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Understanding and Debiasing Investor Behaviour

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List of Abbreviations

adj.	adjusted
Alpha (α)	disposition coefficient
API	Application Programming Interface
avg.	average
CCES	Cooperative Congressional Election Survey
CESR	Committee of European Securities Regulators
CRSP	The Center for Research in Security Prices
CSS	Cascading Style Sheets
DE	disposition effect measure
e.g.	exempli gratia
EONIA	Euro OverNight Index Average
et al.	et alii
EU	European Union
FinTech	financial technology firm

fMRI	Functional Magnetic Resonance Imaging
HIT	Human Intelligence Task
HTML	Hypertext Markup Language
i.e.	id est
IMC	Instruction Manipulation Check
KMO	Kaiser-Meyer-Olkin criterion
KS	Kolmogorov-Smirov
MTurk	Mechanical Turk
OLS	Ordinary Least Squares
p.	page
PGR	proportion of realized gains
PLR	proportion of realized losses
pp.	pages
S₊	sales after price increase
S₋	sales after price decrease
US	United States
VikoDiA	Visualisierungskonzept für digitale Anlageberatung

Introduction

Over the past several decades, financial markets have become increasingly accessible to an ever-growing fraction of the world's population (Lusardi and Mitchell (2014)). Also, individuals have become more active as a result of broader market access (Corgnet et al. (2018)) and the advent of novel financial products and services (van Rooij et al. (2011)). The Internet has, at least in part, contributed to this development: By reducing transaction costs, physical access barriers, as well as information costs, Bogan (2008) observes a positive effect on the number of stock-owning households. More recently, so-called robo-advisors emerged onto the wealth management sphere (Musto et al. (2015)) and further lowered investment barriers (Deluca (2017)) by offering relatively simple passive investment strategies (Phoon and Koh (2017)) to investors who previously would not have been served by traditional wealth managers.

Nevertheless, these developments cannot be seen in a purely positive manner. For example, Barber and Odean (2002) find that well-faring investors perform considerably worse after taking their trading activities online. The depreciation in their performance stems from the fact that online investing leads investors to trade more actively and speculatively. Additionally, Statman (2003) concludes that while investors today possess broader access to more accurate information, they make considerably worse decisions and therefore do not perform better than their precursors. At the same time, technological advancements have not only resulted in broader access to financial markets. Additionally — in combination with higher standards of living — they have also caused the average life expectancy to increase significantly. On average, life expectancy increases by one year, every five years (World Economic Forum (2017b)), which will continue to result in a substantial decrease of the dependency ratio. These demographic changes have already started to force households in developed countries to take financial and pension matters into their own hands (Fecht et al. (2018)) to care for their future.

Furthermore, alterations to pension systems have been making employees increasingly self-responsible for their future financial wellbeing (Lusardi and Mitchell

(2014)). More specifically, a substantial number of retirement systems has switched from the provision of defined benefit to defined contribution schemes (Hanson and Olson (2018)). Today, defined contribution systems globally account for more than 50% of retirement assets (World Economic Forum (2017b)). By shifting decision-making responsibility away from institutions (i.e., governments or employers) towards employees (van Rooij et al. (2011)), individual financial investors are becoming more relevant from an economic and academic perspective (Hoffmann et al. (2013)).

The question thus arises whether individual investors are prepared to appropriately cope with these developments. The World Economic Forum (2017b), for example, notes that the low levels of financial literacy observed globally pose a severe threat to the world’s pension systems. Investors’ future welfare depends on the solidity of their financial decisions to a large degree (Duclos (2014)). In this regard, prior research has shown that individual investors rarely behave rationally (Baker et al. (2018)) and as strict utility maximizers (Kahneman (2003)). Their decision-making does, however, often depart from rationality in a rather systematic way (Trejos et al. (2018)): While Barber and Odean (2008) argue that individual information processing and decision-making is affected by cognitive and temporal boundaries, Gabbi and Zanotti (2018) find that inter-temporal factors such as emotions also play a significant role. This results in the fact that individuals often rely on heuristics (Trejos et al. (2018)), which can lead them to exhibit severe biases: For example, prior research has found that retail investors trade too frequently (see for example Odean (1999)), under-diversify their portfolio (see for example Phan et al. (2018)), or do not invest according to their objective risk attitude (see for example Oehler et al. (2018)). These exemplary behaviours — among many others — are detrimental to their financial welfare (Barber and Odean (2011)).

In relation to the above-described developments, this dissertation sets out to contribute to the following aspect of finance research: **“Understanding and De-biasing Investor Behaviour.”** To do so, Chapter 1, which is a direct proceeding of the VikoDiA¹ project, conducts an experiment where participants are asked to consider a hypothetical investment scenario. The main focus of this experiment is to investigate how visual aids can enhance subjects’ understanding of investment reports in an increasingly digital context. More particularly, we focus on their understanding of the basic characteristics of any investment: risk and return. To briefly

¹ VikoDiA (“Visualisierungskonzept für digitale Anlageberatung”) is a joint project of moneymeets and WHU – Otto Beisheim School of Management. The EU funding by CreateMedia.NRW is gratefully acknowledged.

foreshadow the main results, we find that most investors do not even understand the basic characteristics of their investments and that visual aids can help their understanding under certain circumstances.

As a direct result of this observation, Chapter 2 sets out to investigate one behavioural bias in more detail. Here, we focus on the disposition effect (Shefrin and Statman (1985)), because it has been shown to be a global, ubiquitous, robust phenomenon (Barber and Odean (2011)) that adversely affects investors' performance (Odean (1998)). In particular, we argue that little research has been conducted that aims at debiasing the disposition effect. This is where we contribute to the existing literature: We argue that goal theory (Locke (1968)) can provide an unobtrusive and straightforward to implement debiasing mechanism because goals make the investor focus on the overall performance of their investment, thereby foregoing mental accounting (Thaler (1985)) and augmenting investors' self-control.

Chapter 3 is motivated by the finding that merely 60% of subjects in the previously described experiment exhibit the disposition effect. This substantial heterogeneity with regards to the disposition effect is in line with prior literature (see for example Weber and Welfens (2007)), but it has never been investigated in thorough detail. While there is already some research on the determinants and mitigating factors of the disposition effect, the literature is dispersed and at times even contradictory. Also, most research focuses on the role of single factors such as regret/rejoice or demographic variables only. We fill this gap by conducting another experiment and administering the financial attitudes and behaviour dimensions questionnaire proposed by Fünfgeld and Wang (2009). In doing so, we contribute insights to the relationship between financial attitudes, behaviours, and the disposition effect.

Chapter 1

Visualizing Customer-Centric Digital Investment Performance Reports¹

1.1 Introduction

Customer-centricity is not a novel concept: That the customer determines what a business is had already been proclaimed in the 1950s (Drucker (1954)). Despite the fact that various attempts of its definitions exist, the general agreement is that truly understanding the needs and preferences of the customer constitutes the pivotal foundation for any customer-centric business model (McKinsey (2013), Accenture (2014)). For the financial services industry, customer-centric approaches are of current interest mainly for three reasons: Firstly, the traditional financial industry is confronted with challenging external market dynamics. On the one hand, the financial crisis of 2008 unveiled much of the existing information asymmetry between advisors and clients. As a consequence, customers lost trust in the whole industry (Skowron and Kristensen (2012)) and said loss in trust has not yet recovered (Edelman (2017)). On the other hand, the increasing regulatory and competitive pressure (Accenture (2014)) has resulted in declining revenues and operating profits (Strategy& (2012)). As for all industries facing efficiency claims (van Doorn et al. (2010)), customer-centricity might therefore become a key requirement for business survival (Deloitte (2014)). Secondly, customer preferences are changing: Today, customers

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increasingly use internet platforms for information acquisition and to conduct purchases. Furthermore, the standards for user experiences are set in other industries, such as by the retailer Amazon with its explicitly proclaimed goal to become the world's most customer-centric company (Voigt et al. (2017)). Hence, if financial service providers do not offer the same level of technological comfort (World Economic Forum (2017a)), they will most probably face severe and costly customer frustration (Guibaud (2016)). Thirdly, technological advances offer new opportunities: Structured analytics or Big Data capabilities provide novel insights about customers via sophisticated data processing methods. With the increasing use of application programming interfaces (APIs), client and market data have become ubiquitously available. As a result, new tools and methods aimed at serving customer needs can be developed and allow the industry to align their business model with customer-centric principles (Strategy& (2012), Accenture (2014), KPMG (2017)).

Despite these developments, the traditional market players have not yet extensively focused on customer-centricity in their digital business models. New market participants, so-called financial technology firms (FinTechs) have entered the market, fulfilling customer needs that have not been addressed by incumbent financial services providers (Gomber et al. (2017)). FinTechs have started disrupting the traditional banking models (Auge-Dickhut et al. (2015), Ochs and Riemann (2017)), because they understand the behaviour of internet users, use technological progress to their advantage, and provide adequately designed online applications to market their products and services. These companies have also attacked the area of digital financial advice: In the form of robo-advisors, they provide their clients with investment solutions in a purely digital manner. Investment proposals are created algorithmically with almost no human interaction (Gomber et al. (2017)). As a result of their user-friendly digital processes, their assets under management have increased significantly over the last years. In the US, robo-advisors that started from scratch now manage over \$20 billion (Deutsche Bank (2017)) — with Betterment and Wealthfront as their largest representatives. However, all robo-advisors were created after the last financial crisis and are yet to experience a major market correction. During the temporary market decline at the beginning of 2018, the websites of Betterment and Wealthfront crashed due to unusually high activity (Chaparro (2018)). Apparently, their clients experienced an extraordinary demand for information and advice at that critical point in time, which could not be met by the platforms. A closer look at the current state of robo-advisors reveals that they focus on helping their clients manage relatively simple strategies in passive investments (Phoon and Koh (2017)). As such, today's robo-advisors only provide generic and

poorly individualized advice (Fallon and Scherer (2017)). Consequently, their underlying business model merely constitutes the digitalization of the distribution channel for (simplified) investment strategies, rather than the digitalization of personalized investment advice. Nevertheless, in order to directly benefit the advisor’s operating profits, it is crucial that its clients are satisfied with the whole investment advisory process (Sironi (2016)).

Certainly, it is far from definite if financial advisory services will ever become completely digitalized or whether hybrid solutions will prevail. However, if digital players succeed in creating value by digitalizing the service components of the advisory process, the whole financial services industry will be fundamentally disrupted. Therefore, this paper experiments with the digitalization of an advisor’s central task in the analogue or hybrid world that has received little attention in the literature thus far: to report the results of the investment strategy in a client-adequate way. It tries to represent this duty in a completely digitized application and could thus be considered a natural progression of current robo-advisory offerings. In order to achieve this, the here-presented concept relies on the key aspects of customer-centricity. It includes academic findings as well as practitioner knowledge and experience to define a universal framework of customer-centricity, which is subsequently used to answer the most prominent user questions about the performance of their investment strategy. Furthermore, it presents ideas on how to visualize the respective answers with functional prototypes. Considering that digital investment performance reporting is a rather unexplored topic, some indications from experimenting with the visualized prototypes are presented and discussed. The main finding of these tests is that people react somewhat differently to the same kind of visual tools, depending on whether they find themselves in a positive or a negative economic scenario. Whereas dynamic and interactive applications might help to engage with customers in a positive economic scenario – similarly to the current economic environment – they seem to overburden users in a negative setup. As such, the paper adds to the current discussion about the digitalization of financial advice and hopes to encourage further research and experimenting about related questions.

The detailed approach is presented as follows: Section 1.2 briefly reviews the academic and practitioner literature to derive the key aspects of customer-centricity in a framework — understanding customer needs and building convenient and personalized applications. Section 1.3 builds on the dimensions of customer-centricity to conceptualize a digital investment performance report. Concrete examples on how to visualize and prototype a digital investment performance report are presented. Section 1.4 varies the prototypes in the key aspects of customer-centricity and tests

them to scrutinize the viability of the customer-centricity framework. Afterwards, the results are reported and several recommendations are suggested before the final section concludes.

1.2 Deriving Key Aspects of Customer-Centricity

Despite the fact that customer-centricity is a widespread term, a unique, clear, and thorough definition does not yet exist. As such, while the term might currently be omnipresent, it constitutes a rather fuzzy concept that requires further examination. Traditionally, customer-centricity was a marketing concept that has already been applied in this context for more than 70 years across different industries. In contrast, academic research about the topic has only recently picked up (Shah et al. (2006)). It is of universal acceptance across various streams of research that customer-centricity constitutes the opposite of product-centricity (Lamberti (2013)). Figure 1.1 sums up the major distinguishing criteria of the two approaches.

aspect	product-centric	customer-centric
main focus	sell products	serve customers
business model	transaction-oriented	relationship-oriented
management criterion	portfolio of products	portfolio of customers
customer data	as control	as a valuable asset

Figure 1.1: Product-centric vs. customer-centric approach

Note: The above figure contrasts the main differentiating aspects between the product-centric and the customer-centric approach across various research streams. The figure is adapted from Shah et al. (2006).

As Figure 1.1 depicts, the focus of a product-centric business model is to create, sell, and manage a portfolio of products, where customer data mainly serves as control variables. Product-centric business models are especially effective when standardized products can be sold to a large customer base. On the contrary, customer data are of utmost importance for any customer-centric business model. Those data

help the company serve the client and to improve the mutual (long-term) relationship. Consequently, all business decisions should start with the customer (Shah et al. (2006)), such that the individual customer needs determine what a business model must look like in order to be successful (Auge-Dickhut et al. (2015)). This consequential and determined user focus may yield in a competitive advantage of customer-centric business models due to richer user interactions (Nicoletti (2017)), augmented customer satisfaction, and ultimately higher sales and profits (McKinsey (2013)). Today, technological progress allows more and more businesses to offer their clients a maximum of individualized (digital) customer experience within a standardized operating framework (Auge-Dickhut et al. (2015)). Especially in the typical service industries, these advances in technology are estimated to enable a respectable savings potential in combination with improved customer satisfaction (The Boston Consulting Group (2016)). To focus on customers and their needs has evidently become more important than ever before.

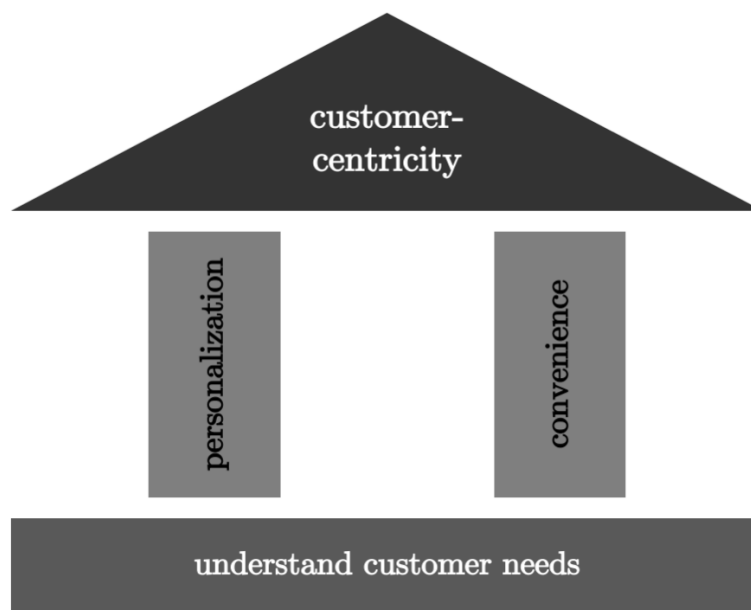


Figure 1.2: A framework of customer-centricity

Note: This figure depicts the proposed framework of customer-centricity. Here, understanding customer needs provides the foundation for any customer-centric offering. Additionally, customer-centricity can only be achieved by personalizing said offer and making it conveniently accessible at the same time.

But what are the key aspects for the development of a digital customer-centric application? A thorough review and analysis of academic and practitioner literature

reveals that three dimensions are most commonly mentioned: As the framework in Figure 1.2 illustrates, understanding and satisfying customer needs constitutes the foundation of any customer-centric business model. At the same time, however, it is equally important that the offering is also presented in a convenient and personalized manner. To elaborate on this newly developed framework, the main aspects for all three dimensions shall be briefly summarized from the existing literature:

1.2.1 Understand Customer Needs

Understanding customer needs is the necessary first step and can hence be regarded as the foundation of any customer-centric business model: The customer-centric company must identify, fulfil, and satisfy those customer needs (Lamberti (2013), Nicoletti (2017), Ochs and Riemann (2017)). In other words, all products and services must be oriented towards the individual customer needs (Auge-Dickhut et al. (2015)). Those needs may be stated or tacit (Accenture (2014)) and hence must sometimes be systematically and iteratively discovered (Vetterli et al. (2016)). A competitive advantage arises when the company deeply understands all customer needs (McKinsey (2013)) and satisfies them better than competitors (Ochs and Riemann (2017)). To do so, personalization and convenience play pivotal roles, as elaborated upon below.

1.2.2 Personalization

A digital offering becomes even more customer-centric when it is personalized to the individual self of the customer (Lamberti (2013), Guibaud (2016)). Therefore, all customer insights must be transformed into customized products and services (McKinsey (2012), Ochs and Riemann (2017)). Consequently, the digital frontend may offer a completely personalized experience (Accenture (2014), Maiya (2017)), showing only those pieces of information that are aligned with the client-specific circumstances at any point in time. In summary, any customer-centric offering has to focus on the personal present and future needs of each individual customer and present them with ubiquitous, individualized advice.

1.2.3 Convenience

Furthermore, a customer-centric offering should make the client's life as easy and convenient as possible (Ochs and Riemann (2017)). For a digital application, convenience comprises state-of-the-art design and loading times (Maiya (2017)), as well as access to information outside of traditional business hours via all devices 24/7

(Strategy& (2012)). Additionally, new information should be presented instantaneously (Nicoletti (2017)), such that customers are able to conduct real-time and forward-looking analyses before completing a transaction (Guibaud (2016)).

1.3 Conceptualizing Digital Customer-Centric Reports

In the previous section, the central aspects of customer-centricity were derived from the existing literature without any industrial or contextual focus. This entails the advantage that the framework can be utilized across a multitude of environments. To illustrate its universality, the framework shall now be applied to an investment advisory process, which is displayed schematically in Figure 1.3.

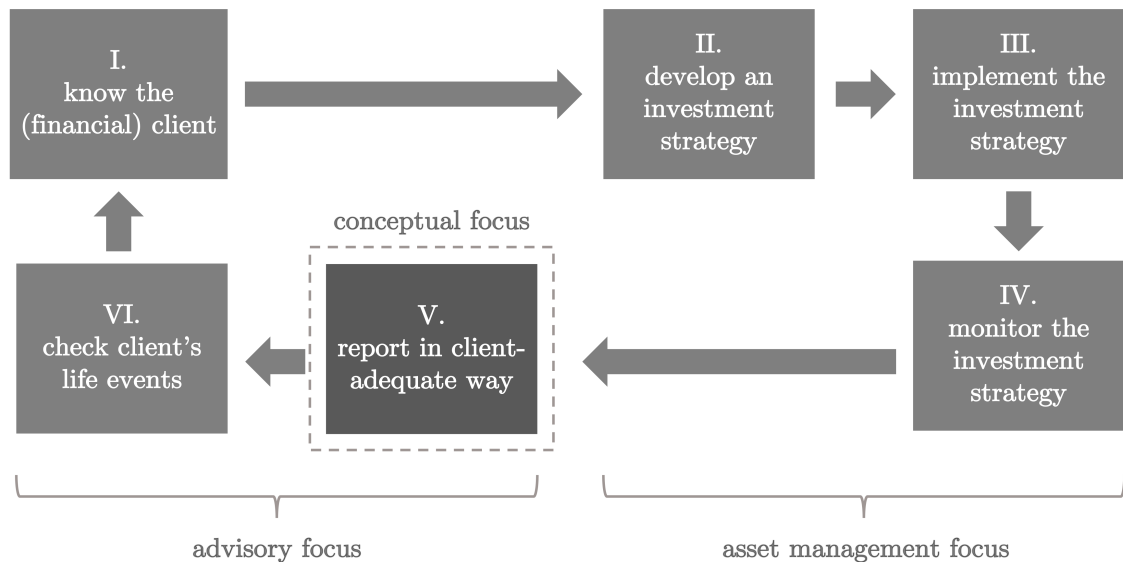


Figure 1.3: Schematic investment advisory process

Note: The investment advisory process can be represented as a continuous process consisting of six distinct steps. Whereas steps I-IV. are mainly offer-driven and hence product-centric, this paper focuses on adequate investment performance reporting (V.), since this step has received relatively little attention in the academic and practitioner literature thus far.

Figure 1.3 describes the comprehensive end-to-end investment advisory process as a combination of advisory-focused steps with asset management-focused steps. Typically, the process starts with getting to know the client (I.), continues by developing, implementing, and monitoring an investment strategy (II. – IV.), and gets back to the client by reporting the investment performance in an adequate way (V.), checking for major life events (VI.) such as marriage, and adapting the client profile (I.), if necessary, before the procedure begins anew.

Traditionally, the investment advisory process (steps I.-VI.) has been regarded in a product-centric manner (Brunel (2015)): Non-discretionary advisors sold asset management products to their clients and were, in turn, remunerated by commissions. Due to potential conflicts of interest, non-discretionary services either faced heavy criticism or commissions were banned altogether such as, for example, in the UK (Burke and Hung (2015)). Consequently, discretionary services that charge an advisory fee and that were originally targeted at wealthy or institutional clients have gained in importance.

Robo-advisors offer such fee-based advisory services in a digital manner and at low cost. Some of them are independent of the banking sector and use a third-party custodian (BlackRock (2016)). Most robo-advisors identify the client's needs by simple questionnaires and focus on implementing, monitoring, and rebalancing exchange-traded funds (i.e., steps I.-IV.) (Lam (2016), Phoon and Koh (2017)). When it comes to the more advisory-intense tasks like checking for the client's life events (i.e., step VI.), current robo-advisors, like e.g. Betterment, turn to a hybrid solution including the advice of human investment professionals (Betterment (2018)). It is thus clear that today's robo-advisors have not (yet) digitalized the whole investment advisory process.

Against this backdrop, the here-presented concept promotes ideas for digital investment performance reporting based on the previously derived framework of customer-centricity. Relating to Figure 1.3, the concept assumes that client and investment data are known (steps I.-IV.) and ergo focuses on the transformation of available data to client-adequate digital tools (step V.), whereas the inclusion of life events (step VI.) remains beyond scope. Such tools may not only be of interest for the advancement of robo-advisors but also for the traditional industry: Their clients request portfolio monitoring and goal-based investing tools, which the advisory firms do not yet offer (Accenture (2015)).

However, research on how to adequately report investment performance to private investors on a digital surface is scarcely available. Investigations on the effects of financial literacy show that visual tools may help to increase the investor's confidence and understanding (Mayer and Moreno (2002), Lusardi et al. (2017)). Related work about the design of trading interfaces reveals that showing more information to the investor results in decisions with decreased confidence (Teschner et al. (2015)) or makes subjects more exposed to financial biases (Kranz et al. (2015)). Therefore, digital platforms in particular should be carefully designed in order to avoid information overload and its accompanying adverse consequences.

