. As previously explained, the disposition effect score is calculated by subtracting the average willingness to sell in loss scenarios from the average willingness to sell in gain scenarios. Higher scores indicate a stronger disposition effect, i.e., a stronger tendency to sell winning assets while continuing to keep losing ones.

The results show a clear pattern. Participants in the high-volatility condition exhibited the strongest disposition effect (M = 0.08, SD = 2.76). Even though this mean value can seem low, it is positive, indicating that participants are more likely to sell winners than losers on average. In contrast, both the low-volatility (M = -1.58, SD = 2.43) and the average-volatility (M = -0.61, SD = 2.64) conditions had negative average disposition effect scores. This implies that the high-volatility group has the greatest tendency to sell winning assets and hold onto losing ones.

These findings are consistent with the hypothesis that investors exhibit a stronger disposition effect when price path variability increases. High-volatility price paths may amplify perceived risk and uncertainty, leading investors to realize winners earlier. Conversely, low-volatility price paths may cause investors to feel less urgency to realize winners.

These descriptive statistics will be further examined to assess whether the observed differences across volatility conditions are statistically significant.

TABLE 8
DISPOSITION EFFECT SCORES PER CONDITION

Volatility Condition	Mean	SD	Min	Max	*N*
Low	-1,58	2,43	-6	4,5	44
Average	-0,61	2,64	-6	5,5	40
High	0,08	2,76	-5	5	40

Table 9 summarizes the variables relating to the twelve different price paths: willingness to sell, satisfaction, percentage of investment willing to sell, willingness to buy, and minimum selling price. As previously mentioned, each volatility condition includes two gain and two loss scenarios, which were further distinguished based on whether they included an interim reversal (interim gain or loss).

In the low-volatility condition, participants showed a clear asymmetry between gains and losses. Willingness to sell was substantially lower for gain scenarios (M = 2.23 and 2.41) than for loss scenarios (M = 3.77 and 4.02). These numbers therefore contradict the disposition effect the most, as it would predict a high willingness to sell for gain scenarios and a low willingness to sell for losing ones. The asymmetry is also reflected in the satisfaction scores. Participants reported high satisfaction with gains (M = 5.50 and 6.10) and low satisfaction with losses (M = 1.80 and 2.00).

When comparing the satisfaction scores to the other price path literature, the average-volatility condition scores are in line with the research done by Grosshans and Zeisberger (2018). Participants are more satisfied if the price path first goes down and then up, and less satisfied if the price path first goes up and then down, compared to those that do not include an interim reversal. For the low-volatility condition, the gain scenarios contradict the results found by Grosshans and Zeisberger (2018), and the loss scenarios support them. Lastly, for the high-volatility condition, the gain scenarios contradict their results, and the loss scenarios support them.

On average, participants were willing to sell a higher portion of their investment (€1000 at the beginning of the period) in loss scenarios (M = 36.36% and 36.84%) than in gain scenarios (M = 21.55% and 24.14%). The overall minimum acceptable selling price for low volatility is equal to €323.54, with the initial price being on average €100. The minimum acceptable selling prices for gain scenarios are substantially higher than in the loss scenarios. This suggests that participants shift their reference prices up once their investment has increased in value. This aligns with prior literature that states that individuals shift their reference price up after a gain but keep the purchase

price as their reference price after a loss (Barberis & Xiong, 2009; Baucells et al., 2011; Grosshans & Zeisberger, 2018).

In the average-volatility condition, willingness to sell for gain scenarios (M = 2.93 and 2.65) was still lower compared to the loss scenarios (M = 3.73 and 3.08). The difference is, however, less pronounced. Satisfaction remains substantially higher for gains (M = 6.23 and 5.83), but loss scenarios were rated slightly better (M = 1.80 and 2.43) than in the low-volatility condition. The average willingness to buy the asset at the current price was comparable across conditions (M = 3.65, 3.65, and 3.57 for low, average, and high volatility respectively). The average minimum acceptable selling price for average volatility increased to €398.16.

Then, in the high-volatility condition, domain differences regarding willingness to sell became even less pronounced. Willingness to sell for gain scenarios (M = 3.10 and 3.53) is now on average higher than for loss scenarios (M = 3.38 and 3.10). The disposition effect is therefore the strongest under high volatility. Satisfaction scores were still substantially higher for gains than for losses. The minimum acceptable selling price increased further to €523.47, which could indicate that volatile price paths may increase participants' internal reference price.

Note further that the average minimum selling prices are very high, up to five times the purchase price for the high volatility condition. However, this question did not specify a time horizon for these minimum selling prices. Perhaps the respondents had a long investment horizon in mind.

To better understand what drives the observed differences in disposition effect scores, willingness to sell in gain and loss scenarios was compared across the three volatility conditions. In gain scenarios, willingness to sell increased clearly with volatility. The average willingness to sell in the low-volatility condition was 2.32. This increased to 2.79 in the average-volatility condition and to 3.32 in the high-volatility condition. This represents an increase of 20.3% from low to average volatility and an increase of 19.0% from average to high volatility.

In loss scenarios, willingness to sell decreased slightly as volatility increased. The average willingness to sell decreased from 3.90 in the low-volatility group to 3.41 in the average-volatility group. This further decreased to 3.24 in the high-volatility group. This represents a decrease of 12.6% from low to average volatility and a decrease of 5.0% from average to high volatility.

These numbers show that the increase in disposition effect scores across volatility conditions is mainly driven by behavior in the gain domain. The upward trend in willingness to sell gains is stronger than the downward trend in willingness to sell losses.