Keeping these findings in mind, the main assumption of the here-presented con-

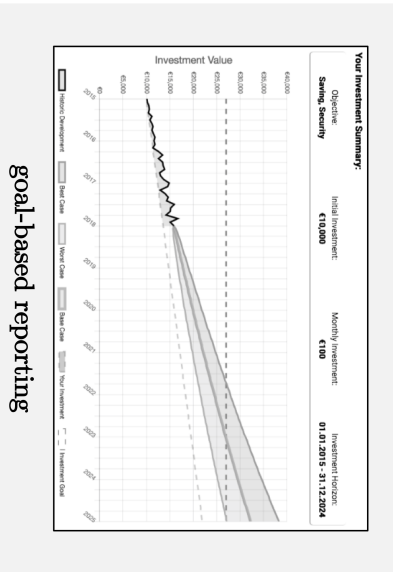
cept is that solely presenting the asset manager’s facts and figures about an implemented investment strategy on a digital surface will not be sufficient to fulfil the client’s needs for investment advice. Instead, the information will have to be reprocessed and structured around the key messages — common tasks of a human advisor when preparing an investment performance report and ensuring the client’s understanding in a face-to-face discussion. However, these tasks are even more crucial in a purely digital context considering the unilateral flow of information and communication. Unfortunately, data about what the client’s fundamental questions are or about what must be explained in more detail are not available — at least not publicly. Consequently, the key aspects for the here-presented digital investment performance reporting were derived in a structured hands-on approach: After a comprehensive review of market practices and academic literature, several discussions in an interdisciplinary team of practitioners and academics about the dimensions of customer-centricity — understanding customer needs, convenience, and personalization — resulted in the following concrete ideas:

1.3.1 Customer Needs in Digital Investment Performance Reporting

When placing oneself in the position of clients reviewing their investment performance report, the questions they want to have answered will most probably comprise: “Am I on track?”, “How do I compare to the market?”, and “How do I compare to other strategies?”. Figure 1.4 exemplary shows how the answers to these fundamental questions could be visualized in a digital context.

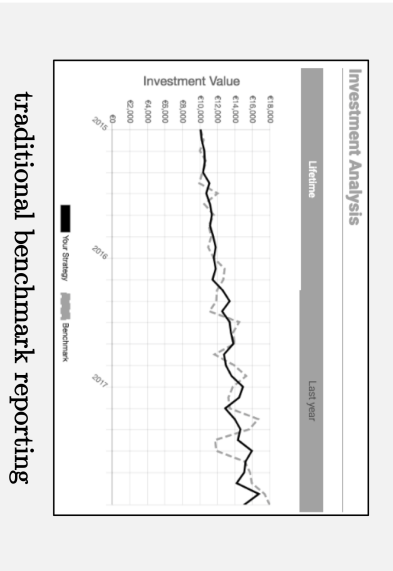
Common to all graphs in Figure 1.4 is the assumption that the sole analysis of market data (e.g., the performance of a fund) is not truly customer-centric. Instead, all graphs directly relate to an analysis of the client’s personal financial situation. However, they do so in different ways: On the one hand, both comparative analyses are based on historical data and the graphical display could be considered common market standard (albeit it is not yet standard in the reporting to private clients). On the other hand, the goal-based report illustrated here relies on the relatively new principles of goal-based investing. Goal-based investing takes the expected values of an investment into account and focuses on the probability with which an investor will reach their goal, i.e., a pre-specified monetary amount within a certain period of time. In doing so, goal-based investing implicitly assumes that investors are more concerned about the risk of not being able to reach their pre-specified investment goals, than about commonly reported risk indicators such as the volatility of returns. This shift away from the standard financial figures also implies the necessity of

Am I on track?



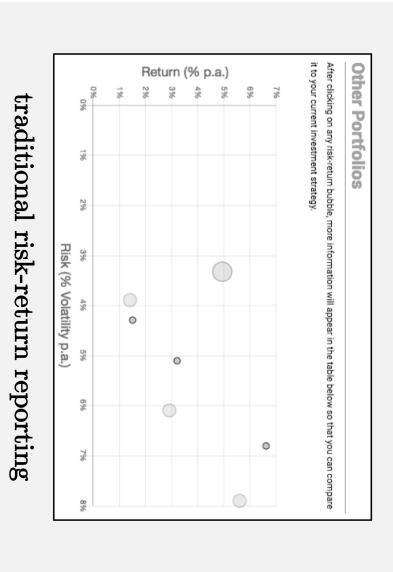
goal-based reporting

How do I compare to the market?



traditional benchmark reporting

How do I compare to other strategies?



traditional risk-return reporting

Figure 1.4: Visualization of a digital investment performance reporting concept

Note: The screenshots above visualize how a digital investment performance report could proactively communicate with the investor in order to answer their most frequently asked questions.

reporting the investment performance in a novel way: With goal-based principles, investors can be continuously informed about their progress to reach their goals in a proactive manner (Sironi (2016)).

The here-presented concept combines the traditional and the goal-based reporting approaches for the following reasons: First, goal-based reporting is only feasible if the client’s initial assessment includes quantifications of time and a monetary goal amount, which is not (yet) a common advisory standard. Second, as individual goals will differ, the goal-based approach alone would not allow for a comparative analysis. Third, despite the fact that its proponents solely consider the goal-based approach as investor-centric (Deguest et al. (2015)), only the minority of today’s robo-advisors actually use goal-based investing principles (Phoon and Koh (2017)). Hence, investors will still expect performance representations that are currently used in traditional investment performance reports. Omitting these would most probably come at the detriment of investor satisfaction. Hence, by definition, they would not be customer-centric.

1.3.2 Personalization in Digital Investment Performance Reporting

For the here-presented concept, taking the client’s perspective already resulted in a digital report focusing exclusively on the client’s financial situation without burdening it with impersonalized market statements. However, in a one-on-one discussion the client might query “How shall I read the report?” Figure 1.5 gives an example on how this guidance may be delivered in a digital application.



Figure 1.5: Ensuring personalization in digital investment performance reporting

Note: The above figure displays a digital assistant that guides the investor through the investment performance report and highlights areas that need their particular attention.

The digital assistant in Figure 1.5 offers a guided user-interaction concept that provides contextual information whenever appropriate. It ensures that the user reads the whole report and not only parts of it by jumping to each following message. Furthermore, the assistant assesses the investor’s economic situation, identifies courses for action, and makes personalized recommendations based on these analyses in order to avoid the negative consequences of information overload (Teschner et al. (2015)). As such, it can be considered as a precursor of applications relying on recommendations resulting from artificial intelligence, which are claimed to become more dominant in the future (Sironi (2016), Phoon and Koh (2017)).

1.3.3 Convenience in Digital Investment Performance Reporting

Whereas a report usually ends by stating the current status quo of the investment to the client, the advisor-client conversation about the report will most probably go one step further: “Should I change my investment strategy?” will certainly also be discussed, particularly in cases where the investor will most likely not reach their pre-determined investment goal. Figure 1.6 presents a visual simulation tool with which this question could be answered conveniently.

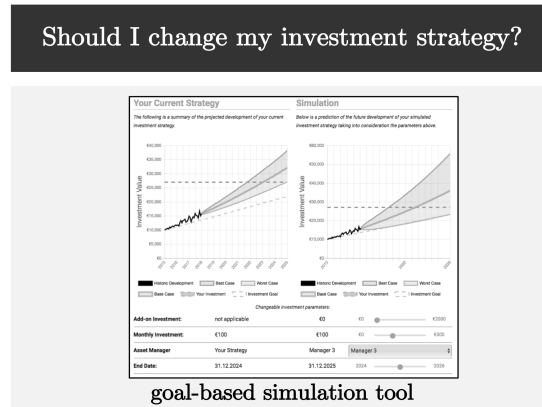


Figure 1.6: Enhancing convenience in digital investment performance reporting

Note: The screenshot above shows the simulation tool proposed to proactively enable the investor to investigate the consequences of a change in their investment strategy. It lets the investor change the investment strategy, the investment horizon, and the investment amount. As a result, it provides the investor with the expected development of this simulated investment.

Including the simulation tool depicted in Figure 1.6 in the reporting context assumes that the client’s life becomes more convenient when they can directly adapt their strategy after investigating the implications of a strategy shift. The tool relies on the presentation of goal-based investment performance (Sironi (2016)) and allows for forward-looking analyses (Guibaud (2016)) at the same time: When changing one or several investment parameters (i.e., the strategy, the investment horizon, or the investment amount) the estimated ex-ante performance is calculated instantaneously. Thereby, it allows the user to interactively assess the personalized impact of a change in their investment strategy before eventually adopting it.

1.4 Testing the Customer-Centric Reporting Concept

Due to a lack of appropriate customer data, the digital investment performance reporting concept presented in the previous section was developed in a thorough, pragmatic way. While the concept is based on state-of-the-art academic research and practitioner input, the logical next step is to empirically test whether this approach really meets the customer’s needs in the digital context. To gather data on how well it fits the user’s requirements, the concept was first transferred to

functional prototypes and subsequently tested. The main insights of these tests are now presented and discussed.

1.4.1 Testing Setup

The aim of testing the concept is to investigate if subjects confronted with the customer-centric investment performance report adequately understand the investment return, if they exhibit a more positive attitude towards the report, and whether they feel well-informed overall. Therefore, the following three prototype-variations were programmed: the “static,” the “interactive,” and the “assisted” version. As previous research documents that the display format impacts the perceived characteristics of an investment (Jordan and Kaas (2002)) and that colour stimuli affect investment decisions (Bazley et al. (2017)), the common design of all three prototype-variants is the same: The color-coding, the iconography, the 24/7 accessibility, and the additional information via a dedicated “Tips & Tricks” section is included identically in all prototypes. However, the prototype mutations vary in the key aspects of customer-centricity, as Figure 1.7 summarizes:

aspect	static	interactive	assisted
needs	✓	✓	✓
personalization	✓	✗	✓
convenience	✗	✓	✓

Figure 1.7: Differentiation of prototype variants

Note: All three prototype variants fulfil the basic requirement of any customer-centric offering by being addressed at investors’ needs. However, they vary with respect to the degree to which they are convenient and personalized. This design allows for a thorough examination of the newly developed customer-centricity framework in a practical setting.

As shown in Figure 1.7, all three prototypes fulfil the fundamental requirement of any customer-centric offering: They are oriented towards the needs and preferences of the customer — in this case the individual investor. Furthermore, the “assisted” prototype captures the whole concept of the here-presented customer-centric investment report by also addressing the personalization and convenience dimensions. The

other two prototypes, on the other hand, vary in personalization and convenience: The “interactive” prototype includes the interactive tool to conveniently simulate and eventually adopt changes in one’s investment strategy but excludes the digital assistant. The “static” prototype includes the personalized content of the digital assistant but presents all information in an online PDF format such that the option of conveniently simulating and changing the investment strategy is omitted. The full PDF investment performance reports for the positive and negative scenario, that were constructed for the prototype, are shown in Appendix A.1.

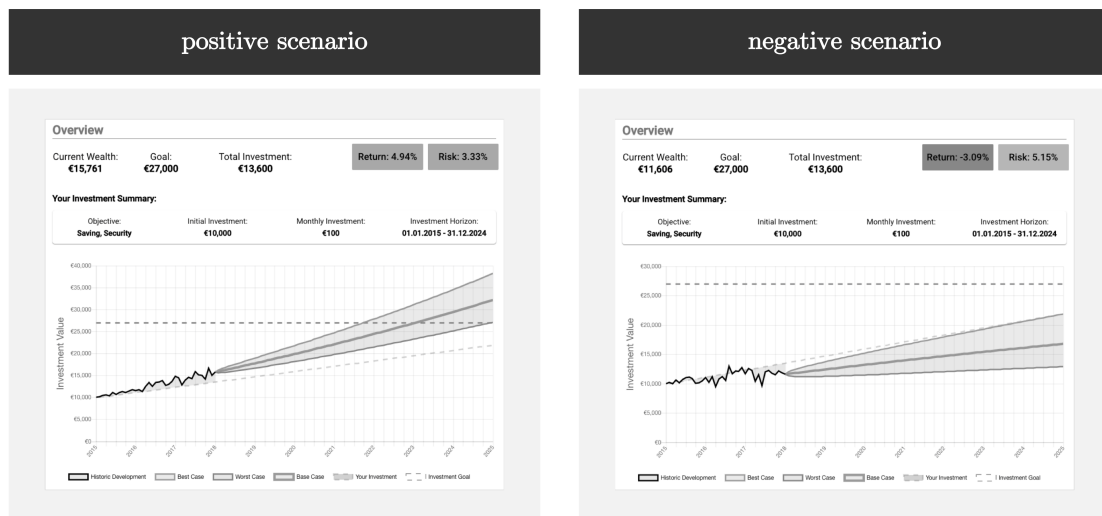


Figure 1.8: Setup of the positive and the negative scenario

Note: This figure shows the main goal-based investing graph that participants in the experiment were confronted with in the positive (left) and negative (right) scenario.

As the concept does not yet constitute a real-world application but is still in prototyping stage, it is neither connected to real-time financial data, nor does it implement the extensive scenario simulation-based optimization techniques goal-based investing was originally formulated for (Deguest et al. (2015), Sironi (2015)). Instead, a simplified showcase sufficient to visually report the performance of an investment strategy against a goal, a benchmark, or other investment opportunities was implemented. Therefore, in line with other research (e.g., Aspara and Hoffmann (2015)), the report was specified for a hypothetical investor with the following characteristics: He invests in one asset with an initial investment of €10,000, a monthly add-on of €100 and an investment target of €27,000 at a 10-year horizon. The investor looks at his investment after 3 years of investing and the report describes it either in a “positive” (return 4.94%; volatility 3.33%) or in a “negative” (return -3.09%; volatility 5.15%) economic scenario. Appendix A.2 summarizes the scenario and the verbatim instructions with which participants were provided at the begin-

ning of the experiment. Figure 1.8 illustrates how both scenarios are visualized.

The “positive” or “negative” risk-return combinations also serve as input for the testing prototype: They are directly displayed in the comparative historical analysis of the traditional reporting. In the reporting against other investment opportunities, the hypothetical investor’s asset is compared with three other assets that all exhibit positive returns. Furthermore, these data serve as inputs for the calculation of the historical and the expected wealth evolution in the goal-based reporting. Its ex-post component consists of an incidentally chosen Monte Carlo simulated path and its ex-ante component of the 95% confidence interval calculated with the standard assumption of lognormality. The simulation tool is constructed in the same way but also contains the so-calculated confidence intervals for an investment in one of the three other assets, in which the investor could chose to invest.² Overall, the three prototype variants and the two scenarios result in six testing conditions as summarized by Figure 1.9.

scenario	static	interactive	assisted
positive	condition 1	condition 3	condition 5
negative	condition 2	condition 4	condition 6

Figure 1.9: Experimental testing conditions

Note: The experiment was set up in a 2x3 (scenario x investment report) between-subjects configuration, resulting in the six conditions depicted above.

To test whether the customer-centric reporting is adequately conceptualized, test persons are randomly shown one of the six conditions as described by Figure 1.9 before they are invited to complete a questionnaire. The questionnaire is adapted from previous research and asks for an estimation of the expected rate of return (Jordan and Kaas (2002)), for the attitude towards the report (Chen and Wells (1999)), and participants’ overall informedness (Li et al. (2013)). Informedness is a central construct in the marketing literature and is considered as an antecedent of customer satisfaction and loyalty, which is why it was regarded to fit the research of this concept particularly well. Taken together, the three measures capture both

² The technical description of the scenario construction in Appendix A.3 provides more detailed descriptions of where the data for the scenarios was obtained from and how the past and future figures were calculated.

subjective and objective characteristics of the investment performance report. The complete questionnaire can be found in Appendix A.4.

1.4.2 Testing Sample

For testing the described setup, the concept of the customer-centric reporting as well as the questionnaire were programmed as one continuous user journey. Relying on standard web technologies and hosted on a web server, the testing setup can be accessed remotely. Against this backdrop, the here-discussed results rely on data collected between February and May 2018. After cleaning these data for incomplete responses, the final sample consists of 138 participants who inspected the digital performance report in detail and answered the whole questionnaire. In total, 65% of the respondents are male and 35% are female. The test persons are on average 26 years old, and the majority of them states that investing is personally relevant to them. In addition, they are particularly financially literate according to the widely adopted measure from Lusardi and Mitchell (2014). This measure examines subjects' understanding of three fundamental financial concepts: compound interest, inflation, and diversification. In the here-described sample, 64% of the respondents answered all three questions correctly. This result compares to 30% for a representative US sample (Mitchell and Lusardi (2011)), 4% for a sample in Romania (Beckmann (2013)), and 53% for a sample in Germany (Bucher-Koenen and Lusardi (2011)).

Further to that, the participants all seem to have engaged with the testing setup sufficiently: Only an insignificant fraction revisited the instructions, implying they well understood the experimental scenario, the instructions, and their task within the experiment. They considerably made use of the assistant and the simulation tool. As such, the observed differences across experimental groups discussed in the following section can be interpreted as a causal result of the different stimuli with which the test persons were confronted.

1.4.3 Results

The results from the above-described experiment show the following insights: First and foremost, customer needs appear to be considerably different in the positive as compared to the negative scenario. Visual tools, which seem to create customer value in the positive scenario, are despised in the negative setting. For example, the higher degree of personalization via the additional contextual information of the assistant is unnecessary in the positive scenario. Even without personalization, the expected rate of return is well understood. In the negative scenario, the test takers'

comprehension is slightly better with personalization. However, most of them still did not understand that the investment strategy is modelled with the assumption of negative expected returns.

Furthermore, the convenient simulation tool yields a better attitude towards the report and a better informedness in the positive scenario. On the contrary, informedness and attitude towards the report are best without the simulation tool in the negative scenario. Apparently, the lonesome changing of the parameters of the investment strategy was experienced as too demanding and hence unwanted in the negative setup.

These testing results are summarized graphically in Figure 1.10. Overall, they indicate that the proposed customer-centric concept may be appropriate (and could even be further streamlined) for a digital performance reporting of positive returns. However, to appropriately communicate with customers about negative returns, further tools and methods will have to be developed in order to sufficiently capture their needs and ensure an adequate understanding.

	scenario	
aspect	positive	negative
personalization (assistant)	not necessary	improves understanding
convenience (simulation)	improves understanding and perception	too demanding

Figure 1.10: Summary of results

Note: The figure above summarizes the main results of the experiment. Whereas personalization is unnecessary in the positive scenario, it improves understanding in the negative one. On the other hand, understanding and perception of the report were enhanced by the convenient simulation tool in the positive scenario, whereas it was regarded as too demanding in the negative one. Altogether, it can be concluded that the form of visual representation used to communicate investment performance should depend on the economic circumstances.

1.4.4 Recommendations

While the discussed testing results are still an early-stage indication for the adequate communication of investment performance to customers in the digital world, they already provide very interesting insights for academics and practitioners alike. In particular, the following three recommendations can be derived from the experiment's findings:

Formulate a Strategy on How to Deal With Adverse Economic Scenarios

In the testing setup, subjects showed different reactions to the same visual tools when used to communicate a positive compared to a negative performance scenario. This finding is generally in line with the common prospect theory finding that investors' perception for losses and gains differs (Kahneman and Tversky (1979)). It may thus be reasonable to further experiment with the distinction of positive and negative scenarios. A possible starting point for future research could be to replace or expand the convenient simulation tool by a concrete (algorithmic) recommendation and to provide the users with that recommendation proactively. Then, the user would not have to find out by themselves whether a better investment opportunity exists. Instead, they would only have to decide if they want to follow the recommendation or not, which may be a more convenient solution even in the negative scenario. For practitioners, the testing results may increase the awareness for the difficulty to deal with a negative scenario in a completely digital environment. Hybrid solutions may thus be necessary to allow communicating negative scenarios at least similarly to the traditional financial services industry.

Rethink Methods, Tools, and Visualizations to Explain (Quant-) Finance

Goal-based reporting is a powerful way to concentrate the quantitative modelling of market risk drivers, product characteristics, and investor preferences into one graphical representation. Due to its connection of past and future performance, it may be a far more intuitive basis for the face-to-face discussion of an advisor with his clients than concepts like the mean-variance efficient frontier. However, the here-presented testing of a stylized showcase suggests that it may not be intuitive enough for a sole digital implementation: In the negative scenario, the overlapping aspects of a positive monthly add-on investment and a negative return expectation resulted in an upward slope of the future wealth evolution. Apparently, subjects misinterpreted this visualization as positive return expectation. Future research and experimenting

could therefore concentrate on additional visualizations in two ways: On the one hand, additional graphics disentangling these potential overlapping aspects can be developed. On the other hand, a further concentration to the main customer-relevant messages may reduce complexity and yield in better, more adequate interpretations.

Better Exploit Customer Data to Improve Communication

A comprehensive analysis of existing customer data was not the starting point of the here-developed concept for customer-centric investment performance reports. However, at least traditional market players possess a documented customer history in their relationship management systems. Such data may be exploited for the development of further digital visualization tools. The previously discussed testing results indicate that customer needs may be different in a positive compared to a negative scenario. Consequently, averaging the available data over the whole customer history may yield in less informative results than their separation according to the market environment when they were collected.

1.5 Conclusion

It is well known that current robo-advisors rather offer their clients generic and impersonalized investment strategies than the digitalization of individualized, long-term financial advice. Furthermore, they entered the market after the financial crisis of 2008 and have not yet faced a substantial market downturn that could have tested their robustness. However, if robo-advisors want to become the lasting alternative for personal financial management, they will have to fulfil customer needs in all market periods. Reporting investment performance in a customer-centric way may therefore become critical. Against this backdrop, this paper presents ideas on how to visualize, design, and implement a customer-centric digital investment performance report. In a first step, it reviews the literature and derives key aspects to develop a universal framework of customer-centricity. Subsequently, it applies these aspects to the context of a digital investment performance reporting concept. This concept is then transferred to functional visual and interactive prototypes, which are empirically evaluated with test persons. The main finding of this test is that subjects perceive the same visual tools differently when these are used to report a positive compared to a negative performance scenario. More specifically, the here-developed and presented concept seems to communicate positive performance adequately. Simultaneously, it shows that the same tools are not appropriate to communicate negative performance. While these contradictory results might seem puzzling at

first, they encourage further research and experimenting about this aspect in particular. As such, the findings may be of interest for FinTechs and the traditional industry, for practitioners and academics, for clients and advisors alike.

Chapter 2

The Causal Influence of Investment Goals on the Disposition Effect¹

2.1 Introduction

The disposition effect describes investors' tendency to hold losing assets for too long while realizing paper gains too quickly (Odean (1998)). Since its first theoretical and empirical investigation by Shefrin and Statman (1985), a wide body of research has focused on the origins, as well as the economic and conceptual consequences of the phenomenon. As a result, the disposition effect has been found to be one of the most robust findings in finance research (Barber and Odean (2011)). It has been observed across various geographies (e.g., Bremer and Kato (1996), Brown et al. (2006), or Barber et al. (2009)), different asset classes (e.g., Genesove and Mayer (2001), Chang et al. (2016), or Heimer (2016)), and a variety of investor types with varying levels of investment sophistication (e.g., Grinblatt and Keloharju (2001), Barber et al. (2007), or Choe and Eom (2009)).

The fact that the disposition effect entails adverse consequences for investors' investment performance (see for example Garvey and Murphy (2004), Lee et al. (2008), or Roger (2009)), proves that it deserves exceptional attention. More specifically, Odean (1998) finds that the assets that investors sold too quickly as a result

¹ This chapter is based on: Wierzbitzki and Seidens (2018). "The Causal Influence of Investment Goals on the Disposition Effect." *Unpublished Working Paper*, and was accepted at the 28th European Financial Management Association (EFMA) Conference, the 7th Spring Conference of the Multinational Finance Society, the Behavioural Finance Working Group Conference, the 26th Annual Global Finance Conference, and the 2019 Financial Markets & Corporate Governance Conference.