TABLE 9
SUMMARY STATISTICS ACROSS ALL TREATMENTS

Volatility Condition	Willingness to sell	Satisfaction	Sell %	Willingness to buy	Minimum selling price	*N*
Low						44
Gain with interim loss	2,23	5,50	24,14	4,05	€ 436,78	
Gain no interim loss	2,41	6,1	21,55	4,02	€ 397,81	
Loss with interim gain	3,77	1,8	36,36	3,36	€ 216,13	
Loss no interim gain	4,02	2,0	36,84	3,18	€ 243,43	
Mean	**3,11**	**3,84**	**29,72**	**3,65**	**€ 323,54**	
Average						40
Gain with interim loss	2,93	6,23	25,88	3,90	€ 462,36	
Gain no interim loss	2,65	5,83	34,48	4,28	€ 478,66	
Loss with interim gain	3,73	1,80	35,25	3,00	€ 313,78	
Loss no interim gain	3,08	2,43	23,75	3,43	€ 337,85	
Mean	**3,09**	**4,07**	**29,84**	**3,65**	**€ 398,16**	
High						40
Gain with interim loss	3,10	5,45	34,58	3,63	€ 672,16	
Gain no interim loss	3,53	5,85	33,00	3,28	€ 568,06	
Loss with interim gain	3,38	1,85	32,88	3,48	€ 397,76	
Loss no interim gain	3,10	2,45	30,13	3,90	€ 455,90	
Mean	**3,28**	**3,90**	**32,64**	**3,57**	**€ 523,47**	

4.3 Hypothesis test

To investigate whether price path variability statistically influences the strength of the disposition effect, a one-way analysis of variance (ANOVA) was conducted. The three experimental conditions: low, average, and high volatility, are used as independent variables, and the disposition effect score is used as the dependent variable.

Before conducting the main analysis, two assumption checks will be performed (Algina & Olejnik, 2003; Davison & Sharma, 1994). First, ANOVA assumes that the data is normally distributed, and for this, a Shapiro-Wilk test will be conducted. Secondly, ANOVA assumes homogeneity of variance. This means that the variance among the different treatment groups should be approximately equal. For this, a Levene's test will be conducted.

Figure 2 displays the distribution of the data and already suggests that the disposition effect scores are normally distributed. Shapiro-Wilk has the null hypothesis that the data set is normally distributed. A score between -1 and 0 is most common. A large p-value indicates that the data set is normally distributed, and a low p-value indicates that it is not normally distributed. According to the test, data were normally distributed ($W = 0.99$, $p = .317$).

Levene's test has the null hypothesis that variances across treatment groups are approximately equal. A large p-value indicates that the variances are not statistically different, and a low p-value indicates that the variances are statistically different. The test confirmed that the assumption of homogeneity of variances was met ($F(2, 121) = 0.531$, $p = 0.59$).

The results of the one-way ANOVA showed a statistically significant effect of volatility condition on disposition effect scores, $F(2, 121) = 4.29$, $p = .016$. This indicates that the average disposition effect scores differed meaningfully across the three levels of price path volatility. The effect size, measured by eta squared, was $\eta^2 = .07$, which is considered a medium effect according to conventional benchmarks (Cohen, 1995). Table 10 summarizes the findings of the ANOVA.

To identify which specific conditions differed from one another, a Tukey HSD post-hoc test was performed. The results, displayed in Table 11, show that participants in the high-volatility condition exhibited a significantly stronger disposition effect than those in the low-volatility condition (mean difference = 1.65, $p = .012$). No statistically significant differences were found between the average-volatility condition and either the low ($p = .210$) or high ($p = .467$) The findings therefore partially support the hypothesis, only when comparing the low and high-volatility conditions.

TABLE 10
ONE-WAY ANOVA RESULTS

	Df	Sum Sq	Mean Sq	F	p-value
Volatility condition	2	58.2	29.11	4.29	.016 *
Residual	121	821.5	6.79		

TABLE 11
TUKEY HSD POST-HOC COMPARISONS

Comparison	Mean Difference	95% CI	p-value
High - Average	0.69	[-0.70, 2.07]	0.467
Low - Average	-0.97	[-2.32, 0.38]	0.210
Low - High	-1.65	[-3.01, -0.30]	0.012 *