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of the disposition effect continue to overperform over the subsequent periods, while the losing assets that these investors held on to for too long remain underperformers. This is particularly troubling considering the more recent developments where pension systems have shifted from defined benefit to defined contribution schemes in the United States (Lusardi and Mitchell (2014)) and where, as a consequence, investors increasingly make their own investment decisions (Rubaltelli et al. (2005)), especially via online trading platforms (Barber and Odean (2001)). While this is not a negative development in itself, cognitive biases have been found to be particularly pronounced in online environments (Barber and Odean (2002)). Hence, being exposed to the disposition effect in this context can incur significant costs, most notably for inexperienced private investors who are most prone to it (Shapira and Venezia (2001)).

While there is an extensive body of evidence on the the origins of the disposition effect (Kaustia (2010)), to date, there is limited literature that sets out to investigate potential ways to mitigate it (Ploner (2017)). In this regard, we agree with Döbrich et al. (2014), who argue that it is not sufficient to merely identify and investigate behavioural biases — rather, measures to prevent these biases from emerging in the first place should be explored in more detail. A few experiments (e.g., Frydman and Rangel (2014) or Fischbacher et al. (2017)) do, however, show that even relatively small interventions can have a significant impact on the reversal or complete elimination of the disposition effect. Considering both the theoretical and practical relevance of the issue, we therefore argue that it is worthwhile investigating additional proactive debiasing strategies (see Soman and Liu (2011)).

In light of these developments, we propose to investigate the influence of investment goals and their presentation format on the disposition effect in an experimental setting. Our motivation stems from the fact that goal theory can provide an unobtrusive and straightforward to implement debiasing mechanism. This is because goals make the investor focus on the overall performance of their investment instead of separating it into several mental accounts (Thaler (1985)) that are evaluated individually. Thereby, they also enhance investors' self-control. Hence, we expect to reduce or even completely eliminate the influence of two of the factors that are argued to cause the disposition effect — mental accounting and missing self-control — and consequently reverse the disposition effect.

We find that providing investors with a specific investment goal that they are primed to achieve in the experiment significantly reduces their disposition effect. In fact, enhanced self-control and the refraining from mental accounting seem to cause these subjects to hold on to paper gains for longer. While their behaviour with

regards to loss realization does not change, they exhibit a reversed disposition effect overall. This finding is robust to two specifications used to measure the disposition effect. However, aggregating subjects' portfolio performance in a single visual graphical representation does not have any significant effect on their subjectivity to the disposition effect. Thereby, we contribute to the current state of research in the following ways: We show that goal theory can provide a simple and unobtrusive way in which the disposition effect can be debiased in a sophisticated experimental setting. Furthermore, we confirm the existence of the disposition effect among MTurk workers, i.e., in a context where it has not been examined before.

This paper is hence structured as follows: Section 2.2 discusses the relevant literature on the disposition effect and goal theory. Subsequently, section 2.3 first describes the basic experimental design. Furthermore, it develops hypotheses that are derived directly from the present body of literature and describes the treatments administered to test said hypotheses. Also, the experimental procedure and the two measures of the disposition effect are explained in detail. Section 2.4 first reports the sample statistics and then carries out the main analysis. Robustness checks are reported in section 2.5, before section 2.6 concludes by providing a summary and presenting avenues for future research.

2.2 Literature Review

2.2.1 Disposition Effect

The term disposition effect was first coined by Shefrin and Statman (1985) and defined by the authors as investors' tendency to "sell winners too early and ride losers too long" (p. 777). The authors base their argument of why a disposition effect occurs on positive theory with four main components: (1) prospect theory, (2) mental accounting, (3) pride seeking and regret aversion, and (4) lacking self-control. Subsequently, they show that their theory is consistent with empirical results derived from mutual fund data and individual stock trading data from Schlarbaum et al. (1978). For both asset classes, they show that a disposition effect can clearly be observed.

Following the first analysis by Shefrin and Statman (1985) and responding to their call for more detailed investigations of the phenomenon, Odean (1998) provides the first large-scale empirical analysis of the disposition effect. He records — whenever a transaction is conducted — the number of realized gains (losses) and

compares it to the number of paper gains (losses).² He finds that in his sample of 10,000 discount brokerage accounts (with transactions between 1987 and 1993) there is significant evidence of the disposition effect. In fact, his results show that investors on average realize 14.8% of paper gains, while merely 9.8% of paper losses are sold. In other words, investors were 50% more likely to sell winning stocks as compared to losing stocks — which was consistent with what Shefrin and Statman (1985) had predicted.

Considering that the dataset employed in the analysis stemmed from a US discount broker reduces the possibility that all investors were influenced by the same pieces of trading advice. Recalling that discount brokerages generally do not advise their clients on transactions, Odean (1998) concludes that it is unlikely that his results were driven by herding behaviour or private information. Furthermore, to investigate whether transactions were influenced by portfolio rebalancing motivations, he excludes partial sales and focuses exclusively on those sales where a stock was completely removed from the portfolio. However, the results remain essentially unchanged, wherefore Odean (1998) dismisses the possibility that the observed pattern is a result of portfolio rebalancing. Lastly, he tests the economic implications of the disposition effect and finds that, over a one-year period, the excess return over the CRSP (The Center for Research in Security Prices) value-weighted index is 3.4% higher for winners that were sold as compared to the losses that remained in investors' portfolios. Hence, investors' belief in mean-reversion seems to be unfounded and the disposition effect is clearly hazardous to their performance.

Weber and Camerer (1998) conduct the first laboratory experiment to shine light on the origins of the disposition effect. Subjects can trade 6 distinct stocks over 14 trading periods. Each stock is associated with a certain probability of a price increase that is constant over all trading periods. Thereby, the experiment is designed in a way such that a mean-reversion belief is clearly unfounded and the exhibition of a disposition effect cannot be explained by strictly rational behaviour. Still, the authors find that 59% of sales are attributed to winners, which makes subjects 50% more likely to realize gains as compared to losses, consistent with the disposition effect. However, when shares are automatically sold at the end of each trading period and can subsequently be bought back for the same price, the disposition effect diminishes significantly and is almost non-existent.

Based on these three fundamental studies, an array of further research has set out to investigate the disposition effect in thorough detail. As a consequence, the

² Focusing on the number of realizations relative to sale opportunities makes the results robust to the influences of market developments in specific time periods.

phenomenon has been found to be surprisingly robust and ubiquitous (Barber and Odean (2011), Chang et al. (2016)). For example, Shapira and Venezia (2001) find the disposition effect among Israeli investors when investigating the duration of round trip trades for winning and losing assets. Feng and Seasholes (2005) use Chinese brokerage data from 1,511 accounts. By employing hazard rate models to estimate how long investors typically hold a position, they find that investors realize losses about 30% less quickly as compared to gains. Other geographies where the disposition effect has been found include Finland (Grinblatt and Keloharju (2001)), Australia (Brown et al. (2006)), Taiwan (Barber et al. (2007)), Korea (Choe and Eom (2009)), and Sweden (Calvet et al. (2009)). Thus, it seems evident that the disposition effect is clearly a global phenomenon.

With regards to asset classes, the disposition effect cannot exclusively be found in stock markets. Instead, research has identified the disposition effect in mutual funds (e.g., Frazzini (2006)), futures markets (e.g., Choe and Eom (2009)), and social trading (e.g., Heimer (2016)), in addition to stock markets (e.g., Kliger and Kudryavtsev (2008)). Even non-financial domains, such as the Boston real estate market in the 1960s, seem to exhibit the disposition effect (Genesove and Mayer (2001)).

Moreover, the disposition effect is present across a variety of investor groups (Amarnani (2010)) — from students in experimental settings (e.g., Oehler et al. (2002)) to professional traders (e.g., Shapira and Venezia (2001), Frino et al. (2004), or Locke and Onayev (2005)). While research generally agrees that professional as well as non-professional traders are subject to the disposition effect, there is contradictory evidence concerning the magnitude of the effect. Whereas Chen et al. (2007) report that institutions suffer from a less severe disposition effect as compared to individual investors, Grinblatt and Keloharju (2001) find that the difference across various investor types (i.e., non-financial corporations, finance and insurance institutions, general government, non-profit institutions, and households) is relatively small.

The question thus arises what constitutes the roots of this widespread anomaly. With regards to the foundation of the disposition effect, Chang et al. (2016) note that: “Empirical work has been much more successful in identifying problems with various proposed explanations than in finding positive evidence that points directly to a particular theory to the exclusion of all others” (p. 268). As mentioned previously, Shefrin and Statman (1985) initially base their theory underlying the disposition effect on four components, including prospect theory (Kahneman and Tversky (1979)). They argue that in a prospect theoretic setting, investors who have experi-

enced a paper loss become more risk seeking and hence agree to hold the investment for a longer period of time. On the other hand, paper gains make investors more risk averse and therefore lead them to sell winning investments more quickly. However, the prospect theoretic explanation is not without its critics. Kaustia (2010) notes that, for reasonable prospect theory parameterizations, the propensity to sell an asset should actually decrease for gains and losses alike when the current price diverts from the original purchase price in either direction. This, however, is in contrast to his (and others') empirical findings and therefore leads him to conclude that prospect theory is unlikely to explain the disposition effect. Similarly, Barberis and Xiong (2009) and Hens and Vlcek (2011) argue that investors with prospect theoretic preferences would not choose to invest in risky stocks in the first place.

Secondly, Shefrin and Statman (1985) argue that, following the mental accounting framework (Thaler (1985)), investors tend to attribute different stocks to separate mental accounts. Hence, rather than evaluating their portfolio's performance as a whole, they only consider individual stocks in their financial decision-making. Thaler (1999) further argues that closing a position at a loss is "painful" (p. 189), wherefore people are reluctant to do it.

Thirdly, Shefrin and Statman (1985) assert that investors are hesitant to admit misjudgments. Hence, rather than admitting having made a mistake by closing a losing position, investors keep the investment and hope that it will recover. Concurrently, gains are realized more readily since they add to investors' pride and reinforce their belief of having made a good decision. This is in line with Chang et al. (2016), who propose that the disposition effect is founded in cognitive dissonance (Festinger (1957)).³ They provide compelling evidence for their theory, showing that the disposition effect is reduced with increasing levels of investment delegation, where investors feel less responsible and hence experience a lesser degree of cognitive dissonance when selling a position at a loss.

Lastly, missing self-control constitutes the fourth component of the framework. Shefrin and Statman (1985) argue that augmented self-control explains the pattern found in empirical results that the disposition effect disappears in December, even though there seems to be no rational explanation for this observation. Rather, they propose that due to its "perceived deadline characteristic" (p. 784), investors become more open towards loss realization in the last month of the year.

A few experiments have thus focused on debiasing the disposition effect by considering these components. In a laboratory experiment, Frydman and Rangel (2014)

³ Cognitive dissonance describes the social psychology theory proposed by Festinger (1957), who argues that individuals experience substantial discomfort as a result of inconsistent choices or beliefs.

find that the disposition effect can be substantially reduced by 25% when making a stock's purchase price less salient. A possible explanation for this could be that when purchase prices are omitted and the investment's value has depreciated, investors experience a lesser degree of regret for having made a bad investment. They are thus more willing to divest losing assets, whereby the disposition effect is greatly reduced. Fischbacher et al. (2017) show that when investors have the possibility to employ automatic selling mechanisms in the form of limit orders, they exhibit a significantly lower disposition effect. Their results can be explained by realizing that limit orders serve as an ex-ante self-control mechanism. Another debiasing example can be found in Döbrich et al. (2014). Here, the authors use a simulated stock market to find that the disposition effect can successfully be eliminated using their debiasing intervention. A rational or emotional warning message about the disposition effect is presented before trading decisions can be submitted. It hence seems that simply making investors aware of the disposition effect could be sufficient to eliminate it.

2.2.2 Goal Theory

We argue, however, that goal theory can provide a less intrusive and more practical debiasing strategy, especially considering that goals exert a significant influence on investors' behaviour (Antonides et al. (2011)). Goal theory traces back to Locke (1968), who posited that confronting people with a goal will make them strive to achieve said goal. Since then, it has been found in more than 500 empirical studies that setting specific, challenging goals is associated with better performance than setting unspecific or so-called "do-your-best" goals (Seijts et al. (2011)). The proposed relationship is of linear nature (Latham and Locke (2007)). Even goals that are impossible to achieve do not harm — but rather enhance — performance (Landers et al. (2017)). Also, the effect persists regardless of whether goals are self-set or assigned by others (Locke and Latham (2002)).

Psychologically, goal theory is founded in self-regulation. Latham and Locke (1991) argue that "goal setting facilitates self-regulation in that the goal defines what constitutes an acceptable level of performance" (p. 234). With regards to the disposition effect, we thus expect that exposing investors to an investment goal will enhance their self-control. Specifically, we expect them to be more inclined to realize losses more quickly and hold on to paper gains for longer in order not to miss their investment goal. This should result in a lower disposition effect. Moreover, instead of separating their investments into several mental accounts that are evaluated independently, setting a goal will force investors to deviate from this behaviour and instead take a more holistic approach to their portfolio management. Additionally,

since Karlan et al. (2016) find evidence of the effectiveness of goal reminders, we expect that providing investors with a performance graph where their goal is clearly displayed will also help to reduce the disposition effect.

Aspara and Hoffmann (2015) show in a simplified experimental setup that the disposition effect can indeed be reversed if investors are primed towards investment goals. However, in their setup participants do not make active trading decisions but are rather confronted with a particular given investment scenario. Subsequently, merely their intention to sell (vs. hold) the two stocks in the scenario is used to calculate the disposition effect and draw conclusions to test the authors' hypotheses.

We argue that while their results seem promising, they should be regarded with caution. Subjects only provide their intention to sell (vs. hold) the stocks but do not conduct any actual trading decisions themselves. Also, they do not have to acquire the assets in the first place and hence can easily blame negative performance on external factors, wherefore regret aversion and cognitive dissonance might not have an influence on their behaviour. This is especially troubling considering that prior research has shown that reference prices and cognitive dissonance (see Chang et al. (2016)) are important factors that contribute to the disposition effect. Lastly, the experiment in Aspara and Hoffmann (2015) only considers one trading period and participants are not adequately incentivized to behave in their best interest. As a result, their observations might suffer from limited external validity.

In order to address these issues, we thus propose to investigate the influence of investment goals on the disposition effect in thorough detail using an experimental setup adopted from Weber and Camerer (1998). Before the experimental treatments and specific hypotheses are summarized in section 2.3.2, we first elaborate on the basic underlying experimental design.

2.3 Data and Methodology

2.3.1 Experimental Design

In order to test for the debiasing effect of investment goals on the disposition effect, we build on an established experimental setup and methodology that closely follows Weber and Camerer (1998), who provided the first experimental study of the disposition effect. Since then, their procedure has been adapted by a wide variety of further research undertakings (see for example Weber and Welfens (2007), Döbrich et al. (2014), Kadous et al. (2014), Rau (2015), or Fischbacher et al. (2017)).

Building on this established methodological setup entails several advantages:

First, considering that the underlying setup has been tested and employed before allows us to focus on the appropriate administration of treatments to the experiments' participants. Second, a comparison of the disposition effect that is expected to occur in the control condition with previous research enables us to conduct a first robustness check of our experimental procedure and results. Last, the disposition effect we expect to find in the control condition will serve as a baseline against which the debiasing effectiveness of our treatments will be assessed.

Within the experimental framework of Weber and Camerer (1998), participants can trade six distinct assets over 14 trading periods. In our setup, these assets are labelled Stock A through Stock F and subjects are told that they will participate in an “experiment about stock market decision-making.” The price developments of all six shares follow a distinct two-stage random process. In the first step, it is determined individually whether the price of each share will increase or decrease. Each share is associated with a certain probability of a price increase or decrease and, hence, prices cannot remain constant from one period to the next. The probabilities remain unchanged over the whole duration of the experiment and are designed in a way such that there are clearly favourable, neutral, and unfavourable stocks. The corresponding price change probabilities, which were directly taken from Weber and Camerer (1998), are summarized in Table 2.1.

Table 2.1: Probabilities of price increases and decreases for each stock

#	Stock	Probability of price increase	Probability of price decrease
1	B	65%	35%
2	D	55%	45%
3	F	50%	50%
4	A	50%	50%
5	E	45%	55%
6	C	35%	65%

Note: This table summarizes the probabilities of price increases and decreases for all six stocks in the experiment. The stocks were randomly labelled according to the first six characters of the alphabet (A – F) in the experiment to avoid order effects. Hence, Stock 1 listed in the table above does not correspond to Stock A in the experiment.

Subjects are told these probabilities in the instructions preceding the experiment. However, they do not know which probabilities are associated with which stock. Therefore, they will have to observe stock prices carefully in order to infer the

more favourable stocks. In a subsequent step, the magnitude of the price change is determined. This process is completely independent from the first random process. Prices can either change by \$1, \$3, or \$5 with equal probability. Again, prices cannot stay constant from one period to the next. Additionally, subjects are told explicitly that their (or other participants') actions would not affect stock prices.

The way in which this experiment has been set up implies that the expected value of a price change for a randomly selected stock will always equal zero. Furthermore, since the probabilities above are communicated to participants, they can identify the most favourable stocks merely by counting the number of price increases. As Barber and Odean (2011) note, the stocks with the greatest number of past price increases are most likely to exhibit the most price increases in subsequent periods. Hence, participants should adopt a trading strategy that merely invests in these stocks for optimal performance. The occurrence of the disposition effect thereby cannot be explained by investors' belief in mean-reversion.

In order to give participants an idea about stock price developments before they can start trading, we also calculate stock prices for periods -3 to -1. Participants can then start trading only from period 0 onwards. In period -3, the initial stock prices are randomly set between \$60 and \$150. While the price determination process is indeed random, prices for all stocks were calculated in advance. This was done to ensure that all participants would make decisions based on the same available information and such that results can be compared across participants without having to consider the potential influence of individual price development paths as a confounding factor. This results in the stock price movements as illustrated in Appendix B.1.

Subjects are initially endowed with \$10,000 in experimental currency, which they can invest over periods 0 to 14. At any time, they can own as many stocks as they want. However, they cannot borrow money to buy more stocks and transaction costs are not considered. Short-selling is also not allowed and subjects are not paid any interest on the amount they choose to hold in cash. At the end of the last trading period, all stocks are automatically sold and converted into cash, following Fischbacher et al. (2017).

2.3.2 Treatments and Hypotheses

All subjects are confronted with the same underlying setup as described above. However, to investigate the debiasing effect of investment goals on the disposition effect, three treatments are implemented in addition to a control condition. Screenshots of the respective trading interfaces for each of the four experimental conditions can

be found in Appendix B.2. The control condition will serve as a benchmark against which the effectiveness of the debiasing strategy can be measured. Considering that the control condition in our setup is similar to that in Weber and Camerer (1998), we expect that there will be a positive disposition effect.

Hypothesis 1 (H1): *Subjects in the control condition (i.e., those who do not receive any treatment) will exhibit a positive disposition effect.*

To test the impact of providing subjects with a specific investment goal, a so-called *Goal Treatment* is implemented. Here, subjects are explicitly told that they have to invest their initial endowment of \$10,000 such that they accumulate \$11,000 by the end of period 14. This is similar to the *Explicit Close Goal Treatment* in Aspara and Hoffmann (2015). Because subjects in this condition will exhibit augmented self-control in order to reach the imposed goal, we expect that they will sell losing stocks more readily and hold winning stocks for longer periods of time, thereby manifesting a reversal of the disposition effect.

Hypothesis 2 (H2): *Subjects in the Goal Treatment (i.e., those who are provided with a specific investment goal) will exhibit a reversed disposition effect.*

Furthermore, by showing subjects in the *Graph Treatment* a line graph that depicts the development of their total assets (hence, their portfolio’s aggregate performance) over all 14 periods, we expect that they will refrain from mental accounting practices. Instead of evaluating their performance on a per-stock basis, they will focus on the cumulative performance of their investments. Thereby, they will be more inclined to sell losing assets and hold winning assets longer to improve their overall performance, resulting in a reversal of the disposition effect. This experimental condition also directly addresses the appeal in Döbrich et al. (2014) to include “a graphical illustration of the personal losses accumulated thus far” (p. 9).

Hypothesis 3 (H3): *Subjects in the Graph Treatment (i.e., those who are shown a performance graph) will exhibit a reversed disposition effect.*

Lastly, by combining the elements of the *Goal Treatment* and the *Graph Treatment*, we create the so-called *Goal & Graph Treatment*. Consistent with the previous two hypotheses, we expect that subjects in this condition will exhibit a reversed disposition effect. Explicitly including this treatment in the experimental setup will allow us to investigate the combined effect of goal setting and display format on the disposition effect.

Hypothesis 4 (H4): *Subjects in the Goal & Graph Treatment (i.e., those who are provided with a specific investment goal and are shown a performance graph) will exhibit a reversed disposition effect.*

2.3.3 Experimental Procedure

The general experimental procedure looks as follows: Subjects who choose to participate in the experiment are first greeted by a welcome screen. Said screen outlines the purpose of the experiment by informing them that they are about to take part in an “experiment about stock market decision-making.” Furthermore, the compensation mechanism (as outlined below) is explained to them. By clicking on a “Start Experiment” button, they are randomly allocated to one of the four experimental conditions with equal probability. Hence, we employ a between-subjects experimental design that allows us to draw causal inference and conclusions from the results that follow. The next screen contains detailed instructions.⁴ Participants are made aware of the two-stage price determination process as explained above. Furthermore, they are shown a screenshot of the trading interface. This is done such that they can familiarize themselves with the interface and in order to explain the buying and selling mechanism in more detail. Lastly, this page includes a section that explains participants what their goal is going to be. This section is fitted directly to the individual experimental conditions as outlined above.

By clicking on a “Continue” button, subjects are redirected to the trading interface, as shown in Figure 2.1. The trading interface again includes a reminder of what the goal (depending on participants’ experimental condition) comprises. On the top right-hand side, participants can click on a “Next Period” button in order to receive next period’s share prices. They can take as much time as they want to complete all stock sales and purchases before moving on to the next period. Warnings are displayed when participants try to (1) buy shares in periods -3 to -1, (2) sell shares they do not own, and (3) buy shares for which they do not hold the required amount of cash.

After period 14, participants are redirected to the aforementioned questionnaire, which contains questions to measure: investors’ expertise (Jordan and Kaas (2002)), financial literacy (Lusardi and Mitchell (2014)), self-regard (Kadous et al. (2014)), perception of regret and rejoice (Rau (2015)), and personal investment relevance (Hüsser and Wirth (2014)). Furthermore, their age, gender, and reason for participation are noted. Seeing that these factors, along with trading volume and the total number of trades (Kumar and Lim (2008)), can influence the disposition effect (Lukas et al. (2017)), we will be able to control for them later on. Lastly, we include a manipulation check to test whether subjects were attentive and could correctly remember their experimental stimuli. Subjects who fail said test will be excluded from the further analysis and also will not be paid in exchange for their participation.

⁴ The full-text instructions can be found in Appendix B.3.