FIGURE 2. HISTOGRAM OF DISPOSITION EFFECT SCORES

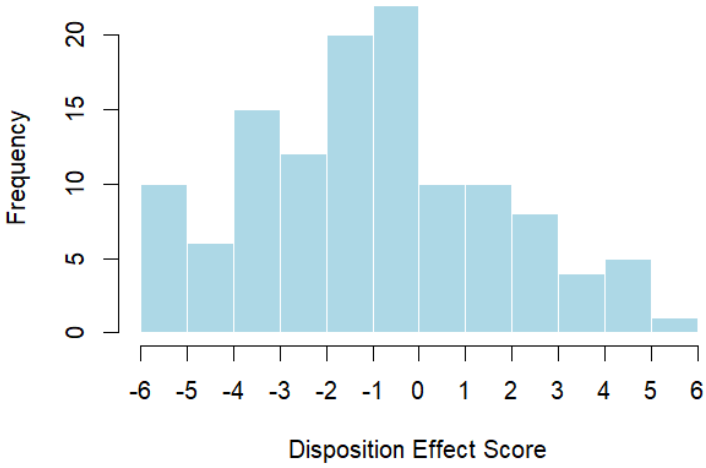
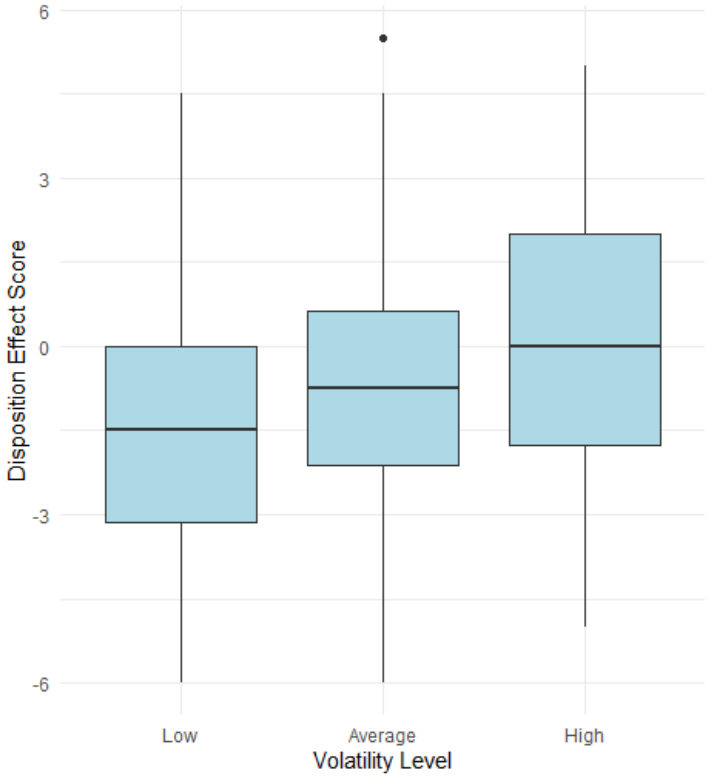


FIGURE 3. DISPOSITION EFFECT BY VOLATILITY CONDITION



4.4 Secondary analysis

To examine whether individual characteristics and demographics influence the strength of the disposition effect, a multiple linear regression was conducted. The model included general risk preference, financial risk preference, confidence level, age, gender, education level, income, investment experience, and volatility treatment groups as predictors, with disposition effect scores as the dependent variable. Results are displayed in Table 12.

Financial risk preference was positively associated with the disposition effect ($\beta = 0.53$, $p = .01$), indicating that participants with a higher willingness to take financial risks were more likely to sell winning stocks and hold on to losing stocks, consistent with the disposition effect. Confidence level was negatively related to the disposition effect ($\beta = -0.59$, $p = .05$), suggesting that less confident individuals were more likely to exhibit the disposition effect.

Participants in the low volatility treatment exhibited a significantly lower disposition effect compared to participants in the high volatility group ($\beta = -1.62$, $p = .01$), consistent with the findings from the main analysis. This supports the hypothesis that the strength of the disposition effect increases with the level of price path variability.

Other variables, including general risk preference, age, gender, income, education level, and investment experience were not significantly associated with the disposition effect. Income, education level, and investment experience were included as dummies because of the high number of categories.

TABLE 12
MULTIPLE LINEAR REGRESSION

Variable	Coefficient	SE	t-value	p-value
Intercept	1.44	1.73	0.83	0.41
General risk preference	-0.24	0.21	-1.15	0.25
Financial risk preference	0.53	0.21	2.55	0.01*
Confidence level	-0.59	0.30	-1.94	0.05 .
Age	0.02	0.03	0.97	0.33
Gender	-0.54	0.55	-0.98	0.33
Income	-0.12	0.52	-0.23	0.82
Education level	-0.24	0.59	-0.41	0.68
Investment experience	-0.15	0.58	-0.25	0.80
Low volatility treatment	-1.62	0.59	-2.76	0.01**
Average volatility treatment	-0.99	0.60	-1.65	0.10
N	124			
R-squared	0.15			
Adjusted R-squared	0.07			
Residual Std. Error	2.58			
F-statistic	1.92			

Signif. codes: 0.001 '**' 0.01 '*' 0.05 '. '

5 Discussion

5.1 Conclusion

The main objective of this study was to investigate whether price path variability influences the strength of the disposition effect. Building on prospect theory and price path literature, the research explored whether individuals react differently when exposed to price charts that vary in volatility, but are identical in trend, initial and final price, and overall return. The results suggest that volatility in a price path can meaningfully influence selling behavior and lead investors to biased decision-making.

The following statistical analysis confirmed this. A one-way ANOVA revealed a statistically significant effect of volatility on disposition effect scores. Post-hoc tests showed that participants in the high-volatility condition exhibited a significantly stronger disposition effect than those in the low-volatility condition. This implies that visual volatility can influence selling intentions and investment behavior in general, even when the underlying returns are the same.

When looking more closely at the underlying selling behavior in different scenarios, the data suggest that this effect is mainly driven by changes in behavior in the gain domain. Specifically, the willingness to sell in gain scenarios increased by 42.89% from the low- to high-volatility condition. In contrast, willingness to sell in loss scenarios decreased by 16.82% across the same range. This asymmetric pattern suggests that volatility mainly affects how individuals act upon winning investments. Losses seem to be treated more consistently across volatility conditions, possibly because of a stronger attachment to the initial reference point. Because investors tend to shift their reference price up after a gain but keep their initial reference price after a loss (Barberis & Xiong, 2009; Baucells et al., 2011).

The secondary analysis investigated whether psychological variables and demographics could help explain variation in disposition effect scores. A multiple linear regression showed that financial risk preference and confidence level were both significant predictors. Individuals with higher financial risk tolerance were more likely to show a stronger disposition effect. Similarly, lower confidence was associated with stronger bias. The analysis also provided support for the hypothesis.

The results also contribute to the literature on visual risk perception. Earlier studies showed that

investors interpret price charts using salient visual features like trend, amplitude, and reversals (Borsboom & Zeisberger, 2020; Raghubir & Das, 2009). This study builds on that by showing that volatility can also shape selling intentions and investment behavior in general.

5.2 Practical implications

The findings of this study have several practical implications. First, they highlight the importance of graphical representations in financial decision-making. Visual volatility, even when variables like initial and final prices are held constant, can shape investor behavior in meaningful ways. Investors may be steered toward biased decisions when they are faced with volatile price paths. Thus, especially when markets are volatile, this could have consequences for investors.

As such, regulators might consider offering guidelines on the use of historical performance graphs in financial products, particularly during times of market stress. Financial literacy programs could be used to teach investors to interpret financial graphs more critically.

5.3 Limitations

As with any experimental study, the findings come with several limitations. First, except from the possibility of winning a bol.com voucher, the decisions were hypothetical and there was no actual money involved. Therefore, participants may not be inclined to answer the questions as accurately and honestly as possible. However, because of financial constraints, this limitation could not have been avoided.

Secondly, participants made choices based solely on price charts. In real investment situations, additional information such as news, fundamentals, and recommendations from experts also plays a role. However, because the research was focused on investigating the potential effects of volatility on investment behavior, the study could not provide any additional context.

Third, the sample was based on convenience and consisted mainly of young, highly educated males. While the treatment groups were approximately balanced in terms of demographics, generalizability is limited.

Lastly, the simulated price paths contain volatility across the whole period. In real financial markets, volatility often appears in clusters, meaning that high or low volatility tends to stay for a while (Enow, 2023). This is not captured in the experiment.

5.4 Future research

First, future research could incorporate volatility clustering within price paths (Duxbury & Summers, 2018). In this experiment, price paths contained a relatively consistent level of volatility across the time horizon used. However, in real financial markets, volatility does not need to be evenly distributed over time. Periods of high volatility often follow periods of low volatility. This phenomenon is referred to as volatility clustering (Enow, 2023). Future research could therefore simulate price paths where volatility is concentrated at the beginning, middle, or end of the time horizon. This would allow for the examination of whether the timing of volatility matters for selling behavior. High volatility near the end of a price path may induce greater fear than earlier in the price path, even if the overall return is the same.

Second, it would be valuable to investigate how contextual information interacts with price path characteristics. This could lead to insights about whether and how such information affects the disposition effect. It could be that contextual information dominates or that it has no influence at all. Future research could therefore combine price path volatility with different forms of contextual framing. This would help assess the robustness of the results under more realistic conditions.

Lastly, future studies may explore how time horizon framing affects visual risk perception and selling intentions. In this study, all price paths used a one-year period. However, using the same price developments but presenting them as short-term (e.g., one week) could lead to different results. Stated differently, future research could explore if volatility still affects the disposition effect under different time horizons.

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Appendix A: Survey Questions Format (EN)

Q1. Instructions and Consent[5]

Thank you for participating in this study. The goal of this research is to better understand how people make investment decisions. There are no right or wrong answers.

The survey takes approximately **3 to 5 minutes** to complete. Participation is completely **voluntary**, and you are free to stop at any time without giving a reason. No personal data will be collected, and your responses will remain **anonymous**. The data will only be used for academic research purposes.

If you choose to enter a prize draw for **a €20 Bol.com voucher** (optional), you may leave your email address at the end of the survey. This will be stored separately and deleted after the draw. Please note that only participants who fully complete the survey will be eligible to participate in the prize draw.

By continuing, you confirm that you:
• Are **18 years or older**,
• Have read and understood the above information,
• And **voluntarily consent** to participate.

If you have any questions, feel free to contact me at timo.aerts@ru.nl.

Please confirm that you consent to participate before continuing.
[] I consent to participate in this study
[] I do not consent to participate

[5] The Dutch version is available upon request from the author.

Experimental instruction

Imagine you are an investor who invested in four financial assets exactly one year ago. Financial assets are instruments that represent value and can increase or decrease in value over time. You are now evaluating the performance of these assets.

You will be shown **a total of four price charts**, each representing the development of one of these assets over the past year. After each chart, you will be asked whether you would like to sell or continue holding the asset.

Please evaluate **each chart independently**. Base your decision solely on the information presented in that specific chart. Do not compare it to earlier or upcoming charts.

Block 1 – Low/Average/High volatility

Q2. Please evaluate the asset based on the price chart below.

[see Appendix B: Price Paths Overview for all price charts]

Would you hold or sell the asset at its current price?

Scale:

1 = Very likely hold

2 = Likely hold

3 = Somewhat likely hold

4 = Neutral

5 = Somewhat likely sell

6 = Likely sell

7 = Very likely sell

Q3. How satisfied are you with the performance of this asset?

Scale:

1 = Very dissatisfied

2 = Dissatisfied

3 = Somewhat dissatisfied

4 = Neutral

5 = Somewhat satisfied

6 = Satisfied

7 = Very satisfied

Q4. Imagine that you previously invested €1000 in this asset at the starting price shown in the chart. Over the past year, the asset increased/decreased by 20%, so your investment is now worth €1200/€800.

What percentage of your investment would you sell right now?