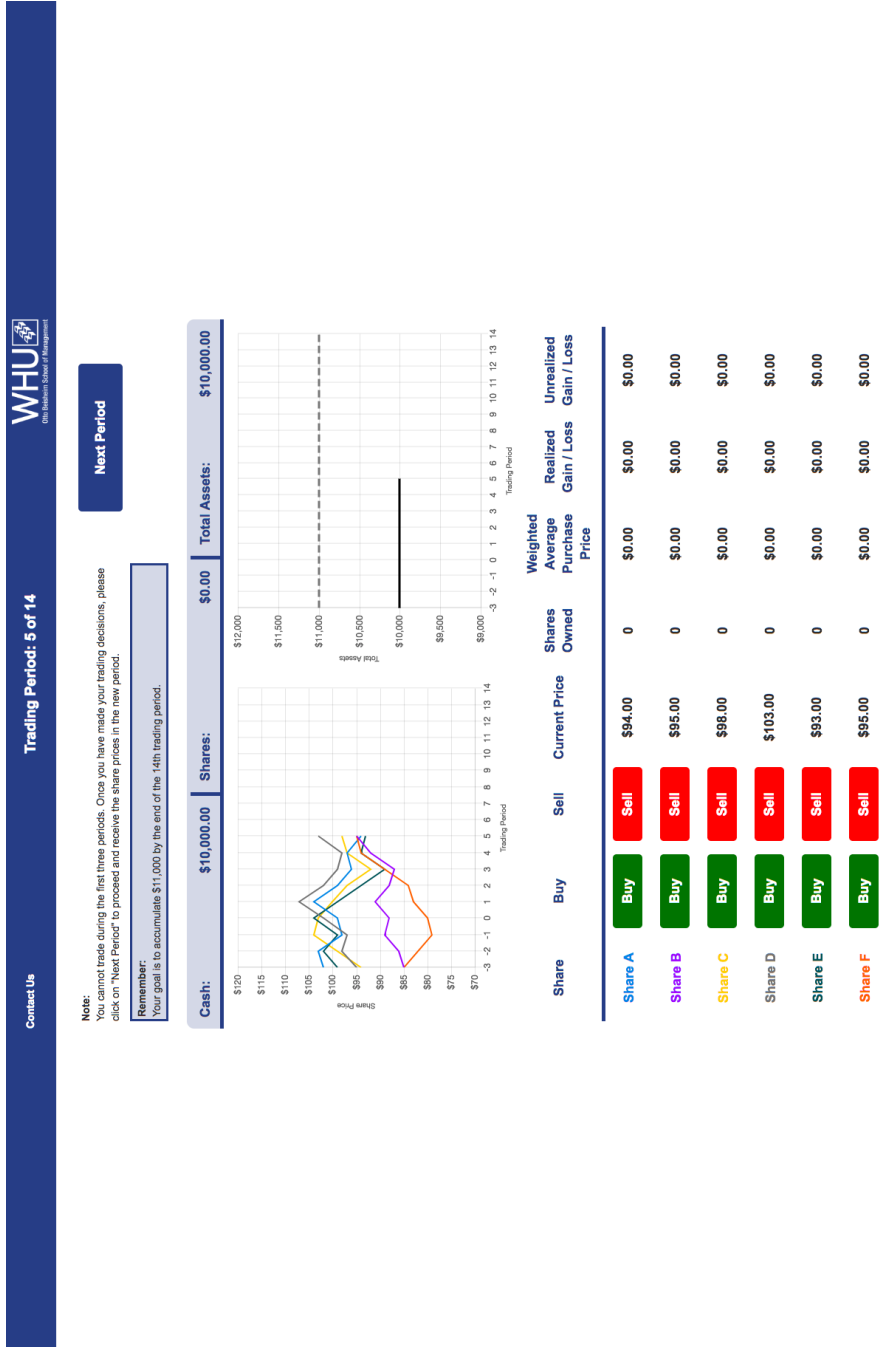


Figure 2.1: Screenshot of the experiment's trading interface

Note: The screenshot displays the trading interface that subjects in the Goal & Graph Treatment were shown. Therefore, it includes both, a performance graph on the right-hand side and a reference to the investment goal of \$11,000 at the top of the screenshot.

2.3.4 Data Analysis

In the experimental literature, two measures of the disposition effect are commonly found. In line with Odean (1998), we first define the disposition effect as the difference between the proportion of realized gains and losses. At the end of each trading period⁵ we calculate the proportion of realized gains (PGR) and the proportion of realized losses (PLR) as follows:

$$PGR = \frac{Gains_{realized}}{Gains_{realized} + Gains_{paper}} \quad (2.1)$$

$$PLR = \frac{Losses_{realized}}{Losses_{realized} + Losses_{paper}} \quad (2.2)$$

To determine whether a position counts as a (realized or paper) gain or loss, the current stock price is compared to its historic weighted average purchase price.⁶ If the current price is higher (lower) than the weighted average purchase price, the position is counted as a gain (loss). A realized gain/loss is counted each time the investor decides to sell a share, while the remaining opportunities to sell shares are counted either as paper gains or paper losses. The disposition effect (DE) is then defined as:

$$DE = PGR - PLR \quad (2.3)$$

It is argued that a disposition effect is present if there is a large difference between PGR and PLR , i.e., if $DE \gg 0$. The disposition effect is measured at the level of the individual investor. At the two extremes, investors with $DE = 1$ solely and immediately realize gains, whereas they never realize losses. The opposite is true for investors who exhibit a disposition effect of $DE = -1$. In line with Weber and Welfens (2007) and Fischbacher et al. (2017), we assume that participants should be equally likely to realize winner and loser stocks. Hence, this implies that the

⁵ For the following measures of the disposition effect, we only consider periods 0 to 13. The first three periods (-3 to -1) are excluded because participants cannot conduct transactions but merely observe price developments during this time. The last period is excluded from the analysis as a precautionary mechanism in order to avoid end-round effects (Kadous et al. (2014)), when subjects might trade obsessively to “lock-in” gains before the experiment concludes.

⁶ Odean (1998) conducts the same analysis while also considering the highest purchase price, the first purchase price, and the most recent purchase price instead of the weighted average. He does not find any substantial deviations from the primary results. Feng and Seasholes (2005), Rau (2015), and Fischbacher et al. (2017) also report that their results do not depend on the method used to calculate the reference price, i.e., that their findings are robust. Therefore, and because subjects were explicitly shown the weighted average purchase price for each stock on the trading interface, we will only conduct the following analyses using the weighted average purchase price.

individual-level disposition effect should — on average — amount to zero.

However, this measure of the disposition effect — while it is most frequently used in the literature — can be sensitive towards portfolio size and trading frequency (see for example Rau (2015)). Therefore, we also examine the disposition effect by calculating a so-called disposition coefficient, α , that Weber and Camerer (1998) define as the “difference in sales of winner and loser stocks by one subject normalized by the total number of sales by that subject” (p. 177). More formally, we specify the disposition coefficient as:

$$\alpha = \frac{S_+ - S_-}{S_+ + S_-} \quad (2.4)$$

Here, S_+ is the number of sales after a price increase over the previous period and S_- is the number of sales after a price decrease. The disposition effect α will also range between -1 and 1 . A value of 0 indicates that there is no disposition effect, while $+1$ (-1) indicates that the subject consistently sold after price increases (decreases).

2.3.5 Participants and Compensation

Participants are recruited on Amazon’s Mechanical Turk (“MTurk”) website.⁷ In order to be able to do so, the experiment was programmed using HTML, CSS, and JavaScript web technologies and hosted on a web server. The succeeding questionnaire was implemented using the Unipark survey platform.⁸ This implies that both parts of the experiment can be accessed remotely by MTurk workers from the United States of America.

The decision to focus exclusively on US MTurk workers was made deliberately because this demographic has been subject to previous research that found that those workers are comparable to the general US population (see for example Berinsky et al. (2012) or Goodman et al. (2013)). Hence, the results presented below will prove more easily generalizable than those derived from, for example, university students or convenience samples. In other words, the MTurk sample is expected to exhibit greater external validity. Specifically, Goodman et al. (2013) report that, when compared to the overall US population, MTurk workers show a similar income distribution — albeit with a marginally smaller mean. Additionally, MTurk workers are only slightly younger than the US average. They also seem to exhibit the same decision-making biases — most importantly, risk aversion in the gains domain and

⁷ <https://www.mturk.com/>

⁸ <https://www.unipark.com/>

risk-seeking in the loss domain — as the general population (Goodman et al. (2013)).

With regards to internal validity, Berinsky et al. (2012) find that MTurk workers are more attentive during experiments than comparable subjects. The authors argue that this is, at least in part, due to the incentive mechanism provided by Amazon on the MTurk platform: By default, when a new “HIT” (human intelligence task, the name for assignments on MTurk) is published, only those MTurk workers who have an approval rating of at least 95% can participate, which is a rather strict requirement. After workers have completed a HIT, the requester can decide whether or not to accept the individual worker’s submission. Acceptance will result in a higher approval rating and the payment of the pre-determined completion fee. Hence, if individual MTurk workers are inattentive to instructions or experimental stimuli, they face the risk of being excluded from future HITs in addition to not receiving payment for the already completed HIT. In summary, we agree with Goodman et al. (2013) who state that they “highly recommend MTurk to behavioural decision-making researchers because of its reliability, low cost, speed of data collection, and heterogeneity of participants” (p. 222).

In order to elicit realistic and truthful behaviour from all participants, their compensation depends on their individual performance in the experiment. Camerer and Hogarth (1999) note that incentives seem to be most effective in judgement and decision-making tasks. Hence, participants are incentivized to perform well and pay close attention to the experiment’s instructions and stimuli. All participants receive a flat payoff that amounts to \$4.50. Additionally, they can earn 0.25% of the amount they generated in experimental currency.⁹ That is, if their total final assets amount to \$11,000, they will receive a flat fee of \$4.50 plus \$2.50 ($\$11,000 - \$10,000 = \$1,000 * 0.25\% = \2.50). Hence, they would receive \$7 in total.¹⁰

2.4 Results

Before the actual experiment was conducted to collect data for the successive analysis, several pretests were carried out to ensure that the instructions could not be misunderstood, to eliminate any technical complications, and to collect general feedback and remarks with regards to the research undertaking. These pretests were administered in two environments: The initial pretest took place during a re-

⁹ This payoff scheme is similar to those used in Weber and Camerer (1998), Döbrich et al. (2014), Kadous et al. (2014), or Goulart et al. (2015).

¹⁰ Please note that participants cannot earn less than \$4.50 and do not have to pay a penalty for negative performance.

search seminar,¹¹ where participants could provide verbal feedback to the authors, whereas succeeding tests were carried out directly via MTurk while making use of the exhaustive technical setup. Subsequently, technical obstacles were surmounted, the instructions were altered slightly to safeguard subjects' accurate understanding, and some questions in the questionnaire were altered to avoid any potential misunderstandings. Additionally, participants' performance was used to establish a realistic wealth target that could be set as a predefined goal in the *Goal* and *Goal & Graph* treatments.¹² Lastly, one pretest session was used to make certain that subjects understood the design of the price movements of the respective stocks.

Once pretests and the corresponding alterations of the setup had been completed, data were collected between August 18 and August 25, 2018. As a first step, participants' trading data and the answers they gave to the questionnaire were combined in a single dataset. The following data cleansing and trimming procedures were then applied: We excluded all subjects who did not trade at all during any of the 14 periods as we argue that they did not follow the basic instructions (i.e., to “perform as well as you can” or to “reach the predefined goal”). Furthermore, all subjects who did not pass our simple manipulation check at the end of the experiment were excluded from the further analysis as well.

Only those subjects who remained in our dataset after these two procedures had been applied were compensated for their participation. Furthermore, in case a subject only bought shares but never realized any profits or losses, the denominator of the disposition coefficient becomes zero and, hence, α is undefined (see equation 2.4). In order to be able to compare the results across disposition measures, we also excluded subjects for which α was undefined from the analysis that focuses on the difference in *PGR* and *PLR*. Note, however, that these subjects still received compensation for their participation since a buy-and-hold strategy could be reasonable in our setting if subjects were able to identify the more favourable stocks early on and then stuck with their decisions for the remaining periods.

2.4.1 Sample Statistics

Before discussing the results of the disposition effect analysis, we first examine our basic sample composition and several descriptive statistics. Subjects' demographic characteristics are summarized in Table 2.2. Overall, 160 subjects remained in our dataset after the above-described data cleansing procedures had been applied. These

¹¹ As part of the Burgenland seminar (Austria, July 11, 2018).

¹² However, it should be noted that, as stated before, even impossible goals should have the desired effect.

procedures are also one reason as to why the number of participants per condition is not equal but instead ranges from 38 to 43. Furthermore, we did not impose any maximum on the number of participants per condition but rather employed pure random allocation.

This resulted in the fact that while the number of females (83) and males (77) in our sample is relatively balanced overall, there is a significant imbalance in the *Goal & Graph* treatment, with merely 15 females and 23 males. This imbalance is purely due to chance. Additionally, participants' age varied across conditions, with an overall average of 37.9 years. This is significantly older than the average age of student samples, making our sample more representative overall, which reinforces our motivation to use MTurk to acquire participants. In order to counteract the sample imbalances, we chose to run OLS regressions and include gender and age as control variables in a later part of our analysis to see if our results sustain and were, hence, not driven by differences in these demographic characteristics.

Table 2.2: Demographic characteristics by experimental condition

Condition	Participants	Gender		Avg. age
		Female	Male	
Control	40	22	18	40.0 (13.4)
Goal	43	24	19	39.7 (14.6)
Graph	39	22	17	36.9 (10.4)
Goal & Graph	38	15	23	34.5 (9.6)
Overall	160	83	77	37.9 (12.4)

Note: This table shows the number of participants per experimental condition and overall. Furthermore, it reports the gender composition and participants' average age. Standard deviations are reported in parentheses.

On average, subjects took 7 minutes and 15 seconds to complete the investment task (excluding reading the instructions and answering the questionnaire). Their investment-related characteristics are summarized in Table 2.3. We used the widely adopted measures from Lusardi and Mitchell (2014) to establish participants' financial literacy. Their three questions focus on the understanding of (1) numeracy/interest rates, (2) inflation, and (3) risk diversification, as the authors argue that these three dimensions capture the most important fundamental financial concepts. A person is classified as financially literate if they manage to answer all three questions correctly.

Table 2.3: Investor characteristics by experimental condition

Condition	Literacy	Relevance	Avg. expertise	Leisure
Control	67.5%	47.5%	2.02 (0.85)	27.5%
Goal	60.5%	48.8%	1.92 (0.70)	23.3%
Graph	79.5%	48.7%	2.34 (0.66)	23.1%
Goal & Graph	76.3%	47.4%	2.38 (0.88)	21.1%
Overall	70.6%	48.1%	2.15 (0.79)	23.8%

Note: This table reports investment-related characteristics of all participants per condition. Participants were classified as financially literate if they answered all three financial literacy questions correctly. As for investment relevance and the leisure vs. money motivation, we looked at the two extremes of the respective scales and classified investors according to a dummy variable of 1 if they were mostly motivated by leisure and if they claimed that investments are personally relevant for them. Average expertise measures the average of the four expertise items. Standard deviations are reported in parentheses.

What is particularly conspicuous is that, overall, 70.6% of our participants can be classified as financially literate. Compared to Mitchell and Lusardi (2011), who administer the same set of questions to a representative US sample and find that merely 30.2% of their respondents are financially literate, this is a strikingly high number. Even internationally, the picture persists: While in Romania only 3.8% of respondents are financially literate (Beckmann (2013)),¹³ Bucher-Koenen and Lusardi (2011) report a financial literacy rate of 53.2% in Germany. Hence, it seems that our sample is composed of particularly (financially) informed participants.

One reason for this observation might be that our sample suffers from self-selection issues. The task was advertised as an “experiment about stock market decision-making” and consequently might have attracted particularly those MTurk workers who are more financially sophisticated, while repelling those who are not. Self-selection issues are not unique to our experiment, however. Because incentives are linked directly to subjects’ performance, it is feasible to assume that experiments will always overproportionally attract those subjects who believe they can perform well on the task. In our particular case, this could have resulted in a significantly more sophisticated sample than the general US population.

About half of the experiment’s subjects stated that financial investments are also relevant to them in their personal lives. Hence, we believe that our sample consists of subjects that either regard investments as more or less relevant, which is likely to be the case in the general population as well. With regards to their reason

¹³ It should be noted, however, that Beckmann (2013) uses slightly altered wording to phrase the inflation-related question.

for participating in the experiment, merely 23.8% of participants stated that they were more motivated by the fun or leisure aspect of the task. On the other hand, this implies that more than three-quarters were mostly motivated by the monetary reward they expected to achieve. Hence, we are confident that our compensation was set at an attractive level and that subjects did in fact behave rationally and in a manner that would maximize their payoff at the end of the experiment.

Table 2.4: Trading statistics by experimental condition

Condition	# purchases	# sales	# total trades	Avg. final wealth
Control	112.5 (90.0)	58.2 (66.3)	170.6 (152.6)	\$10,034 (\$328)
Goal	103.7 (99.6)	52.6 (69.8)	156.3 (166.3)	\$10,005 (\$486)
Graph	112.9 (94.6)	62.6 (78.3)	175.5 (168.6)	\$10,045 (\$260)
Goal & Graph	137.6 (160.9)	75.3 (144.2)	212.9 (302.3)	\$10,070 (\$420)
Overall	116.2 (113.7)	61.8 (93.4)	178.0 (203.7)	\$10,037 (\$383)

Note: The table summarizes participants' investment behaviour. It reports the number of share purchases, sales, and the resulting number of total trades per experimental condition. Also, it shows the average wealth at the end of period 14. Standard deviations are reported in parentheses.

While the previous discussion has mostly focused on exogenously given sample characteristics, we also examined subjects' trading behaviour, which is summarized in Table 2.4. Firstly, it can be seen that subjects conducted on average 178 transactions (defined as the sum of purchases and sales). Hence, we argue that they were actively involved in the experimental task. Moreover, it can be observed that this number varies significantly across experimental conditions. We see this as compelling evidence that the experimental stimuli induced subjects to exhibit distinct behaviour. In other words, we deem our treatments effective in influencing trading behaviour, which implies that potential variations in the disposition effect can also be linked back to the treatments.

With regards to the average final wealth at the end of the experiment, we were surprised to find that there were no substantial differences across the conditions. On average, subjects ended the experiment with \$10,037 in wealth, generating merely \$37. However, there were wide performance variations even within conditions, as can be seen in Figure 2.2.

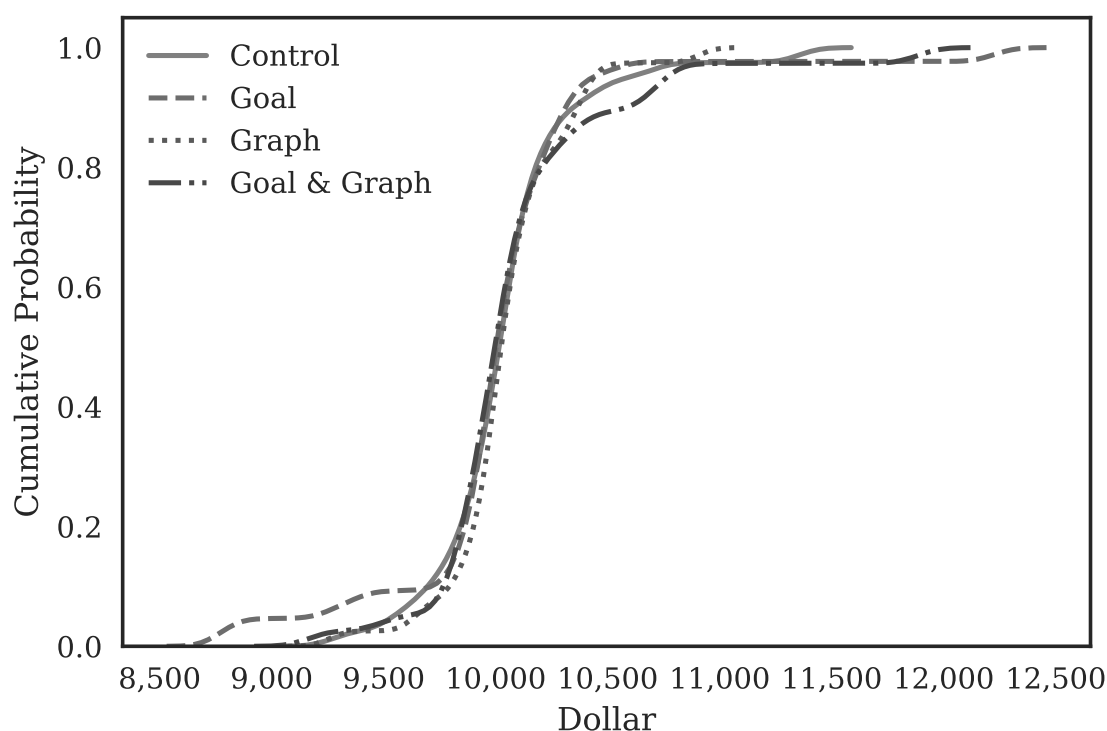


Figure 2.2: Cumulative distribution of total assets at the end of period 14

Note: This figure shows the cumulative probability distributions of subjects' final wealth at the end of period 14 by experimental condition.

What is particularly striking is that, on average, subjects in the *Goal* and *Goal & Graph* treatments were noticeably far away from the imposed goal of \$11,000. Nevertheless, since some subjects did achieve these goals and because our pretests had also shown that it is possible to generate more than \$11,000, we are confident that our treatments worked as intended nevertheless.¹⁴

2.4.2 Analysis of the Disposition Effect

Now that the sample statistics have been reported and we are confident that the treatments affected subjects' behaviour in the experiment, we will focus on the analysis of individual-level disposition effects. To do so, we will first limit the analysis to the disposition measure (*DE*) as proposed by Odean (1998), since it is the most widely adopted measure of the disposition effect. As a robustness check, we will, however, also consider the disposition coefficient (α) that was proposed by Weber and Camerer (1998) in section 2.5. Section 2.6 will then discuss the aggregate findings from both measures and draw conclusions regarding the previously stated hypotheses.

¹⁴ As stated above, even impossible to reach goals should have the desired effect.

As a first indicator, we focus on the mean DE by condition, as summarized in Table 2.5, where we also report $PGRs$ and $PLRs$. In the control condition, we find a positive disposition effect of 0.09. We test the statistical significance of this result by applying a two-tailed t-test and find that the result is significantly different from zero at the 5% level. Economically, our disposition measure is slightly lower than the ones reported of control groups in experiments that use a similar setup: Whereas Rau (2015) does not find a disposition effect in the control group, Döbrich et al. (2014) report a DE of 0.14, Fischbacher et al. (2017) of 0.29, Weber and Welfens (2007) of 0.24, and Goulart et al. (2015) of 0.11.

Table 2.5: Disposition measures by experimental condition

Condition	PGR	PLR	DE	Positive DE	Negative DE
Control	0.19*** (5.60)	0.10*** (6.12)	0.09** (2.51)	62.5%	32.5%
Goal	0.08*** (4.90)	0.11*** (5.22)	-0.03 (-0.99)	41.9%	58.1%
Graph	0.11*** (4.81)	0.12*** (4.36)	-0.01 (-0.17)	43.6%	51.3%
Goal & Graph	0.14*** (4.61)	0.12*** (3.29)	0.02 (0.45)	52.6%	47.4%

Note: This table summarizes subjects' PGR , PLR , and DE , as proposed by Odean (1998). The parentheses report the t – statistics for the null hypothesis that the measures are equal to zero. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.10$. Also, the percentage of subjects with positive or negative disposition measures are reported. Values might not necessarily add up to 100% due to rounding and since some subjects exhibited a DE measure of exactly zero.