Please enter a number between 0 and 100 (no percent sign).

Q5. If you had not yet invested in this asset, how likely would you be to buy it right now?

Scale:

1 = Definitely not buy

2 = Unlikely to buy

3 = Somewhat unlikely to buy

4 = Neutral

5 = Somewhat likely to buy

6 = Likely to buy

7 = Definitely buy

Q6. What would be a reasonable minimum price at which you would sell your asset?

(Please enter a number only, without currency symbols.)

Block 2 – General questions

Q7. What aspects did you focus on when deciding whether to sell or hold the assets?

(open text field)

Q8. Which segment of the price charts did you consider most important when deciding whether to sell the assets?

Scale:

1 = The first three months

2 = The second three months

3 = The third three months

4 = The last three months

5 = All parts were equally important

Q8. To what extent did the lowest and highest values of the price charts influence your perception of how risky the assets were?

Scale:

1 = Not at all

2 = Slightly

3 = Moderately

4 = Strongly

5 = Very strongly

Block 3 – Psychological control questions

Q10. How would you describe your general risk preference?

Scale:

1 = Highly risk-averse

2 = Risk-averse

3 = Somewhat risk-averse

4 = Neutral

5 = Somewhat risk-seeking

6 = Risk-seeking

7 = Highly risk-seeking

Q11. How would you describe your financial risk preference?

Scale:

1 = Highly risk-averse

2 = Risk-averse

3 = Somewhat risk-averse

4 = Neutral

5 = Somewhat risk-seeking

6 = Risk-seeking

7 = Highly risk-seeking

Q12. How confident are you in your investment decisions?

Scale:

1 = Not confident at all

2 = Slightly confident

3 = Moderately confident

4 = Very confident

5 = Extremely confident

Q13. How often do you evaluate your investments?

☐ Daily

☐ Weekly

☐ Monthly

☐ Quarterly

☐ Yearly

☐ Never

☐ I do not currently have any investments

Block 4 - Demographics

Q14. What is your age?

(open text field)

Q15. What is your gender?

☐ Male

☐ Female

☐ Non-binary

☐ Prefer not to say

☐ *Other, namely:

(open text field)

Q16. What is your marital status?

☐ Single

☐ Married / registered partnership

☐ Divorced

☐ Widowed

☐ Prefer not to say

Q17. What is your highest level of education you have completed?

☐ Primary school

☐ High school diploma (e.g., vmbo, havo, vwo)

☐ Vocational education (mbo)

☐ Higher professional education (hbo)

☐ University bachelor's degree (wo)

☐ University master's degree (wo)

☐ PhD (doctorate)

☐ *Other, namely:

(open text field)

Q18. What is your gross annual income level? (before taxes)

☐ Less than €10,000

☐ €10,000 - €19,999

☐ €20,000 - €29,999

☐ €30,000 - €39,999

☐ €40,000 - €49,999

☐ €50,000 - €59,999

☐ €60,000 - €79,999

☐ €80,000 - €99,999

☐ €100,000 or more

☐ Prefer not to say

Q19. What is your experience with investing?

☐ No experience

☐ Less than 1 year

☐ 1-3 years

☐ 4-6 years

☐ More than 6 years

Q20. What is your current job?

(open text field)

Q21. What is your current employment status?

☐ Employed full-time

☐ Employed part-time

☐ Self-employed

☐ Student

☐ Unemployed

☐ Retired

☐ *Other, namely:

(open text field)

➔ Directed to new survey

Q1. Optional: Prize Draw Entry

Would you like to participate in a prize draw to win a €20 Bol.com voucher?

If yes, please enter your email address below.
Your email address will be stored separately from your survey responses to ensure your anonymity and will be deleted immediately after the prize draw.

If you do not wish to participate, you can simply leave this field empty and submit your survey.
(open text field)

End of survey

Thank you very much for completing the survey!

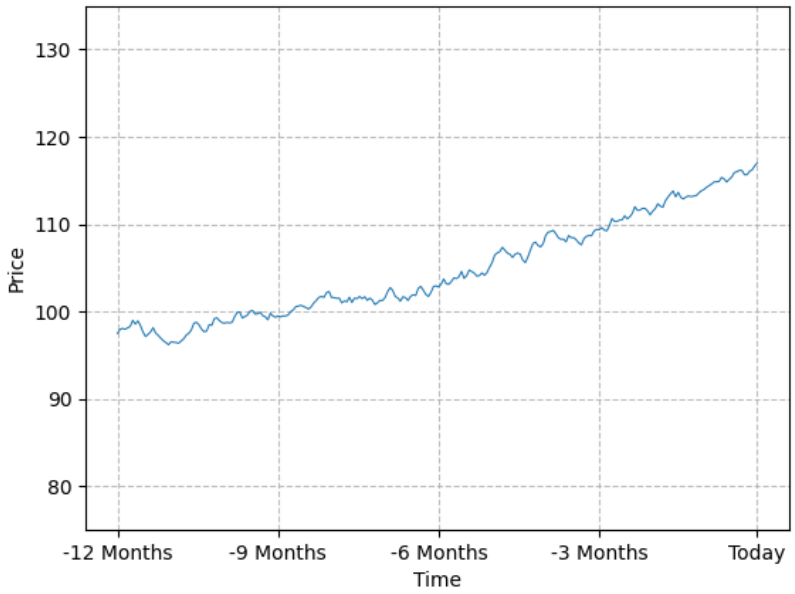
Your input is highly valuable and will contribute to a better understanding of how people make investment decisions based on price charts. Your responses have been recorded anonymously and will only be used for academic research purposes.