Considering the particularly high financial literacy rates found across our subjects, we argue that it is not counterintuitive that our disposition measure is lower than the ones found in the studies cited above. Previous research has shown that the disposition effect decreases with investor sophistication (e.g., Feng and Seasholes (2005) or Dhar and Zhu (2006)). While investor sophistication is typically measured in terms of the number of trades executed or the years of investment experience, it seems likely that financial literacy is another proxy of investor sophistication. Hence, seeing that our sample is particularly literate, it is not surprising to find that the disposition effect, while it is still present and significant, is lower than in comparable studies.

Looking at this first result more closely, it can be seen that while subjects in

the control condition realized around 19% of their available paper gains, only about 10% of available paper losses were realized. In other words, gains were realized more readily, while losses were held on to for too long, resulting in a positive disposition effect measure. Moreover, there is mentionable heterogeneity in our sample. While 62.5% of participants in the control group did in fact exhibit a positive *DE*, 32.5% of participants are associated with a negative, reversed *DE*. This result is in line with prior research. Weber and Welfens (2007), for example, also report that around one-third of their subjects sell losses more often than or equally as often as gains. Furthermore, subjects with a positive disposition effect accumulated lower final assets (\$10,022) than subjects with a negative disposition effect (\$10,077). Hence, the disposition effect was associated with worse trading performance, which reiterates our motivation that debiasing the disposition effect can have positive welfare implications for investors. Overall, this leads us to conclude that there is a positive and significant disposition effect in the control group which we expected considering the existing literature. Also, the first result reinforces our confidence that the experimental setup was properly understood by participants and that they behaved according to our expectations.

Next, we investigate the *DE* measures in all three treatment conditions. As can be seen in Table 2.5, none of the conditions show a disposition measure that is significantly different from zero. Recalling our hypotheses from section 2.3.2, these results are unexpected since we anticipated to find negative disposition measures (i.e., reversed disposition effects). Consequently, we look at these results in more detail. A mere comparison of *PGRs* and *PLRs* of treatments with the control condition indicates that while subjects did not alter their behaviour in terms of loss realization, they significantly reduced their propensity to realize paper gains.

This conjecture is analysed by conducting Kolmogorov-Smirnov (KS) tests on the distributions of *PGR*, *PLR*, and *DE*. The values in parentheses in Table 2.6 report the *p* – values for the hypothesis that any given combination of two distributions are the same. It can be concluded from this analysis that none of the *PLR* distributions are significantly different from the *PLR* distribution of our control group. Hence, this implies that subjects did not change their loss realization behaviour as a result of any of our administered treatments. On the other hand, the distributions of *PGR* in the control group and the *Goal* treatment are significantly different from each other ($p = 0.0108$). Overall, this picture persists when looking at the resulting disposition measure. While the distributions of *DE* in the control group and the *Goal* treatment are significantly different from each other, there is no significant difference when considering the distributions in the *Graph* or *Goal* &

Graph treatments. Graphically, these results are also evident from Figure 2.3, where we plot the cumulative probability distributions of *PGRs*, *PLRs*, and *DEs*.

Table 2.6: KS-statistics for *PGR*, *PLR*, and *DE* by experimental condition

Condition	Control	Goal	Graph
PGR			
Goal	0.3441 (0.0108)		
Graph	0.2154 (0.2828)	0.1640 (0.6016)	
Goal & Graph	0.2500 (0.1487)	0.1885 (0.4298)	0.1107 (0.9630)
PLR			
Goal	0.1192 (0.9127)		
Graph	0.1442 (0.7735)	0.179 (0.9615)	
Goal & Graph	0.2197 (0.2680)	0.1273 (0.8771)	0.1262 (0.8992)
DE			
Goal	0.2959 (0.0420)		
Graph	0.2417 (0.1709)	0.2224 (0.2315)	
Goal & Graph	0.2079 (0.3301)	0.1603 (0.6384)	0.1417 (0.8040)

Note: This table shows Kolmogorov-Smirnov test statistics for *PGR*, *PLR*, and *DE* for all possible combinations of experimental conditions. The parentheses report the *p-values* for the hypothesis that the two distributions are the same.

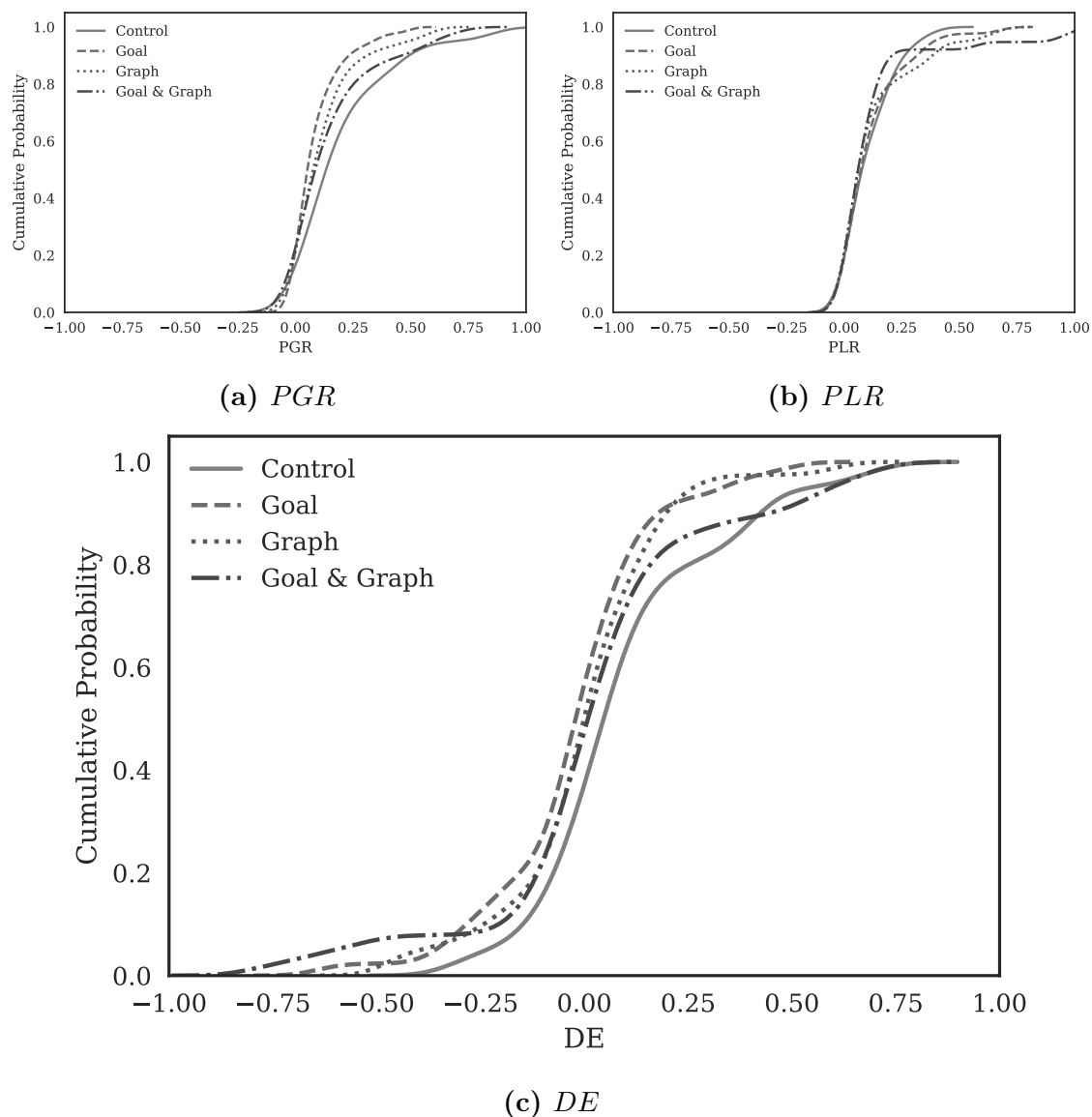


Figure 2.3: Cumulative distributions of individual (a) PGR s, (b) PLR s, and (c) DE s

Note: We show the cumulative probability distributions of (a) PGR s, (b) PLR s, and (c) DE s separately. Each plot includes the distributions for all four experimental conditions.

It thus seems as if at least the *Goal* treatment was in fact effective in reducing the disposition effect. In order to be able to make more robust conclusions in relation to all our hypotheses, we run several ordinary least squares (OLS) regressions on PLR , PGR , and DE . There, we include a constant that represents the control condition and dummy variables for each of the three treatment conditions. This implies that the coefficients of these dummy variables represent the change in DE relative to the control condition. In other words, they represent the magnitude of the debiasing mechanism.

Furthermore, since we have seen substantial imbalances with regards to age and

gender across the conditions in section 2.4.1, we also run regressions where we include age and gender as control variables. Gender was included as a dummy variable equal to 1 for *Females* and *Age* is a continuous variable. Age was mean-centred around the grand mean across conditions to make its coefficient more readily interpretable. The resulting regressions are reported in Table 2.7.

Table 2.7: OLS regressions on *PGR*, *PLR*, and *DE*

Variable	(1a) PGR	(1b) PGR	(2a) PLR	(2b) PLR	(3a) DE	(3b) DE
Constant	0.1894*** (0.034)	0.2262*** (0.038)	0.1011*** (0.017)	0.1177*** (0.022)	0.0882** (0.035)	0.1085** (0.042)
Goal	-0.1073*** (0.038)	-0.1064*** (0.037)	0.0105 (0.027)	0.0110 (0.027)	-0.1177** (0.046)	-0.1174** (0.046)
Graph	-0.0762* (0.041)	-0.0724* (0.041)	0.0171 (0.032)	0.0205 (0.032)	-0.0933** (0.047)	-0.0929* (0.048)
Goal & Graph	-0.0484 (0.046)	-0.0542 (0.046)	0.0188 (0.040)	0.0189 (0.038)	-0.0672 (0.059)	-0.0731 (0.059)
Age		0.0009 (0.001)		0.0009 (0.001)		-0.0000 (0.001)
Female		-0.0702** (0.027)		-0.0335 (0.024)		-0.0367 (0.035)
Observations	160	160	160	160	160	160
Adj. R^2	0.036	0.065	-0.017	0.008	0.019	0.013

Note: This table summarizes various linear ordinary least squares regressions on *PGR*, *PLR*, and *DE*. *Age* is a continuous, mean-centered variable, whereas *Female* is binary. Heteroskedasticity-robust standard errors are reported in parentheses. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.10$.

Focussing on regression 1b confirms our prior statement with regards to subjects' *PGRs*. Even when controlling for age and gender, subjects in the *Goal* condition realize their paper gains significantly less frequently ($p < 0.01$) as compared to the control condition. The same conclusion can be drawn for subjects in the *Graph* treatment ($p < 0.10$), even though the effect is slightly less pronounced, wherefore it is particularly surprising that there is no significant effect with regards to gain realization in the *Goal & Graph* treatment. It is furthermore worth mentioning that women generally realize significantly less paper gains than men ($p < 0.05$).

With regards to *PLRs*, there are no significant differences across the experi-

mental conditions. This conclusion can be drawn from regressions 2a and 2b. In other words, the treatments did not affect subjects' behaviour with regards to their propensity to hold versus realize paper losses and the behaviour seems to be independent from gender and age.

Lastly, regression 3b confirms a positive and significant disposition effect (DE) in the control condition ($p < 0.05$) even when controlling for age and gender. By providing subjects with a specific investment goal, their disposition effect could be significantly reduced ($p < 0.05$) and in fact turned slightly negative. These two observations provide evidence in favour of our first two hypotheses. Showing subjects a graph that depicts their aggregate portfolio performance graphically also has a significantly negative effect on the DE measure ($p < 0.10$). Surprisingly, however, the combination of the two debiasing mechanisms (i.e., the *Goal & Graph* treatment) does not significantly affect the DE measure in either direction. The reason for this lies in the fact that subjects did not significantly and substantially reduce their propensity to realize gains. This is a startling result that requires further examination in section 2.5.

To summarize, we can conclude that we have found a positive disposition effect in the control condition, thereby providing evidence the first hypothesis. Furthermore, the *Goal* and *Graph* treatments taken separately significantly reduced the DE measure, even though we did not find evidence of a reversed disposition effect in both cases. Hence, hypotheses two and three cannot be supported. Lastly, the combined *Goal & Graph* treatment did not have any significant debiasing effect, wherefore hypothesis four also cannot be supported.

2.5 Robustness Checks

To test whether our results are robust, we use the disposition coefficient (α) as defined by Weber and Camerer (1998) and check if our results sustain in this alternative specification of the disposition effect. To recall, the disposition coefficient considers whether subjects sold more shares after price increases or after price decreases. Thereby, it adopts the previous period's share price as the reference price for the disposition effect. Since it only considers sales transactions, it is also less sensitive to portfolio size. Analogously to the previous analysis, we first consider the mean disposition coefficients for each experimental condition. The results of this analysis are summarized in Table 2.8.

Table 2.8: Disposition coefficients (Alpha) by experimental condition

Condition	Alpha	Positive Alpha	Negative Alpha
Control	0.15* (1.75)	60.0%	35.0%
Goal	-0.25** (-2.34)	32.6%	65.1%
Graph	-0.08 (-0.69)	38.5%	59.0%
Goal & Graph	0.12 (1.01)	55.3%	44.7%

Note: This table summarizes subjects' disposition coefficients (Alpha), as proposed by Weber and Camerer (1998). The parentheses report the t -statistics for the null hypothesis that the measures are equal to zero. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.10$. Also, the percentage of subjects with positive or negative disposition measures are reported. Values might not necessarily add up to 100% due to rounding and since some subjects exhibited an Alpha measure of exactly zero.

Starting with the results of the control condition, it can be seen that subjects on average exhibited a positive disposition coefficient of 0.15 ($p < 0.10$). Again, this result is of slightly smaller magnitude than results of previous experiments: While Rau (2015) reports a disposition coefficient of 0.22, Döbrich et al. (2014) find a coefficient of 0.27 in their control group. Analogously to the previous investigation, we argue that our Alpha is potentially smaller because our subjects are more financially literate and, hence, more sophisticated. Also in line with the previous results, there is significant heterogeneity across participants. Merely 60% of subjects exhibited a positive disposition coefficient, while the measure was negative for 35% of respondents. Furthermore, subjects with a positive disposition coefficient performed significantly worse. Their average final wealth amounted to merely \$9,967, indicating that they exhibited negative trading performance. On the other hand, subjects with negative disposition coefficients performed considerably better, ending up with an average of \$10,152 in total wealth at the end of period 14.

With regards to the implemented treatment conditions, it seems that the *Goal* treatment led subjects to exhibit a significantly negative disposition coefficient of -0.25 ($p < 0.05$). This result again provides evidence for our second hypothesis. While the Alpha measure is also negative in the *Graph* condition, it is not significantly different from zero and we find a positive, though insignificant, disposition coefficient in the *Goal & Graph* treatment. This is contrary to what we had expected based on our hypotheses.

Kolmogorov-Smirnov test statistics (see Table 2.9) show that the distributions of disposition coefficients in the *Goal* and in the *Graph* treatment are, in fact, significantly different from their distribution in the control condition. This conclusion cannot be drawn for the *Goal & Graph* treatment, however ($p = 0.42$).

Table 2.9: KS-statistics for disposition coefficients (α) by experimental condition

Condition	Control	Goal	Graph
Goal	0.40 (0.00)		
Graph	0.34 (0.02)	0.18 (0.49)	
Goal & Graph	0.19 (0.42)	0.25 (0.14)	0.19 (0.43)

Note: This table reports Kolmogorov-Smirnov test statistics for individual disposition coefficients (α) for all possible combinations of experimental conditions. The parentheses report the p -values for the hypothesis that the two distributions are the same.

As a last step, we therefore run OLS regressions on disposition coefficients. The specifications here are the same as before and are reported in Table 2.10. We initially run a regression of all treatments on Alpha (1a), and subsequently include gender and age as control variables (1b) to account for imbalances in our sample composition.¹⁵ Since the results are essentially identical, we focus our discussion on regression 1b.

First, the regression reports a positive and highly significant ($p < 0.01$) constant, which represents the disposition effect in the control group. The constant (0.2802) is now also in the range of the previously reported disposition coefficients of Döbrich et al. (2014) or Rau (2015). The coefficient of the *Goal* treatment is negative and also highly statistically significant ($p < 0.01$). This provides evidence that equipping subjects with a specific investment goal will help reduce their disposition effect. In fact, the regression allows us to conclude that subjects in the *Goal* treatment will, on average, exhibit a reverse disposition effect, which is in line with our second hypothesis.

As for the coefficients representing the *Graph* and *Goal & Graph* treatments, we find that they are not statistically significantly different from zero. This leads us to conclude that the stimuli presented in these conditions do not help reduce or even reverse the disposition effect. It is worth mentioning, however, that females seem to exhibit a significantly ($p < 0.05$) lower disposition effect than males. While the

¹⁵ The control variables are coded in the same way as before.

magnitude of the gender effect seems startling at first, the fact that gender affects the disposition effect is not new and hence our finding is in line with prior research (e.g., Da Costa et al. (2008)).

Table 2.10: OLS regressions on disposition coefficients (Alphas)

	(1a)	(1b)
Variable	Alpha	Alpha
Constant	0.1479*	0.2802***
	(0.085)	(0.100)
Goal	-0.4009***	-0.3985***
	(0.137)	(0.134)
Graph	-0.2235	-0.2154
	(0.139)	(0.140)
Goal & Graph	-0.0286	-0.0585
	(0.145)	(0.147)
Age		0.0015
		(0.004)
Female		-0.2458**
		(0.109)
Observations	160	160
Adj. R^2	0.040	0.059

Note: This table summarizes linear ordinary least squares regressions on disposition coefficients (Alphas). *Age* is a continuous, mean-centered variable, whereas *Female* is binary. Heteroskedasticity-robust standard errors are reported in parentheses. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.10$.

Lastly, after conducting the experiments and proceeding with the data analysis, we noticed that the share price developments seemed to not always match their exogenously set return characteristics. Consequently, we investigated our suspicion more closely and found that the stock with the lowest probability of showing a price increase (Stock C) in fact exhibited a positive average return of 0.49% per period. This is a result of the fact that, purely due to chance, the stock's price increased 8 times, while it decreased only 9 times over the 17 periods for which prices were made available. In order to check for the gravity of this issue, we rerun the whole analysis while excluding Stock C. Seeing that the results essentially remain unchanged, we are confident that this unexpected development did not affect participants' behaviour or our results in any significant manner.

2.6 Conclusion

2.6.1 Summary and Implications

The aim of this research paper was to investigate whether providing investors with a specific investment goal or displaying their portfolio's performance on an aggregated level (or the combination of these two mechanisms) could reverse their susceptibility to the disposition effect. Having conducted an in-depth analysis of two measures of the disposition effect in sections 2.4 and 2.5, we will now aggregate the findings and relate them to our hypotheses from section 2.3.2.

In the control condition, we find a positive and significant disposition effect. This result is robust to both measures of the disposition effect (i.e., the disposition measure as proposed by Odean (1998) and the disposition coefficient as proposed by Weber and Camerer (1998)). The magnitude of the effect is, depending on the specification used, slightly lower than the disposition effect in comparable experiments. We suspect that this could be due to the fact that our sample is considerably more financially literate, i.e., more sophisticated. Overall, we find evidence in favour of our first hypothesis, which we summarize as follows:

Result 1 (R1): *Subjects in the control condition (i.e., those who did not receive any treatment) exhibited a positive and significant disposition effect under both specifications.*

Next, we hypothesized that providing subjects with a specific investment goal would reverse their disposition effect because these subjects should exhibit augmented self-control. Our results show that our subjects did report a lower *DE* measure as compared to the control group. In fact, their *DE* measure turned slightly negative when controlling for demographic differences in age and gender. This result is due to the fact that while subjects did not alter their behaviour with regards to loss realization, they realized their paper gains less frequently. It thus seems that investment goals cause investors to focus more on the long-term, augmenting their self-control, wherefore they hold on to gains for longer periods of time, foregoing early gain realization. Under the alternative specification, we find that subjects in the *Goal* condition also exhibited a reversed disposition effect, wherefore we overall find compelling evidence in favour of the second hypothesis, in line with Aspara and Hoffmann (2015):

Result 2 (R2): *Subjects in the Goal Treatment (i.e., those who were provided with a specific investment goal) exhibited a significant reversed disposition effect because they realized paper gains less frequently.*

In the *Graph* condition, subjects were provided with a graphical illustration of their overall portfolio performance. This treatment was implemented as a direct response to the call in Döbrich et al. (2014) to display portfolio performance graphically. We expected that this treatment would lead subjects to refrain from mental accounting practices and instead focus on their overall portfolio, leading them to exhibit a reversed disposition effect. The previously discussed regression on *DE* shows that subjects in this treatment condition did, on average, have a lower disposition effect. However, the resulting *DE* was still positive. Also, when adopting the alternative specification, we found that the disposition coefficient α was not significantly reduced in the *Graph* treatment. Hence, while there is some evidence for a debiasing effect, we cannot accept the third hypothesis in any case:

Result 3 (R3): *Subjects in the Graph Treatment (i.e., those who were shown a performance graph) did not show a reversed disposition effect.*

Lastly, we also expected subjects in the *Goal & Graph* treatment to exhibit a reversed disposition effect. However, our results show that this is not the case under either specification. The coefficients are statistically insignificant in both cases. By decomposing the *DE* measure, we find that subjects did not alter their behaviour with regards to gain or loss realization. Hence, this treatment is deemed ineffective and we subsequently reject the fourth hypothesis:

Result 4 (R4): *Subjects in the Goal & Graph Treatment (i.e., those who were provided with a specific investment goal and were shown a performance graph) did not exhibit a reversed disposition effect. Their behaviour with regards to gain and loss realization did not change as compared to the experimental control group.*

2.6.2 Future Research

While the present research evidently shows that goals can be effective in reversing the disposition effect, it also raises several questions that should be subject to further detailed investigation in potential follow-up work. First, we were surprised to find no substantial differences in subjects' investment performance across the four experimental conditions. Building on prior research alone, we had expected to find that subjects in the *Goal* treatment would perform significantly better than those in the control group. Adding to this, the fact that these subjects exhibited a reversed disposition effect but the same level of performance is another startling fact that we cannot explain with the data available from our experiment. Hence, future research might look at this phenomenon in more detail.

Furthermore, we were surprised to find that the *Goal & Graph* treatment did not have any significant effect on the disposition effect overall. While the *Goal* treatment was effective and the *Graph* treatment did not have any significant effect, we had expected to find that the *Goal & Graph* treatment would also reverse the disposition effect, considering that it is merely a combination of the other two treatments. Again, the data available from the present experiment unfortunately does not allow us to investigate this observation more thoroughly, wherefore an additional, dedicated experiment might be considered as part of future research.

Chapter 3

Financial Attitudes, Behaviours, and the Disposition Effect¹

3.1 Introduction

Investors' welfare is mostly determined by the quality of their financial decisions (Duclos (2014)). However, these decisions are not always strictly rational (Frydman and Camerer (2016)) but affected by cognitive and behavioural biases (De Bondt et al. (2008)). Investors' widespread tendency to hold losing assets for too long while realizing paper gains too quickly is one such bias. This behaviour was first termed the *disposition effect* by Shefrin and Statman (1985). Meanwhile, the disposition effect has been replicated in multiple laboratory studies (for example, see Weber and Camerer (1998), Kadous et al. (2014), or Rau (2015)) and empirical settings (for example, see Shapira and Venezia (2001), Feng and Seasholes (2005), or Pelster and Hofmann (2018)). Thereby, the disposition effect has become one of the most robust findings in finance research (Barber and Odean (2011)). This is also at least in part due to the observation that various investor types and asset classes have been shown to be subject to the disposition effect, making it a ubiquitous phenomenon. Furthermore, the fact that it leads investors to make sub-optimal decisions (for example, see Garvey and Murphy (2004), Lee et al. (2008), or Roger (2009)), illustrates that the disposition effect deserves particular academic attention. To provide a more specific example, Odean (1998) finds that the assets that investors sold too quickly due to the disposition effect continue to outperform over the following periods. On the

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other land, the losing assets that these investors held on to for too long subsequently remain underperformers, resulting in negative portfolio performance overall.

Despite the widespread attention that it has received thus far, the origins of the disposition effect are still widely debated (Kaustia (2010)). Furthermore, previous research undertakings find substantial heterogeneity with regards to the magnitude of subjects' disposition effects (for example, see Weber and Welfens (2007)). On a related note, Wierzbitzki and Seidens (2018) show that merely 60% of subjects in their experimental control condition exhibit a positive disposition effect. While this result is in line with the previous literature, it is startling nevertheless. Other research also mostly considers the mean disposition effect, but does not investigate which types of investors exhibit a more pronounced disposition effect — in other words, the heterogeneity that is found is not investigated in more detail.

In this regard, we propose to shine light on which factors could cause investors to exhibit a positive (or negative) disposition effect by considering the financial attitudes and behaviour dimensions put forward by Fünfgeld and Wang (2009). To do so, we conduct an experiment based on the setting described in Frydman et al. (2014) and focus exclusively on US investors. While there is already some research on the determinants and mitigating factors of the disposition effect, the literature is dispersed and at times even contradictory. Also, most research focuses on the role of single factors or demographic variables only. However, using the questionnaire from Fünfgeld and Wang (2009), we see the opportunity to more closely shed light on which financial behaviours and attitudes correlate most strongly with the disposition effect. In doing so, we contribute to the current state of research in the following ways: First, we test the questionnaire from Fünfgeld and Wang (2009) on a US sample to see whether factor analysis reveals the same underlying dimensions of financial attitudes and behaviours as originally identified and thereby test its external validity. Second, and most importantly, we provide more insights as to which of the dimensions are most strongly related to the exhibition of a positive disposition effect.

We find that US investors' self-stated financial attitudes and behaviours can be captured by the following four dimensions: “financial planning,” “anxiety,” “interest in financial issues,” and “impulsive financial decision-making.” Hence, while these are not the exact same dimensions as identified by Fünfgeld and Wang (2009) in the German-speaking region of Switzerland, there is a significant overlap between the extracted factors in both geographies. Furthermore, we find that subjects in our experiment exhibit a significantly positive disposition effect overall. However, we also observe the previously discussed heterogeneity in that roughly one-quarter

of participants show a negative disposition effect. Upon closer inspection, we find that investors who score high on the “financial planning” dimension and low on the “impulsive financial decision-making” dimension exhibit lower disposition effects and vice versa. These investors seem to have in common that they focus more on the long-term implications of their financial decisions, thereby being less prone to the disposition effect on average.

This paper is therefore structured as follows: Section 3.2 reviews the relevant literature on the disposition effect, including its foundation and the factors that are known to mitigate it. Furthermore, it presents the contribution on financial attitudes and behaviours by Fünfgeld and Wang (2009), before deducting the research questions that are to be answered in this research paper. Next, section 3.3 describes the experimental design and procedure in detail. Also, it introduces the measures used to calculate the disposition effect and provides information on the experiment’s participants and the chosen compensation mechanism. Section 3.4 summarizes sample statistics before reporting the results of the main analysis. Lastly, section 3.5 concludes by providing answers to our research questions and hinting on ideas for future research avenues.

3.2 Literature Review

3.2.1 Disposition Effect

In one of the first empirical studies of individual investor behaviour,² Schlarbaum et al. (1978) observe that investors are more inclined to realize investment gains than losses. Based on the same dataset, Shefrin and Statman (1985) confirm these findings and subsequently term the behaviour to “sell winners too early and ride losers too long” (p. 777) the *disposition effect*. Responding to their call for a more detailed investigation of this observation, Odean (1998) provides the first large-scale analysis of the disposition effect. In contrast to earlier studies, which had used data from a retail brokerage house, he employs a dataset that stems from a US-based discount broker. The author argues that his empirical strategy entails the advantage that all investors in his sample are improbable to be influenced by the same pieces of advice. Hence, the disposition effect he finds in his analysis is unlikely to be a result of herding behaviour or private information — instead, it seems that it is a trading disposition inherent in and exhibited by individual investors. Concurrently, Weber and Camerer (1998) conduct a laboratory experiment to investigate the phenomenon

² Earlier studies had focused almost exclusively on the investment performance and behaviour of American institutions.

in more detail. Their setup is designed in a way such that rational investors should not exhibit a disposition effect. Still, the authors find that their participants are 50% more likely to sell gains as compared to losses, thereby providing the first experimental evidence of the disposition effect.

Following these pivotal examinations, the disposition effect has been found to be one of the most robust and ubiquitous phenomena in finance research (Barber and Odean (2001), Chang et al. (2016)). The interest in the topic is, at least partly, due to the fact that the disposition effect has been shown to entail adverse consequences on investors' performance. Odean (1998) provides the first evidence for this claim: The excess return over the CRSP (The Center for Research in Security Prices) value-weighted index over a one-year period is 3.4% higher for winning stocks that investors sold too early as compared to the losing stocks that remained in their portfolios. Other studies have since also found that the exhibition of the disposition effect leads investors to make sub-optimal decisions (see for example Garvey and Murphy (2004), Lee et al. (2008), or Roger (2009)).³ Brown and Kagel (2009) find that while their subjects in an experimental investigation do try to trade for better stocks, they still fall short in terms of their investment performance because they ignore new pieces of information and consequently hold stocks regardless of their performance.

Furthermore, the disposition effect has been observed globally. To provide just a few examples, evidence for the disposition effect has been found in Australia (Brown et al. (2006)), China (Feng and Seasholes (2005)), Finland (Grinblatt and Keloharju (2001)), Israel (Shapira and Venezia (2001)), Korea (Choe and Eom (2009)), Sweden (Calvet et al. (2009)), Taiwan (Barber et al. (2007)), and the United Kingdom (Richards et al. (2017)). With regards to asset classes, the disposition effect cannot exclusively be found in stock markets. Instead, research has identified the disposition effect in mutual funds (e.g., Frazzini (2006)), futures markets (e.g., Choe and Eom (2009)), and social trading (e.g., Gemayel and Preda (2018)), in addition to stock markets (e.g., Kliger and Kudryavtsev (2008)). Even non-financial domains, such as the Boston real estate market in the 1960s, seem to exhibit the disposition effect (Genesove and Mayer (2001)). Moreover, the disposition effect is present across a variety of investor groups — from students in experimental settings (e.g., Oehler et al. (2002), or Frydman and Rangel (2014)) to professional traders (e.g., Shapira and Venezia (2001), Frino et al. (2004), or Locke and Onayev (2005)).

³ A notable exception is found in Locke and Mann (2005), who find that full-time traders who exhibit the disposition effect in their sample do not show significantly worse performance.

3.2.2 Foundation of the Disposition Effect

In this regard, it is surprising that — despite the widespread attention that it has received in the academic literature for several years — the origins of the disposition effect are still unknown (Kaustia (2010), Talpsepp (2011)). Several reasons for the existence of the disposition effect have been postulated. Shefrin and Statman (1985) initially base their theory of why investors carry a disposition to overproportionally realize investment gains on positive theory that encompasses four components: (1) prospect theory (Kahneman and Tversky (1979)), (2) mental accounting (Thaler (1985)), (3) pride seeking and regret aversion, and (4) lacking self-control. Concisely, they argue that prospect theory’s s-shaped utility function predicts that investors become more risk seeking after experiencing a (paper) loss and more risk averse after (paper) gains. This, in turn, leads them to overproportionally sell gains and hold losses. However, the pure prospect theoretic explanation has since been scrutinized (e.g., Meng and Weng (2018)). Barberis and Xiong (2009) and Hens and Vlcek (2011) argue that investors with prospect theoretic preferences would choose not to invest in stocks in the first place. Even if they did, Barberis and Xiong (2009) and Kaustia (2010) show that prospect theory would more often than not lead investors to exhibit a reversed (i.e., negative) disposition effect.

Alternatively, investors might believe that asset prices are characterized by mean reversion. Consequently, they expect the prices of assets that have recently decreased to increase in the future and vice versa. This would imply that they sell winners because they expect their prices to decrease while keeping losers due to a conviction that their prices will increase in the short-term. However, Odean (1998) shows ex-post that this belief is unfounded: Losing stocks continue to underperform while winning stocks continually outperform. To investigate whether transactions were influenced by portfolio rebalancing motivations, he excludes partial sales and focuses exclusively on those sales where a stock was completely removed from the portfolio. However, the results remain essentially unchanged, wherefore he dismisses the possibility that the observed pattern is a result of portfolio rebalancing. Kaustia (2010) provides additional evidence that investors’ actions are not motivated by a belief in mean reversion. Lastly, experimental setups such as the one employed by Weber and Camerer (1998) are designed in a way such that a belief in mean reversion is clearly unfounded. Still, an array of research has found the disposition effect also in these experimental settings.⁴

⁴ It should be noted, however, that recently Corneille et al. (2018) cast doubt on the assumption that subjects in experimental settings truly understand the design of the experimental asset markets. They argue that mean reversion beliefs cannot completely be ruled out as a contributing factor to the disposition effect.

Consequently, Chang et al. (2016) propose that investors experience cognitive dissonance (Festinger (1957)) each time they are confronted with an investment loss. This is due to the fact that they held a belief that the investment would perform well while it eventually turned out that this was not the case. They provide compelling evidence for their theory, showing that the disposition effect is reduced with increasing levels of investment delegation, where investors feel less responsible for their investment and hence experience a lesser degree of cognitive dissonance when selling a position at a loss. The authors also show that their hypothesis is largely in line with results from previous research, as well as an experiment which they conduct. Ultimately, they argue that investors' behaviour is not driven by economic, but rather by psychological costs.

3.2.3 Mitigators of the Disposition Effect

Despite the fact that the disposition effect is a well-studied phenomenon in finance research (Koestner et al. (2017)), its theoretical foundation is still actively debated. At the same time, research has continuously shown that not all investors are subject to the disposition to overproportionally sell gains (see for example Dhar and Zhu (2006), Weber and Welfens (2007), or Jiao (2017)). Therefore, it is particularly surprising that the mitigating factors that influence the disposition effect have received relatively little attention thus far.

Analyses that do exist are mostly limited to investors' demographic characteristics and are often even contradictory. To provide an example, while Feng and Seasholes (2005) find that younger investors are more prone to the disposition effect, Cheng et al. (2013) provide evidence that more mature traders exhibit larger disposition effects, and Talpsepp (2010) argues that the disposition effect only slightly decreases with age. The same can be said for investors' gender: While Feng and Seasholes (2005), Fischbacher et al. (2017), or Hermann et al. (2017) find that males are less prone to the disposition effect, Wong et al. (2006) find the exact opposite and Da Costa et al. (2008) and Talpsepp (2010) conclude that there might not be any difference in gender susceptibility at all.⁵

Furthermore, investors' experience and sophistication have been investigated in relation to the disposition effect. In this regard, experience refers to an investor-level characteristic that changes over time, whereas sophistication refers to the static

⁵ Talpsepp (2010) shows that the disposition effect is similar for both genders when controlling for other factors in the analysis and the results in Da Costa et al. (2008) depend on the adopted reference point.

differences across investors that do not evolve (Feng and Seasholes (2005)).⁶ The authors find that while trading experience can decrease the disposition effect by up to 72%, the effect does not completely disappear even among the most experienced investors. Furthermore, they show that sophisticated investors are 67% less affected by the disposition effect. Taken together, sophisticated and experienced traders do not show a reluctance towards loss realization, but they are still less more to realize paper gains overproportionally. This implies that even experienced sophisticated investors, on average, still exhibit the disposition effect. These results have since been supported by additional research (see for example Shumway and Wu (2006), Cerqueira Leal et al. (2008), or Heimer (2016)).

3.2.4 Financial Attitudes and Behaviour

On a somewhat related note, Fünfgeld and Wang (2009) set out to classify investors based on their attitudes and behaviour (Fishbein and Ajzen (1975)) in everyday financial affairs. They do so since they observe that existing literature on individual financial and economic behaviour mostly focuses on single dimensions of behaviour only. The authors argue, however, that this scope of analysis is too narrow and therefore propose to investigate individual financial management behaviour from a multitude of perspectives.

Consequently, they administer a 17-item questionnaire to 1,282 investors in the German-speaking region of Switzerland. In doing so, they aim at investigating the self-stated financial attitudes and behaviours of individual investors. By conducting a principal component analysis, the authors expose five underlying dimensions: (1) anxiety, (2) interest in financial affairs, (3) intuitive decisions, (4) need for precautionary savings, and (5) free-spending. Investors who score high on the respective dimensions are: (1) anxious about money-related issues, (2) interested in financial matters and more financially literate, (3) more intuitive, as opposed to planned, decision-makers, (4) worried if they do not possess a financial cushion for unforeseen events, and (5) more likely to spend money spontaneously.

⁶ In practical terms, experience has been proxied by age, trade volume, or the number of trades (see for example Feng and Seasholes (2005), Chen et al. (2007), or Seru et al. (2010)), while sophistication has been approximated by portfolio size, diversification, investors' occupation, or the types of assets that investors trade (see for example Shapira and Venezia (2001), Brown et al. (2006), or Boolell-Gunesh et al. (2009)).

3.2.5 Research Questions

While it has been argued that such context-specific attitudes have a stronger relationship with subsequent behaviour (Glasman and Albarracín (2006)), and Paluri and Mehra (2016) also advocate the advantages of segmentation based on psychographic characteristics, the empirical link between the two has not yet been subject to investigation. In fact, Fünfgeld and Wang (2009) directly state that: “More research needs to be undertaken to investigate the relationships between actual behaviour with the self-stated behaviour” (pp. 124-125). In this regard, we follow their call for research by administering their questionnaire to a sample of US investors in an experimental setting. In doing so, we aim at answering the following two research questions:

Research Question 1 (RQ1): *Do investors in the US exhibit the same underlying financial attitudes and behaviour dimensions as their counterparts in the German-speaking region of Switzerland?*

Research Question 2 (RQ2): *Is there a significant relationship between the financial attitudes and behaviour dimensions and the extent to which investors exhibit a positive disposition effect?*

By answering these two questions, we hope to provide an empirical test of the dimensions proposed by Fünfgeld and Wang (2009) while also shining a more comprehensive light on potential mitigating factors of the disposition effect.

3.3 Data and Methodology

3.3.1 Experimental Design

The experimental trading setup described here is based on Frydman et al. (2014). We adapt their setup because we deem it suitable to investigate the key motivations of this paper since: (1) it is programmed such that it can be accessed remotely, (2) it consists of a simple and transparent asset market with three stocks, and (3) it is designed in a way such that the exhibition of a disposition effect cannot be explained by rational behaviour.

As part of the setup, subjects are confronted with a simplified stock market where they can trade three distinct stocks ($i = 1, 2, 3$) over 100 periods ($t = 0, 1, 2, \dots, 99$). The stocks are labelled A, B, and C, respectively. Subjects are initially endowed with \$350 in experimental currency in period $t = 0$ and can start trading in period

$t = 9$. The prior periods are merely observation periods such that subjects get accustomed to the price change mechanism in the market.

Each period consists of two distinct phases: First, one stock is randomly selected as part of the *price update phase*. In this phase, the stock's price change is determined using the mechanism explained below. Secondly, another stock is randomly selected (this could, but does not have to be, the same stock as before) as part of the *trading phase* and subjects can decide if they want to buy or sell the selected stock. During the trading phase, subjects are only asked to make a trading decision but they are not provided with any new pieces of information. The price update screen is shown for three seconds before the trading screen appears, where subjects can enter their trading decision. This was done deliberately to ensure that subjects spend a sufficient amount of time processing the new price information before deciding if they want to trade the newly selected stock. The trading screen, however, is shown as long as subjects have not entered a trading decision.⁷ Once they have done so, they move on to the next period where the process begins anew.

Decisions in the Trading Phase

At any point in time from period $t = 9$ onwards, subjects can hold up to one unit of each stock. Hence, the decision they face during the trading phase is if they want to buy the selected stock conditional on not holding it, or if they want to sell the stock conditional on holding it. This also implies that short-selling is not allowed. In period $t = 0$, all subjects have to buy one unit of each stock before they can proceed. Hence, because all stocks initially start at a price of \$100, they are left with \$50 in “available cash.” If, in the subsequent periods, subjects do not hold the required amount of cash to buy a stock, they can incur a negative cash balance. At the end of the experiment, this negative balance will be deducted from their total assets, and hence also from the variable part of their compensation (more detail on the incentive structure will follow in section 3.3.4).⁸

⁷ Note that the price update screen in Frydman et al. (2014) is shown for only two seconds and the trading screen for only three seconds. Their rationale for limiting the time subjects can spend in the two phases is different, however. First, because the fMRI scanner they use to detect brain activity can overheat after a certain period of time, subjects cannot spend an indefinite amount of time in the trading setup. Secondly, they separate the price update and trading phases in order to measure brain activity during each phase separately, which helps them investigate their hypotheses.

⁸ Note, however, that no subject ended the experiment with a negative cash balance.

Stock Price Development in the Price Update Phase

The prices for all three stocks are determined by three independent two-state Markov chains (Markov (1906)). More specifically, any stock i can, in any period t , be either in a good or a bad state (s). Formally,

$$s_{i,t} \in \{good, bad\} \quad (3.1)$$

If, during the price update phase, stock i is chosen, the probability that it switches states is equal to 0.2. This results in the following state switching probabilities:

Table 3.1: State switching probabilities

	$s_{i,t} = good$	$s_{i,t} = bad$
$s_{i,t-1} = good$	0.8	0.2
$s_{i,t-1} = bad$	0.2	0.8

Note: This table shows the state switching probabilities for stock i , chosen in period t , relative to period $t-1$. The two other stocks that are not chosen during the price update phase do not switch states.

The states of the other two stocks not chosen in period t will stay the same. Before the experiment starts, all stocks are randomly allocated to one of the two states in $t = 0$. After the new state $s_{i,t}$ has been determined, the stock's price will increase or decrease according to the following probabilities:

Table 3.2: Price change probabilities

	Price increase	Price decrease
$s_{i,t} = good$	0.55	0.45
$s_{i,t} = bad$	0.45	0.55

Note: This table shows the price change probabilities for stock i , chosen in period t . The prices of the two stocks not chosen during the price update phase do not change.

Last, the magnitude of the price change, $|\Delta p_{i,t}|$, is chosen from the following set with equal probability:

$$|\Delta p_{i,t}| \in \{\$5, \$10, \$15\} \quad (3.2)$$

In contrast to Frydman et al. (2014), however, who only provide subjects with the price change, the new price, and the purchase price (when available) during the price update phase, we continuously provide all subjects with a chart that shows all stocks' prices by period during the price update and trading phases.⁹ In order to make our results comparable across subjects, we determine the prices for all three stocks once according to the mechanism described above. Then, the same set of prices and draws (that establish the price updates and which stocks can be traded in the trading phase) are used for all subjects who participate in the experiment. Overall, this results in the price realizations illustrated in Figure 3.1.

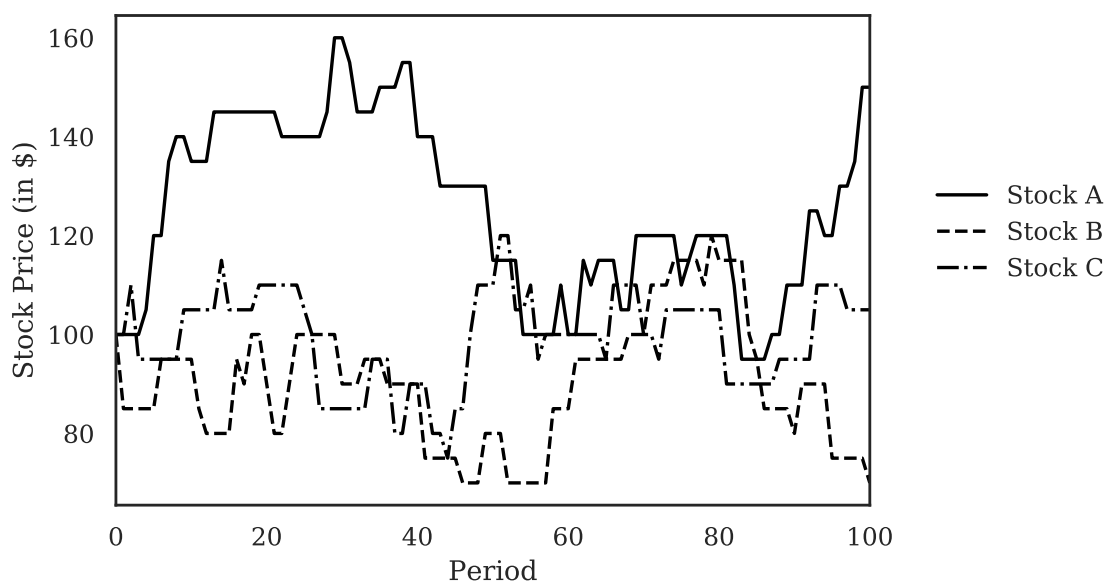


Figure 3.1: Simulated stock price development over time

Note: The graph shows the simulated price development for all three stocks. Prices are determined randomly once before the start of the data collection period according to the process described above. Consequently, all participants are shown the same price developments.

Rationale and Properties

Several important remarks should be made with regards to the design of the experimental stock market. First, subjects are only given the pieces of information provided above, excluding the future price realizations. Also, they are never told what states the stocks are in. However, because price changes are positively serially autocorrelated, they can — and should — infer the states from recent price changes.

⁹ This deviation was deemed necessary as subjects during our pretests (see section 3.4 for more information) indicated that they encountered substantial difficulties while trying to follow the price changes.

This is also the reason why they are forced to observe prices during the first few periods and cannot start trading until period $t = 9$.

Secondly, the market was designed in a way such that there is no rational explanation as to why subjects would exhibit a positive disposition effect. Risk-neutral Bayesian participants should buy (if they currently do not hold) or hold (if they do) a stock if they believe that the price is likely to increase in the subsequent period. On the other hand, they should sell (if they currently hold the stock) or not buy (if they don't) the stock, if they believe that the price is more likely to decrease. A stock's price is more probable to increase in the next period if its price has recently increased. This is because in that case the stock is more likely to be (and remain) in the good state, where the probability of a price increase is higher, making the price changes positively serially autocorrelated.

3.3.2 Experimental Procedure

Subjects who agree to participate in the experiment are first shown a welcome screen, which explains that they are about to participate in an academic experiment about "stock market decision-making." Furthermore, the compensation mechanism (discussed in section 3.3.4) is explained to them. On the next page, they can find detailed instructions on the design of the experimental stock market. These instructions are largely based on section 3.3.1 and the instructions provided in the internet appendix of Frydman et al. (2014).¹⁰ Here, we also include a screenshot of the interface they will find on the subsequent page such that they can familiarize themselves with it while reading the instructions. At the end of the instructions, subjects are told that their goal is to maximize their wealth over the 100 trading periods because this will also be reflected in the variable part of their compensation.