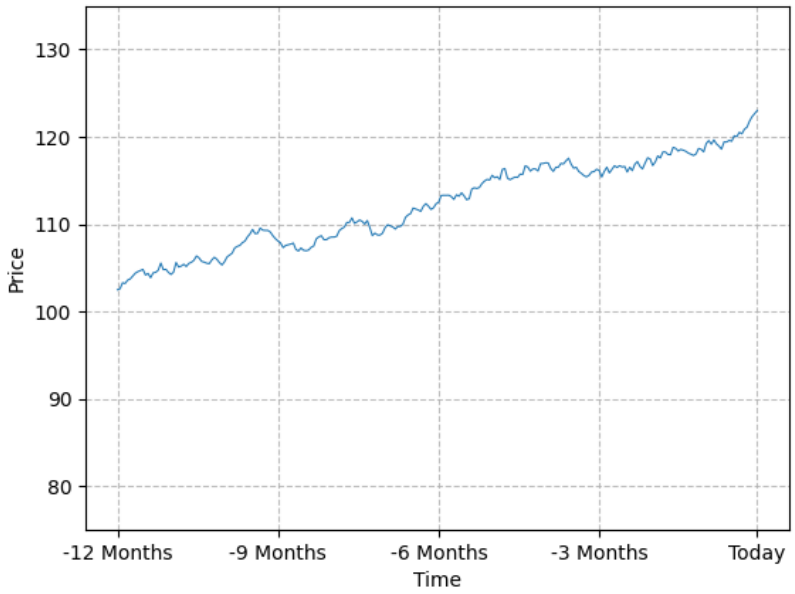
I will contact the winner of the prize draw after the survey closes.

If you have any further questions or would like to know more about this research, feel free to contact me at timo.aerts@ru.nl

Appendix B: Price Paths Overview

B1. Low Volatility (Treatment 1)



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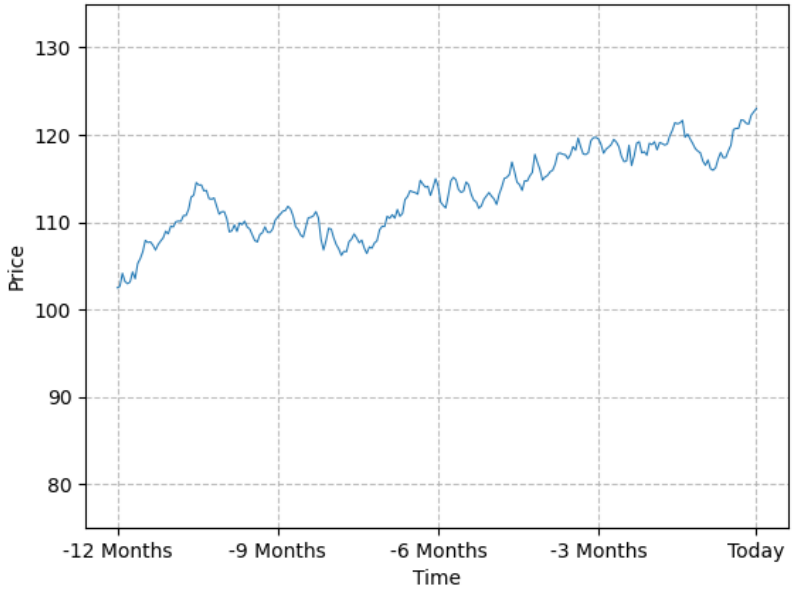
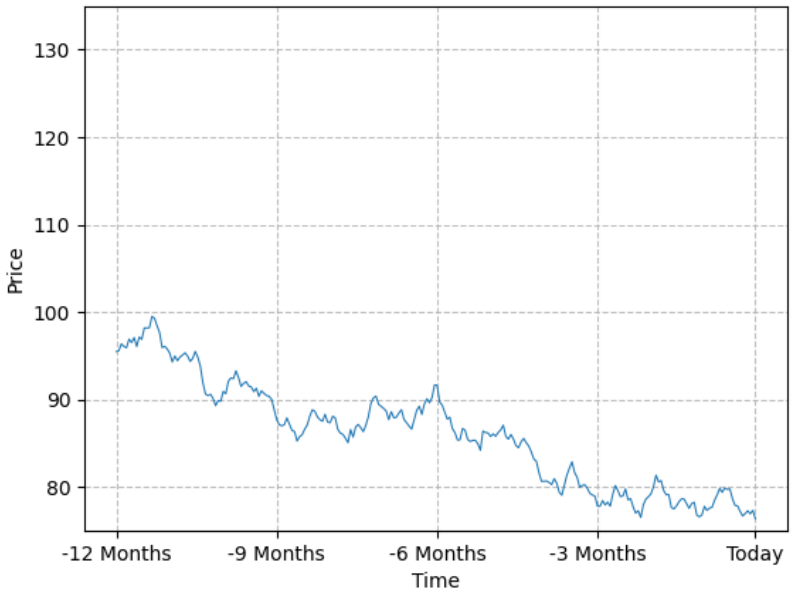
B2. Average Volatility (Treatment 2)