A screenshot of the trading interface is shown in Figure 3.2. Once subjects have entered a decision, the next period starts with a price update screen. Warnings are shown when participants try to (1) proceed to period 1 without having bought one unit of each stock, or (2) when they try to sell shares during the observation period.

In period 100, subjects are automatically redirected to a questionnaire. Here, we measure the following: participants' financial attitudes and behaviours (Füßfeld and Wang (2009)), their expertise (Jordan and Kaas (2002)), financial literacy (Lusardi and Mitchell (2014)), self-regard (Kadous et al. (2014)), perception of regret and rejoice (Rau (2015)), and personal investment relevance (Hüsser and Wirth (2014)). Furthermore, participants' age, gender, level of education, profession, stock ownership, and reason for participation are noted such that they can be controlled

¹⁰ The verbatim instructions can be found in Appendix C.1.

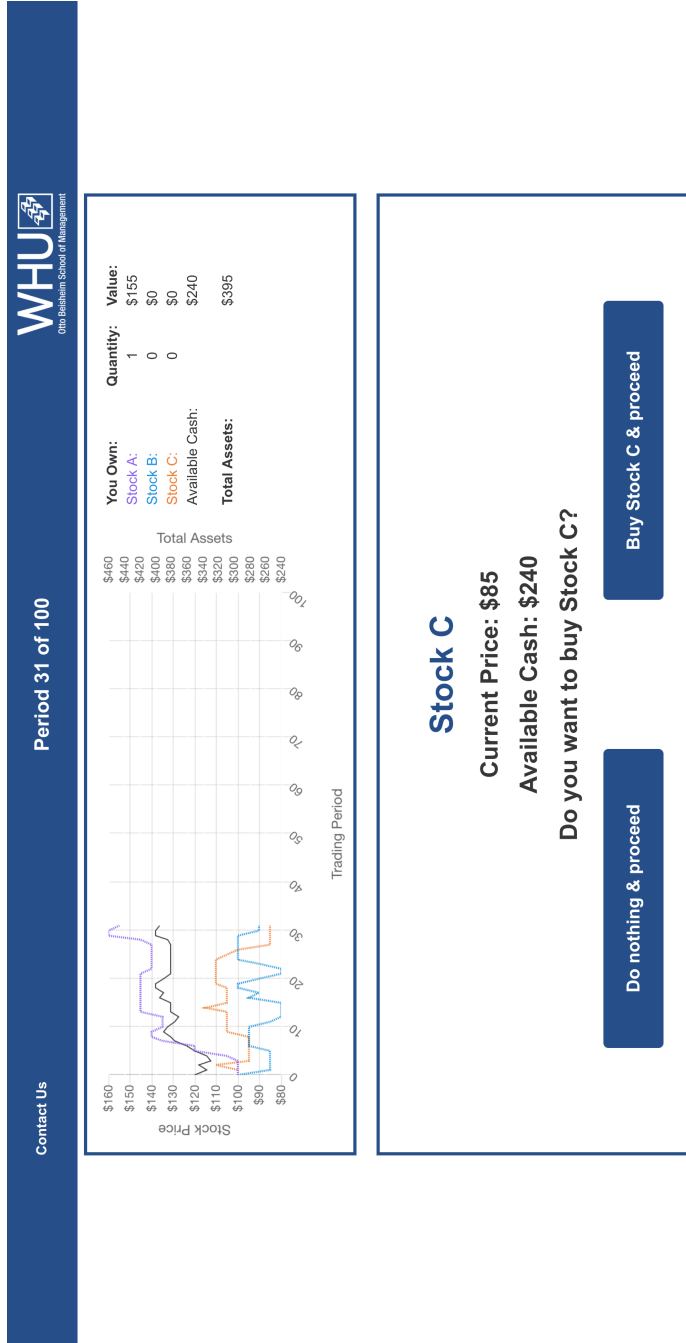


Figure 3.2: Screenshot of the experiment's trading interface

Note: The screenshot displays the stock market simulation interface that all subjects are shown. More specifically, it shows the trading screen, where the subject can choose between holding Stock B or selling Stock B because they currently own one unit of the stock, as can be seen in the top right-hand corner. Note that the price update screen looks similar. More screenshots of the trading interface can be found in Appendix C.2.

for in the subsequent analysis.¹¹ Lastly, we include a manipulation check to test whether subjects were attentive and could correctly remember an important detail of the price change mechanism. Subjects who fail said test will be excluded from the further analysis and also will not receive any form of compensation since we argue that they either did not read the instructions carefully or they were inattentive while completing the questionnaire. Either way, it is likely that their results would distort our further analysis. More detail on our motivation to include such a mechanism can be found in section 3.3.4.

3.3.3 Data Analysis

Disposition Effect

In the experimental literature on the disposition effect, two measures are commonly found. In line with Odean (1998), we define the disposition effect as the difference between the proportion of realized gains and losses. At the end of each trading period¹² we calculate the proportion of realized gains (PGR) and the proportion of realized losses (PLR) as follows:

$$PGR = \frac{Gains_{realized}}{Gains_{realized} + Gains_{paper}} \quad (3.3)$$

$$PLR = \frac{Losses_{realized}}{Losses_{realized} + Losses_{paper}} \quad (3.4)$$

To determine whether a position counts as a (realized or paper) gain or loss, the current stock price is compared to its historic purchase price.¹³ If the current price is higher (lower) than the purchase price, the position is counted as a gain (loss). A realized gain/loss is counted each time the investor decides to sell a share, while the remaining opportunities to sell shares are counted either as paper gains, paper losses, or not at all, if the current price equals the historic purchase price. The

¹¹ The complete questionnaire can be found in Appendix C.3.

¹² For the following measures of the disposition effect, we only consider periods 10 to 99. The first few periods (0 to 9) are excluded because participants cannot conduct transactions but merely observe price developments during this time.

¹³ Odean (1998) conducts the same analysis while also considering the highest purchase price, the first purchase price, and the weighted average purchase price instead of the purchase price. He does not find any substantial deviations from the primary results. Feng and Seasholes (2005), Rau (2015), and Fischbacher et al. (2017) also report that their results do not depend on the method used to calculate the reference price, i.e., that their findings are robust. In our setup, because subjects can only hold a maximum of one unit per share, we only regard the last purchase price of each stock.

disposition effect (DE) is then defined as:

$$DE = PGR - PLR \quad (3.5)$$

The disposition effect is measured at the level of the individual investor. It is argued that a disposition effect is present if there is a substantial difference between PGR and PLR , i.e., if $DE \gg 0$. In this case, subjects are more likely to realize gains than they are to realize losses, which is evidence of the disposition effect. At the two extremes, investors with $DE = 1$ solely and immediately realize gains, whereas they never realize losses. The opposite is true for investors who exhibit a disposition effect of $DE = -1$. In line with Weber and Welfens (2007) and Fischbacher et al. (2017), we assume that participants should be equally likely to realize winner and loser stocks. Hence, this implies that the individual-level disposition effect should — on average — amount to zero.¹⁴

Financial Attitudes and Behaviours

The items used to measure subjects' financial attitudes and behaviours are directly taken from Fünfgeld and Wang (2009). Participants have to state their agreement with the statements in Table 3.3 on a 5-point Likert scale with (1) “absolutely” to (5) “absolutely not” as the two extremes of the scale. In an effort to avoid order effects, the sequence in which the statements appear is randomized for each subject.

¹⁴ Alternatively, the disposition coefficient (α) has also frequently been used in the experimental literature on the disposition effect since it was introduced by Weber and Camerer (1998). It examines if subjects are more likely to sell a stock after a price increase or price decrease. However, we argue that it is not a suitable measure of the disposition effect in our trading setup since the information on price changes is clearly separated from subjects' trading decisions. More specifically, if a subject decides to sell a stock in period t , it could well be the case that the last time the stock's price changed was in period $t - x$. Therefore, it would neither be coherent to count the sale in period t as a sale after a price increase, nor as a sale after a price decrease. As a result, we focus our analysis exclusively on the disposition measure (DE), which is in line with the empirical strategy in Frydman et al. (2014).

Table 3.3: Items used to measure financial attitudes and behaviours

Number	Item
1	I get unsure by the lingo of financial experts.
2	I am anxious about financial and money affairs.
3	I tend to postpone financial decisions.
4	After making a decision, I am anxious about financial and money affairs.
5	I read the business section of the newspaper attentively.
6	I like to join conversations about financial matters.
7	I compare and calculate risks.
8	Even on large purchases, I tend to spend spontaneously.
9	I enjoy reading about the results of product comparisons.
10	I do not complain very often, even if I have reason to do so.
11	At the end of the day, I decide intuitively in financial affairs.
12	I find it hard not to have some money away for a rainy day.
13	To care for the future is essential for me.
14	I spend money when I am unhappy or frustrated.
15	Special offers can entice me into buying.
16	I enjoy spending money more than saving.
17	I feel annoyed when things don't go my way.

Note: This table shows the 17 items that are implemented in the questionnaire to determine subjects' financial attitudes and behaviours. All statements are directly taken from Fünfgeld and Wang (2009) and subjects have to state their agreement with each of them on a 5-point Likert scale with (1) "absolutely" to (5) "absolutely not" as the two extremes of the scale.

3.3.4 Participants and Compensation

The experimental setup is programmed using standard web technologies (HTML, CSS, and JavaScript), such that it can be uploaded onto a web server and consequently can be accessed remotely. The questionnaire that follows the trading task is implemented on the Unipark survey platform,¹⁵ where financial attitudes, behaviours, and several control data are collected. This implies that participants are not bound to a laboratory setting, exposing the possibility that they can be recruited via online survey platforms. All participants are recruited directly from Amazon's Mechanical Turk ("MTurk")¹⁶ service. We choose to focus our empirical investigation exclusively on participants from the United States for several reasons.

First, the research conducted by Fünfgeld and Wang (2009) exclusively directs

¹⁵ <https://www.unipark.com/>

¹⁶ <https://www.mturk.com/>

its attention on Switzerland as the geography of interest. Therefore, we deem it important to extend their analysis to additional geographies in order to examine the validity of their results and thereby further contribute to our understanding of financial attitudes and behaviours. The United States seems to be the most intuitive extension considering that it constitutes the geography with one of the world’s largest domestic stock market participation rates (e.g., Giannetti and Koskinen (2010)).

Second, the US MTurk community has been subject to several empirical investigations due to the rising interest in MTurk as an online survey platform that is increasingly used in academic research (Paolacci and Chandler (2014)). As compared to conventional university student samples, MTurk provides researchers with older and more diverse samples (see for example Behrend et al. (2011), Johnson and Borden (2012), or Jilke et al. (2016)). With regards to employment status and geographic dispersion across the US, Huff and Tingley (2015) do not find any significant differences between their MTurk sample and participants of the Cooperative Congressional Election Survey (CCES). The CCES is a nationally stratified sample and while it focuses on political aspects, it also collects demographic data. Goodman et al. (2013) show that, as compared to the general US population, MTurkers are slightly younger, are affected by the same decision-making biases, and exhibit a similar income distribution with a marginally lower mean.

Third, MTurk samples have been shown to be characterized by high internal validity and reliability. For example, Buhrmester et al. (2011) report test-retest reliabilities of $r = 0.88$ for their MTurk sample, which compare very well with other samples. Additionally, Berinsky et al. (2012) find that participants recruited via MTurk are particularly attentive during experiments. They attribute this observation to the incentive mechanism implemented on the MTurk platform, where workers have an interest to carry a high approval rating.¹⁷ Furthermore, because we have previously administered a comparable experiment via MTurk with positive experiences, we do not see any reason to abstain from MTurk.

Still, Smith et al. (2015) recommend implementing a “quality check” to identify responses that suffer in terms of answer quality or response fatigue. Hauser and Schwarz (2016) conclude that MTurk workers are more attentive to instructions and show larger effects to subtle text manipulations, but still note the importance of such quality checks. Hence, we concur and implement an instruction manipulation check (IMC) as part of the questionnaire where we check if respondents understand the price change mechanism. In line with Chandler et al. (2014), we exclude subjects who fail the IMC from receiving any form of compensation, as mentioned before.

¹⁷ For a more detailed discussion of this mechanism, see Wierzbitzki and Seidens (2018).

Following Camerer and Hogarth (1999), who note that financial incentives are most effective in judgement and decision-making tasks, participants' compensation depends directly on their performance in the stock market simulation task. By linking these two aspects, we hope to elicit more truthful answers and increase participants' effort. Consequently, all participants receive a flat payoff of \$2.00 in exchange for their participation. Additionally, they earn 1% of their total assets at the end of the experiment.¹⁸ This implies that if they can sustain the \$350 in experimental currency they are initially endowed with, they receive an additional \$3.50.¹⁹ Hence, their total compensation would amount to \$5.50.²⁰

3.4 Results

In order to ensure the appropriateness and the frictionless functioning of the technical setup, several pretests were carried out before the actual experiment was conducted. In a first step, fellow on-premises researchers were invited to test the experimental stock market. They were not given any additional information other than what was provided in the instructions. As a direct result of their feedback, the trading interface was altered to show the stock price and total asset development in one comprehensive graph, as all subjects deemed it very difficult to track the stocks' recent price changes. In this regard, our setup differs from Frydman et al. (2014). However, we deem this deviation necessary as we fear that subjects otherwise would not understand the price change mechanism and hence our results would occur purely due to chance. Additionally, we used this pretest to establish a realistic performance level which we could expect from MTurk workers and slightly altered our compensation mechanism to the one described above in order to ensure a fair and competitive compensation. Subsequently, the experimental setup was implemented in MTurk and tested on the platform to ensure that any technical glitches could be eliminated in advance.

Once the setup had been finalized, data were collected between November 20 and

¹⁸ This compensation mechanism (consisting of a fixed flat fee and a variable performance-based component) is comparable to those employed by, for example, Döbrich et al. (2014), Kadous et al. (2014), or Goulart et al. (2015).

¹⁹ At the same time, this implies that participants cannot earn less than \$2.00 and that negative performance is not penalized.

²⁰ While the total compensation might seem low at first glance (Corgnet et al. (2018) pay their subjects \$48.00 on average for participation in a 2.5 hour experiment), Stritch et al. (2017) report that the average hourly rate on MTurk is as low as \$2.00. Considering that the experiment is, ex-ante, expected to be considerably shorter than one hour, our compensation level can be regarded as particularly attractive for MTurk workers. This makes us confident that they will exert a significant level of effort during the experiment.

December 07, 2018, in several batches.²¹ In preparation of the analysis, the data on subjects' trading activity were combined with the answers they provided to the subsequent questionnaire. Next, we applied the following data trimming and cleansing procedures: First, we excluded all subjects who failed the IMC, as mentioned in section 3.3.4. Those subjects also did not receive any compensation and their "HIT" (human intelligence task, the name for assignments on MTurk) was cleared to be completed by another worker. Next, we noticed that a few participants continuously gave the same answers to the financial attitudes and behaviour questions. By design of the questionnaire, this observation was highly unlikely and indicates that subjects did not read the questions attentively. Consequently, we excluded them from our dataset. Lastly, we excluded subjects who claimed to be younger than 18 years old and those who conducted less than three trades over the course of the experiment (i.e., without counting the three initial buys). Overall, this resulted in 190 subjects in our final dataset.

3.4.1 Sample Statistics

Before discussing the results of the disposition effect and factor analyses, we first examine our basic sample composition and several descriptive statistics. Note that, as mentioned earlier, there is inconclusive evidence with regards to whether males or females are more inclined to exhibit the disposition effect. Therefore, we decided to report all statistics for males and females separately to add to the literature investigating gender differences in trading.

As Table 3.4 shows, our sample consists of 69 female and 121 male subjects. While this constitutes a significant imbalance in our sample, it should be stressed that it is purely due to chance. On a related note, it is likely that our sample suffers from self-selection issues. The experiment was advertised as a "stock market simulation"²² task on the MTurk platform. Since MTurk workers are free to decide which HITs to complete, it seems likely that our task was particularly attractive to those workers who were already somewhat experienced in stock markets and trading, or at least to those who believe they are. While this issue should continually be kept in mind over the course of the further analysis, it should also be noted that it is not unique to our sample. Most experimental research will suffer from self-selection issues, simply because subjects cannot be forced to participate.

²¹ These batches were spread over several weekdays and times of the day in order to ensure that a balanced sample of MTurk workers could be reached in an effort to maximize external validity.

²² The verbatim description was: "Participate in a Stock Market Simulation task and receive a bonus based on your performance!".

With regards to their age, it is notable that subjects in our sample are significantly older than what the average age in a student sample would have been. This reinforces our decision to use MTurk for participant acquisition ex-post. With regards to their education, it is worth pointing out that most participant seem to be very well educated.²³ Still, the sample consists of participants with a variety of vocational and educational backgrounds, thereby making our results more generalizable.

Table 3.4: Demographic characteristics

	Gender		Overall
	Female	Male	
Participants	69	121	190
Average age	37.8 (11.4)	34.4 (8.7)	35.5 (9.9)
Profession			
Professional/technical	16	39	55
Managerial/administrative	13	16	29
White collar/clerical	17	28	45
Blue collar/craftsman	2	11	13
Services/sales	12	15	27
Unemployed	9	12	21
Education			
Secondary school	2	1	3
Apprenticeship	0	0	0
High school diploma	25	42	67
University degree	42	78	120

Note: This table reports subjects' demographic characteristics, where subjects are grouped by their gender. In addition to their average age, it also shows their profession and level of education. Standard deviations are reported in parentheses.

With regards to investment-related characteristics, Table 3.5 provides some additional insights into our sample's composition. In order to measure subjects' financial literacy, we used the widely adopted three-item measure from Lusardi and Mitchell

²³ It is not surprising that no participant indicated an apprenticeship as their highest level of education, as apprenticeships are not a common form of education in the United States.

(2014).²⁴ A subject is regarded as financially literate if they answer all three questions correctly. Using their measure, 65.8% of our sample can be regarded as literate, where males are significantly more literate than females. Compared to previous research, this is a particularly high percentage. Mitchell and Lusardi (2011) administer the same set of questions to a representative sample in the United States. They observe that merely 30.2% of their respondents are able to answer all three questions correctly.²⁵ Other research focused on MTurk workers (e.g., Wierzbitzki and Seidens (2018)) does, however, find similarly high financial literacy rates. Therefore, we conclude that our sample consists of particularly financially literate participants.

Table 3.5: Investor characteristics

Gender	Literacy	Relevance	Avg. expertise	Leisure	Stock ownership
Female	56.5%	56.5%	2.34 (0.77)	20.3%	30.4%
Male	71.1%	71.9%	2.52 (0.82)	25.6%	43.0%
Overall	65.8%	66.3%	2.46 (0.80)	23.7%	38.4%

Note: This table reports investment-related characteristics of all participants grouped by gender. Participants were classified as financially literate if they answered all three financial literacy questions correctly. As for investment relevance and the leisure vs. money motivation, we looked at the two extremes of the respective scales and classified investors according to a dummy variable of 1 if they were mostly motivated by leisure and if they claimed that investments are personally relevant for them. Average expertise measures the average of the four expertise items. Stock ownership indicates if subjects were in possession of stocks or stock funds at the time of the experiment. Standard deviations are reported in parentheses.

When asked for their reason for participation in the experiment, 23.7% stated that they were mostly motivated by the fun/leisure aspect of the task. On the other hand, this implies that around three-quarters of our sample participated because of financial motives. This makes us confident that the compensation was set at an attractive level and that it elicited truthful and realistic behaviours from the majority of participants.

²⁴ They argue that their questions on (1) numeracy/interest rates, (2) inflation, and (3) risk diversification capture the most important fundamental financial concepts and hence suffice to establish a holistic measure of financial literacy.

²⁵ From an international perspective, this observation still persists. Using the same or a similar set of questions, Bucher-Koenen and Lusardi (2011) find the highest financial literacy rate of 53.2% in Germany, while the Beckmann (2013) reports the lowest rate (3.8%) in Romania.

Table 3.6: Trading statistics

Gender	# purchases	# sales	# total trades	Avg. final wealth
Female	9.62 (6.13)	8.07 (6.18)	17.70 (12.27)	\$396.52 (\$43.01)
Male	8.74 (5.56)	7.32 (5.55)	16.06 (11.06)	\$394.42 (\$45.77)
Overall	9.06 (5.77)	7.59 (5.78)	16.65 (11.51)	\$395.18 (\$44.68)

Note: The table summarizes participants' investment behaviour. It reports the number of share purchases, sales, and the resulting number of total trades. Also, it shows the average wealth at the end of the experiment. Standard deviations are reported in parentheses.

Lastly, we also asked if subjects currently owned stocks or stock funds. On average, merely 38.4% of our subjects indicated that they did so. While this figure might seem low at first glance, the Board of Governors of the Federal Reserve System (2017) reports that, in 2016, merely 13.9% of households held stocks and merely 10.0% were invested in pooled investment funds. In comparison, our sample seems to consist of relatively experienced investors.

On average, subjects took 15 minutes and 12 seconds to complete the trading part of the experiment (i.e., not including the time taken to read instructions and answer the questionnaire). During this time, they purchased 9.06 and sold 7.59 stocks, resulting in an average of 16.65 trades per subject. Table 3.6 reports these statistics by gender, indicating that females traded slightly more than males. We see the total trades per subject and the substantial time spent in the trading part of the experiment as considerable evidence that subjects took the task they were given — and thereby the experiment — seriously.

At the end of the experiment, subjects had accumulated an average of \$395.18 in total assets. The difference between males and females is negligible and not statistically significant. Considering that all subjects were initially endowed with \$350, the average performance was considerably positive. However, as Figure 3.3 shows, some subjects also incurred significant losses. Hence, our sample includes both, traders with positive and negative performance.

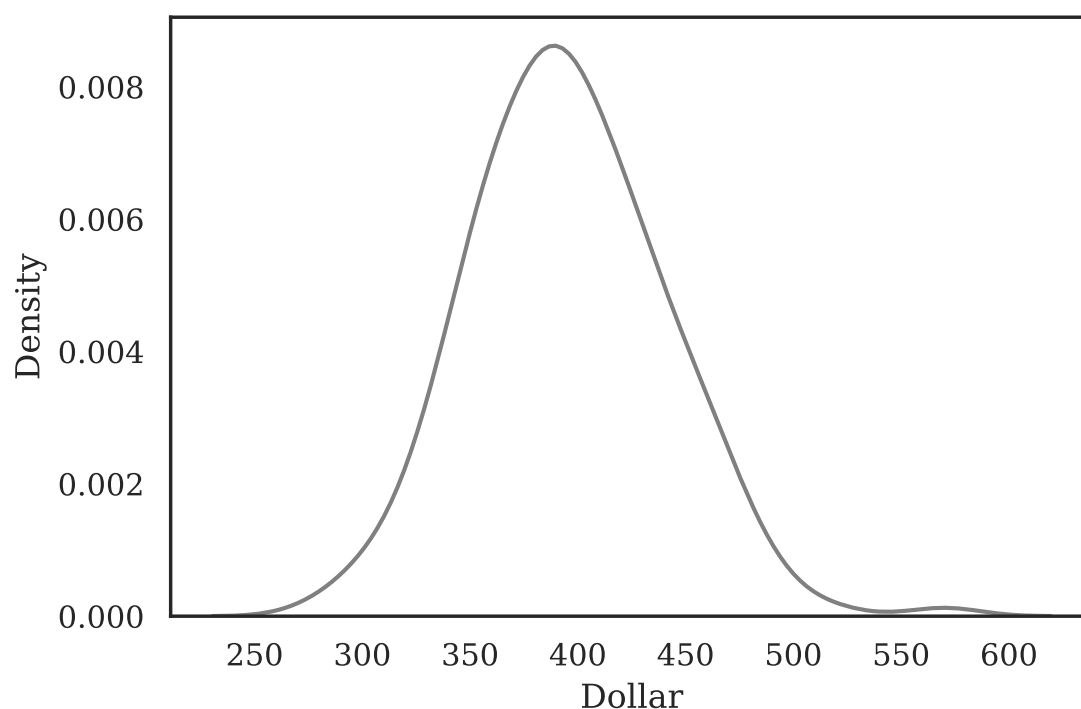


Figure 3.3: Distribution of total assets at the end of the experiment

Note: This figure illustrates subjects' distribution of total assets at the end of the experiment. On average, subjects had accumulated \$395.18 in total assets before proceeding to the questionnaire.