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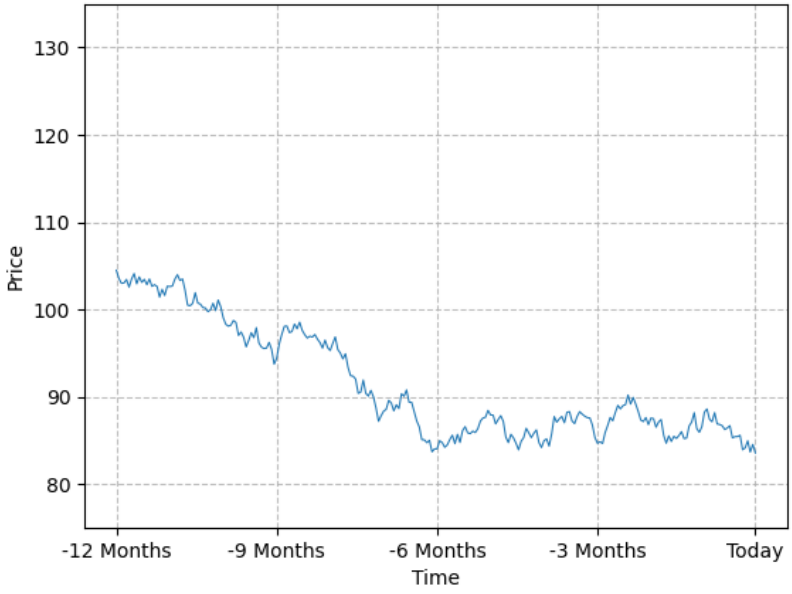
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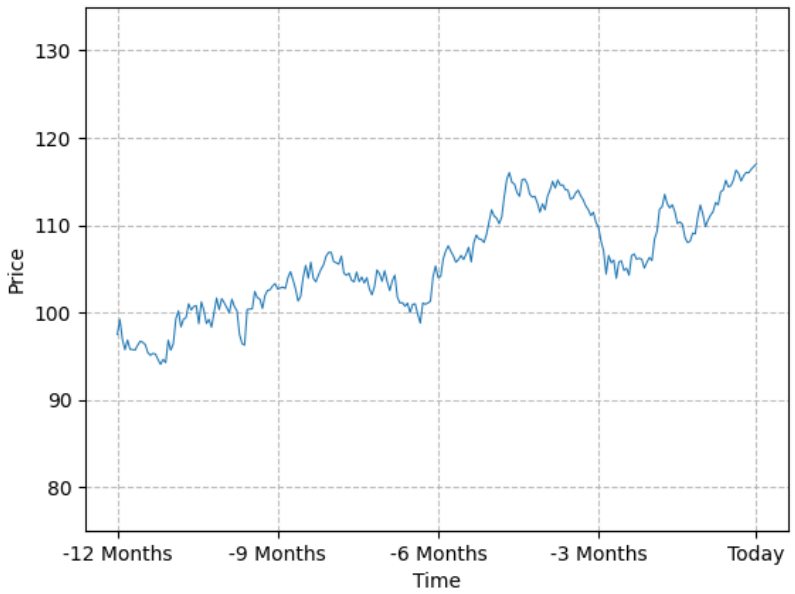
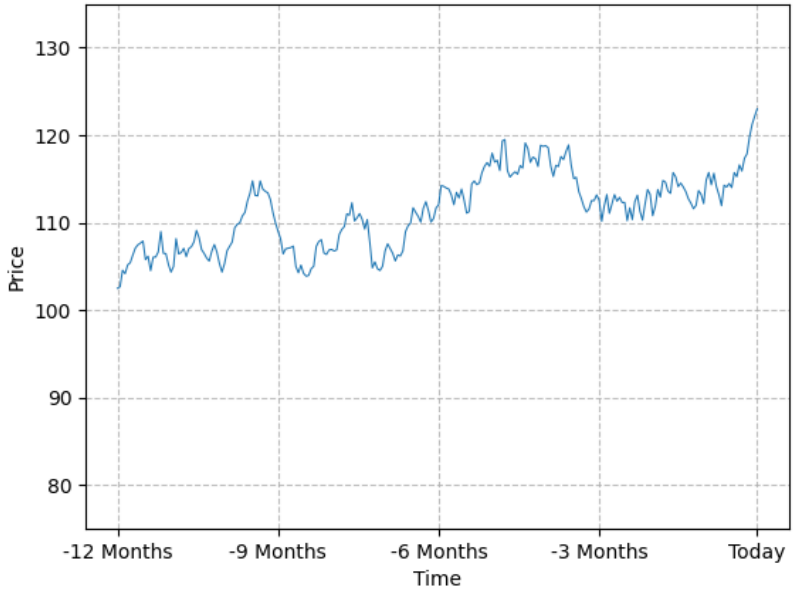
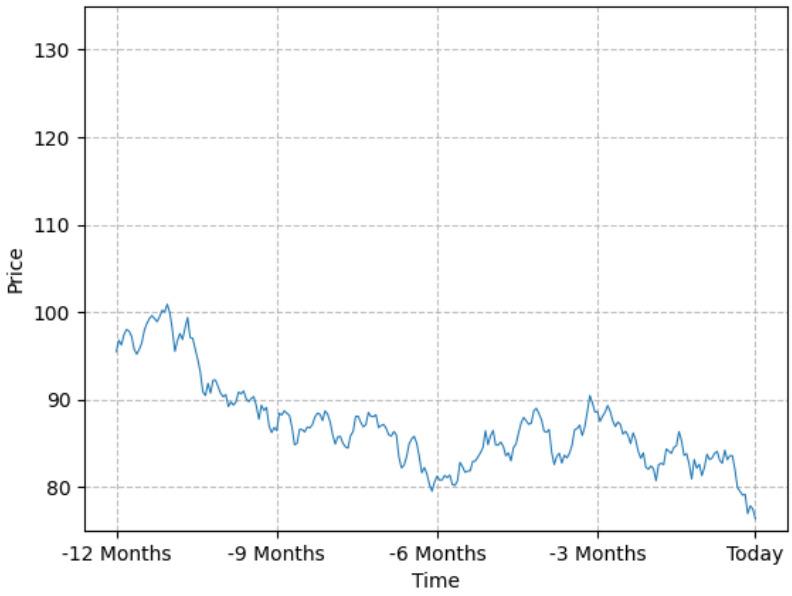
B3. High Volatility (Treatment 3)



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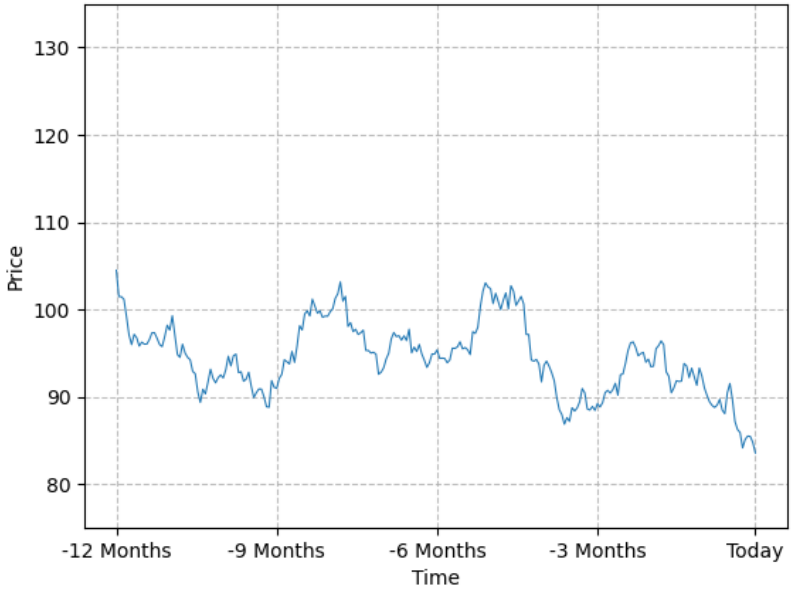
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Appendix C: Use of Generative AI Tools in Thesis Development

1. **Statement of Purpose**

   "This appendix provides a detailed description of how generative AI tools were used in the process of writing the research proposal and thesis. The different tools used, their scope and the complete log of AI Interaction are provided below."

2. **Tools used**

   - **Tool name:** ChatGPT 4o
   - **Tool name:** QuillBot

3. **Scope of Use**

3.1. Coding and Data Analysis

- **Description:**
  - Tool: ChatGPT 4o
  - Purpose: Assisting with data analysis and writing code for Excel, R and Python.
  - My Role: The AI suggestions were reviewed and provided inspiration on how to code a certain action.
  - My reflection: The AI were sometimes helpful because it provided codes which I didn't know before.
  - Applied in Section 4

3.2. Writing and Grammar Refinement

- **Description:**
  - Tool: ChatGPT 4o
  - Purpose: Assisting with language refinement.
  - My Role: The AI suggestions were used when I thought I could write down a certain sentence more academically/concisely.
  - My reflection: AI helped me with the suggestions in the sense that it provided me with ideas on how I could better write down a certain sentence.
  - Applied in Sections 1, 2, 3, **Fout! Verwijzingsbron niet gevonden.**, and 5.

3.3. Data visualization

- **Description:**
  - Tool: ChatGPT 4o, R and Python
  - Purpose: Assisting with the code on how to visualize a certain graph.
  - My Role: The AI suggestions were reviewed, and I assessed which graph was most useful.
  - My reflection: AI helped me with the suggestions in the sense that it made me way faster create certain tables/graphs.
  - Applied in Sections 3, 4 and Appendix B: Price Paths Overview

4. Complete log of AI Interaction

4.1. Coding Assistance

- **Query to ChatGPT 4o:** "How can I randomly assign participants in Qualtrics to different volatility conditions and show them two price paths for both the gain and loss domain?"
- **Output from ChatGPT 4o:** Provided step-by-step instructions on how to implement random assignment using the Qualtrics randomizer, including how to use branching logic.
- **How It Was Used:** Utilized to set up the survey structure in Qualtrics with three randomized treatment groups (low, average, and high volatility).
- **Iterations back and forth needed:** 4

4.2. Writing Assistance

- **Query to ChatGPT 4o:** "Can you help me rewrite this paragraph on myopic loss aversion in a more structured way, starting with explaining the concept before applying it?"
- **Output from ChatGPT 4o:** Suggested alternative phrasings that improved fluency and structure while maintaining the original meaning.
- **How It Was Used:** The AI suggestions were used to improve sentence clarity and to reduce redundancy. All suggestions were reviewed and adjusted manually to retain authenticity.

- **Iterations back and forth needed:** 2

4.3. Data visualization

- **Query to ChatGPT 4o:** "How can I plot hypothetical price paths with different volatility conditions using Python?"
- **Generated Code:** ChatGPT provided Python code using *matplotlib* and *numpy* to simulate price paths with low, average, and high volatility.
- **How It Was Used:** The code was used as a starting point for creating the stylized price paths for the experiment. The outputs were further customized to ensure that the price paths looked like they were intended to look (see Appendix B: Price Paths Overview).
- **Iterations back and forth needed:** 10