3.4.2 Disposition Effect

Subsequent to presenting some general information on our sample after applying several data trimming and cleansing procedures, we are confident that our sample provides a good indication of the average investor in the United States and therefore carries considerable external validity. Therefore, this section briefly focuses on individual-level disposition effects using the measures presented in section 3.3.3. To do so, Table 3.7 shows the disposition measures (PGR , PLR , and DE) in general and for males and females separately.

Overall, we find a positive average disposition effect of 0.11. A two-tailed t-test is applied in order to determine the statistical significance of this result. Here, we find that the disposition effect is significantly different from zero at the 1% level. In relative terms, our DE is slightly lower than what previous research reports: For example, Fischbacher et al. (2017) find a DE of 0.29, Weber and Welfens (2007) of 0.24, and Döbrich et al. (2014) of 0.14. On the other hand, Goulart et al. (2015) report a DE of 0.11 and Wierzbitzki and Seidens (2018) of 0.09. Hence, while our result seems to be at the lower end of what previous research has found, it is not substantially smaller and therefore our results should not be worrisome. Also,

considering that the disposition effect is expected to decrease with increasing levels of investor sophistication and because our sample is particularly financially literate (which can be regarded as a form of sophistication), and also consists of particularly experienced investors (seeing that the stock ownership rate is comparatively high) one would expect our disposition measure to be relatively lower.

Table 3.7: Disposition measures (*PGR*, *PLR*, and *DE*)

Gender	DE	PGR	PLR	Positive DE	Negative DE
Female	0.09*** (3.75)	0.20*** (10.17)	0.11*** (5.96)	69.6%	29.0%
Male	0.12*** (7.75)	0.21*** (14.40)	0.09*** (7.93)	74.4%	24.0%
Overall	0.11*** (8.29)	0.21*** (17.65)	0.10*** (9.83)	72.6%	25.8%

Note: This table summarizes subjects' *PGR*, *PLR*, and *DE*, as proposed by Odean (1998). The parentheses report the *t* – statistics for the null hypothesis that the measures are equal to zero. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.10$. Also, the percentage of subjects with positive or negative disposition measures are reported. Values might not necessarily add up to 100% due to rounding and since some subjects exhibited a *DE* measure of exactly zero.

Inspecting this result more closely, it can be seen that subjects realized a significant proportion of their available paper gains (21%), while they only realized 10% of paper losses. Both measures are significantly different from zero ($p < 0.01$). In terms of gender differences, we find that females and males alike display a positive disposition measure (both $p < 0.01$). However, the effect seems to be more pronounced for males (0.12) as compared to females (0.09). When investigating this difference in more detail, it can be seen that females realized slightly less gains while realizing losses more readily. Hence, there seem to be gender differences in both, the gains and losses domains. Additionally, we also find substantial heterogeneity with regards to the exhibition of a disposition effect. Overall, while the average disposition effect is positive, 25.8% of our participants displayed a negative disposition effect. This heterogeneity was discussed earlier and is subject to further examination in this paper.

3.4.3 Financial Attitudes and Behaviour

As a next step, we first consider subjects' self-stated financial attitudes and behaviours independently of the disposition effect or other measurable trading char-

acteristics. Considering that any factor analysis or principal component analysis is always subjective to some degree, we present the steps and results of the following analysis in greater detail. Thereby, the informed reader can follow the authors' rationale more attentively. We do this in order to make our analysis more transparent.

First and foremost, we deviate from Fünfgeld and Wang (2009) by conducting a factor analysis instead of a principal component analysis, as suggested by Bollen and Lennox (1991).²⁶ Following Backhaus et al. (2016), our first step consists of investigating our data for its adequacy to be used as part of a factor analysis. More specifically, we conduct Bartlett's test of sphericity (Bartlett (1937)). This test is used to assess whether the our correlation matrix is equal to an identity matrix. This would indicate that our variables are completely unrelated and hence unsuitable for consideration in a factor analysis or other dimensionality reduction techniques. In our case, Bartlett's test of sphericity was highly significant ($\chi^2 = 939.6$, $p < 0.01$), indicating that our dataset possesses meaningful correlations.

As an additional measure, we also calculate the Kaiser-Meyer-Olkin (KMO) criterion (see Kaiser and Rice (1974)), which also seeks to assess whether a particular dataset is suited for factor analysis. KMO values exist between 0 and 1. Generally, values > 0.5 are seen as acceptable, while some researchers consider values > 0.7 as appropriate. In the present case, the KMO value amounts to 0.714, which is often referred to as "middling" (see Backhaus et al. (2016)). In either case, because our KMO value exceeds both thresholds, the KMO criterion states that it is acceptable to proceed with the factor analysis based on our dataset.

After having ensured that our data is suitable for factor analysis, we first standardize all variables to have a standard deviation of 1 and a mean of 0. This step was undertaken because it facilitates several of the following calculations and interpretations. Next, we run the factor analysis with varimax orthogonal rotation (in line with Fünfgeld and Wang (2009)).

In order to decide which number of factors should be kept for the consecutive analysis, we again draw on two commonly used criteria. First, Kaiser's criterion (Kaiser (1961)) states that a factor should be kept in the analysis if it exhibits an eigenvalue > 1 . The rationale here is that an eigenvalue > 1 indicates that the respective factor accounts for more variance than one of the initial variables. Hence, it is deemed worthwhile to include said factor. In our case, there are four factors for which this is the case, as can be seen in Figure 3.4. Another commonly used criterion (see for example Jolliffe (2002) or Peres-Neto et al. (2005)) is a visual inspection

²⁶ We would also like to thank Walter Herzog for this suggestion and for pointing us towards the relevant literature.

of a so-called scree plot, which is also reported in Figure 3.4. Here, the factors are sorted in order of declining eigenvalues. If one observes a significant kink in the resulting line plot, the rule is to include the number of factors before and including the kink. Again, this leads us to include four factors in the following analysis. The resulting factors account for 43.4% of the total variance in our financial attitudes and behaviours sample. This compares to 53.3% of the total variance in Fünfgeld and Wang (2009).

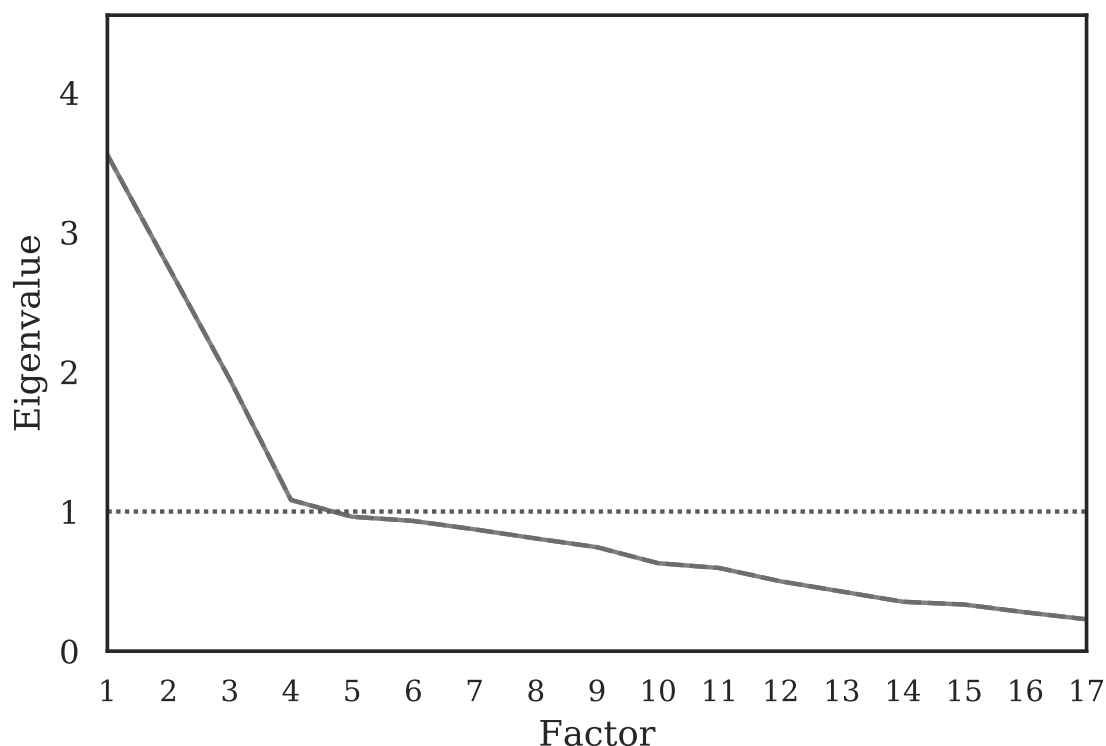


Figure 3.4: Scree plot

Note: This scree plot shows the eigenvalues for each factor after varimax orthogonal rotation, where the factors were sorted by descending eigenvalues. The dotted horizontal line indicates an eigenvalue of 1 and was included to illustrate the recommended number of factors that result when applying Kaiser’s criterion.

Table 3.8 shows the factor loadings for all 17 items on each of the four factors in a pattern matrix. As a next step, we eliminate all items with rotated factor loadings < 0.5 , as is done in comparable research (see for example Floyd and Widaman (1995) or Fünfgeld and Wang (2009)).²⁷ This procedure results in 9 residual items. These items were then assigned to the factor on which the absolute value of the corresponding factor loading was at a maximum.

²⁷ Note that the exact threshold differs from one research methodology to another. By setting our cutoff at 0.5, we employ the strictest commonly used threshold.

Table 3.8: Items and corresponding factor loadings

Number	Item	Factor 1	Factor 2	Factor 3	Factor 4
1	I get unsure by the lingo of financial experts.	-0.0794	0.3901	-0.2848	0.1873
2	I am anxious about financial and money affairs.	-0.0509	0.6976	-0.1414	0.1131
3	I tend to postpone financial decisions.	-0.1294	0.3850	-0.0495	0.2968
4	After making a decision, I am anxious about financial and money affairs.	-0.0606	0.9533	0.1002	-0.0440
5	I read the business section of the newspaper attentively.	-0.0228	-0.1380	0.6306	0.1074
6	I like to join conversations about financial matters.	0.2590	-0.1916	0.7772	0.1510
7	I compare and calculate risks.	0.7157	-0.0220	-0.0169	-0.2263
8	Even on large purchases, I tend to spend spontaneously.	-0.4685	0.0685	0.3340	0.6012
9	I enjoy reading about the results of product comparisons.	0.4890	0.0559	0.2159	0.0487
10	I do not complain very often, even if I have reason to do so.	0.2984	-0.1913	0.1431	-0.1068
11	At the end of the day, I decide intuitively in financial affairs.	-0.2330	0.0554	0.1319	0.3347
12	I find it hard not to have some money away for a rainy day.	0.1672	0.2190	-0.0977	-0.0815
13	To care for the future is essential for me.	0.6619	0.1230	-0.0227	-0.3514
14	I spend money when I am unhappy or frustrated.	-0.3525	0.2361	0.0734	0.6136
15	Special offers can entice me into buying.	0.2769	0.3431	0.0552	0.3431
16	I enjoy spending money more than saving.	-0.0511	0.0060	0.0036	0.7032
17	I feel annoyed when things don't go my way.	0.1093	0.4883	-0.2084	0.0624

Note: This table reports all 17 items which subjects were shown in the questionnaire. Additionally, it shows the corresponding factor loadings for each item on all four previously identified factors. Items with rotated factor loadings < 0.5 were stricken through and excluded from the further analysis. Bold figures indicate the maximum absolute factor loading for all remaining items.

Table 3.9 summarizes the results of this analysis. It shows which items loaded most strongly on which of the four identified factors. Also, it reports each factor's eigenvalue and names all extracted factors. Again, because this naming procedure is somewhat subjective, we provided several additional researchers with the items and asked them to name the common factor. After analysing their results, we came up with the factor names "financial planning," "anxiety," "interest in financial issues," and "impulsive financial decision-making." All researchers agreed that these names sufficiently capture the nature of each factor. As a last step, one would normally calculate Cronbach's alpha (Cronbach (1951)) in order to assess the internal consistency of the factors. However, because all factors except for the fourth consist of less than three items, and Cronbach's alpha cannot be calculated in this case, we refrain from using it altogether.

Table 3.9: Factors and corresponding items

Factor & Corresponding Items	Eigenvalue	Factor loading
<i>Factor 1: Financial planning</i>	3.5554	
7. I compare and calculate risks.		0.7157
13. To care for the future is essential for me.		0.6619
<i>Factor 2: Anxiety</i>	2.7502	
2. I am anxious about financial and money affairs.		0.6976
4. After making a decision, I am anxious about financial and money affairs.		0.9533
<i>Factor 3: Interest in financial issues</i>	1.9476	
5. I read the business section of the newspaper attentively.		0.6306
6. I like to join conversations about financial matters.		0.7772
<i>Factor 4: Impulsive financial decision-making</i>	1.0827	
8. Even on large purchases, I tend to spend spontaneously.		0.6012
14. I spend money when I am unhappy or frustrated.		0.6136
16. I enjoy spending money more than saving.		0.7032

Note: This table reports the four identified factors sorted by descending eigenvalues. Furthermore, it shows the rotated factor loadings for all items on their corresponding factor.

The resulting four factors shall now be looked at in some more detail. Here, we also want to explicitly mention the similarities and differences between the factors we identified in the United States and those reported by Fünfgeld and Wang (2009).

Thereby, we hope to provide input to answer the first research question.

1. **Financial planning:** The first factor extracted from the above analysis deals with people’s attitudes towards financial planning. People who score high on this dimension are more likely to be long-term focussed and future-oriented. They are careful before taking risks and agree that providing and explicitly planning for their future is important.
2. **Anxiety:** Fünfgeld and Wang (2009) also identify an anxiety factor. While the items that constitute our and their anxiety factors overlap, they find that two additional factors substantially load on their factor. However, because of the significant intersection, the two constructs are similar. A person who scores high on this dimension can hence be characterized as someone who is unsure and worried about monetary affairs. The anxiety factor is also manifested in the fact that those people are worried about their decision-making in hindsight.
3. **Interest in financial issues:** This factor is exactly identical with the one identified by Fünfgeld and Wang (2009). Hence, we borrow from their characterization and assert that a person who scores high on this dimension is interested in financial matters and consequently more exposed to financial information.
4. **Impulsive financial decision-making:** While there is some overlap with the “free-spending” factor identified by Fünfgeld and Wang (2009), this factor goes a step further and considers subjects’ financial decision-making in general. People who score high on this factor decide spontaneously and intuitively while focusing more on the short-term, which is manifested by the fact that they prefer spending money over saving. In this regard, the factor is also similar to the “intuitive decisions” factor extracted by Fünfgeld and Wang (2009).

While our analysis reveals that the financial attitudes and behaviours of US investors can be captured by merely four factors, the above descriptions clearly show that there seems to be a significant overlap between the extracted factors in the United States and the German-speaking region of Switzerland, which was subject to prior investigation by Fünfgeld and Wang (2009). More specifically, “anxiety” and “interest in financial issues” can be seen as two dimensions that characterize people’s financial attitudes and behaviours in both geographies. The items that constitute these two factors, while not exactly the same, are also highly similar. As for the other two dimensions — “financial planning” and “impulsive financial decision-making” — while they do not directly correspond to the remaining three

dimensions in Switzerland, they are somewhat related and capture similar underlying concepts in fewer factors.

3.4.4 Financial Attitudes, Behaviours, and the Disposition Effect

Finally, we combine the two previous sections and thereby set out to investigate if there is a significant relationship between the above-identified financial attitudes and behaviours in our US sample and the actual behaviour — particularly in relation to the disposition effect — of participants in our experiment. In order to answer this question, we first calculate individual factor scores by taking the average score of the corresponding items for each factor.²⁸ Because all financial attitudes and behaviour questions were answered on a 5-point Likert scale, the corresponding factor scores are also bound between 1 (low factor score) and 5 (high factor score). Next, we classify all individuals into one of four equally spaced buckets for each factor separately and report the mean *DE*, *PGR*, and *PLR* for each bucket separately.²⁹ The results of this exercise are reported separately for each factor from Table 3.10 onwards.

Table 3.10 shows that subjects who score low on the “financial planning” factor exhibit a disposition measure of 0.1604 on average. On the contrary, subjects with high scores in this dimension exhibit a mean disposition measure of only 0.0977. Both figures are significantly different from zero ($p < 0.01$ and $p < 0.05$, respectively). Looking at these two extremes and reconsidering our description of this factor from section 3.4.4, we can postulate that people who are more focussed on the long-term implications of their actions, and hence more future-oriented, are less prone to the disposition effect (even though it has to be noted that this decrease is not strictly monotonic). This observation can also be reconciled with previous research. For example, Wierzbitzki and Seidens (2018) find that providing investors with specific investment goals in an experimental setting (and thereby making them focus more on the long-term implications of their decisions) significantly reduces their propensity to exhibit the disposition effect. In fact, the average disposition effect for those subjects even reverses. The difference in the disposition measure between the two extremes stems from the fact that people who score high on the

²⁸ More explicitly, in order to calculate an individual’s factor score for the “financial planning” dimension, we take their answers to items 7 and 13 and average them to form one factor score which will be used in the further analysis.

²⁹ Note that the number of buckets chosen here is somewhat arbitrary. One could classify investors more granularly, however, this would result in buckets with only few observations, especially at the two extremes of the scale. In order to avoid drawing conclusions from random effects, we are confident that four buckets account for the optimum classification mechanism in our case.

“financial planning” factor seem to realize paper gains less quickly, while being more inclined to realized paper losses earlier.

Table 3.10: Financial planning and the disposition effect

	DE	PGR	PLR
$1 \leq \text{factor score} < 2$	0.1604*** (4.97)	0.2535*** (8.70)	0.0931*** (5.02)
$2 \leq \text{factor score} < 3$	0.1080*** (5.89)	0.1783*** (11.25)	0.0703*** (5.91)
$3 \leq \text{factor score} < 4$	0.0740** (2.37)	0.2129*** (8.83)	0.1389*** (4.52)
$4 \leq \text{factor score} \leq 5$	0.0977** (2.70)	0.2145*** (6.66)	0.1168*** (4.98)

Note: This table reports subjects’ mean *DE*, *PGR*, and *PLR* after placing them in four equally spaced buckets that classify them according to their score on the “financial planning” factor. The parentheses report the *t* – statistics for the null hypothesis that the measures are equal to zero. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.10$.

In order to test these claims with regards to their statistical validity, we conduct Mann-Whitney U-tests (Mann and Whitney (1947)) for mean *DE*, *PGR*, and *PLR* values in the high and low buckets. Table 3.14 reports the results of these tests for all four factors separately. As can be seen there, the mean disposition measure in the high and low buckets are, in fact, significantly different from each other ($U = 3, 578.5$, $p = 0.0900$). However, contrary to our earlier postulation, subjects’ behaviour did not change significantly in the gains domain, regardless of whether they were more long-term oriented or not ($U = 3, 770.0$, $p = 0.2327$). However, the difference in disposition measures results from the fact that future-oriented investors realized losses more readily ($U = 3, 277.5$, $p = 0.0164$).

With regards to the second extracted factor, “anxiety,” it seems that more anxious participants exhibited a more pronounced disposition effect (with a mean *DE* of 0.1240; $p < 0.01$) than those who are less anxious (with a mean *DE* of 0.0691; $p < 0.10$). From a normative perspective, this would imply that investors who are unsure and worried about financial matters (also in hindsight after already having made the decision), are more inclined to realize gains than losses. However, testing this claim for its statistical significance, Table 3.14 reports that the difference in disposition measures between more and less anxious people is not statistically significant ($U = 4, 103.0$, $p = 0.1644$). Consequently, the analysis also reveals that

Table 3.11: Anxiety and the disposition effect

	DE	PGR	PLR
1 \leq factor score < 2	0.0691* (1.80)	0.1841*** (6.50)	0.1150*** (5.00)
2 \leq factor score < 3	0.1112*** (6.16)	0.1939*** (12.05)	0.0826*** (5.09)
3 \leq factor score < 4	0.1378*** (5.19)	0.2319*** (8.16)	0.0952*** (4.34)
4 \leq factor score \leq 5	0.1240*** (3.64)	0.2275*** (7.96)	0.1035*** (5.52)

Note: This table reports subjects' mean *DE*, *PGR*, and *PLR* after placing them in four equally spaced buckets that classify them according to their score on the "anxiety" factor. The parentheses report the *t* – statistics for the null hypothesis that the measures are equal to zero. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.10$.

Table 3.12: Interest in financial matters and the disposition effect

	DE	PGR	PLR
1 \leq factor score < 2	0.1087 (1.36)	0.2040*** (3.25)	0.0953** (2.53)
2 \leq factor score < 3	0.1323*** (3.59)	0.2556*** (9.18)	0.1233*** (4.19)
3 \leq factor score < 4	0.1121*** (5.04)	0.2043*** (10.19)	0.0922*** (6.13)
4 \leq factor score \leq 5	0.1040*** (5.57)	0.1901*** (10.95)	0.0861*** (6.19)

Note: This table reports subjects' mean *DE*, *PGR*, and *PLR* after placing them in four equally spaced buckets that classify them according to their score on the "interest in financial matters" factor. The parentheses report the *t* – statistics for the null hypothesis that the measures are equal to zero. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.10$.

there is no significant difference with regards to investors' gain and loss realization ($U = 4,033.5$, $p = 0.1228$ and $U = 4,178.0$, $p = 0.2150$, respectively).

Furthermore, an individual's propensity to be interested in financial matters does not seem to impact their exhibition of a disposition effect, as Table 3.12 depicts. People who are less interested in financial matters exhibit a mean disposition measure of 0.1087 ($p > 0.10$), while the disposition measure for those who are more interested was on average 0.1040 ($p < 0.01$). Similarly, no economically meaningful differences with regards to their *PGRs* (0.2040 versus 0.1901, both with $p < 0.01$) or *PLRs* (0.0953 versus 0.0861, with $p < 0.05$ and $p < 0.01$ respectively) can be observed. Conducting U-tests additionally reveals that the resulting difference in *DE* is not significant ($U = 3,136.5$, $p = 0.2053$).

Upon closer inspection, one can think about reasons why this factor does not seem to impact the disposition effect in either direction. As mentioned earlier, the discussed factor merely measures an individual's *interest* in financial matters. More specifically, it does not measure any objective characteristic, such as their actual knowledge of financial issues. Hence, while previous literature has shown that financial sophistication is accompanied by a decrease in the disposition effect, merely being interested in financial matters does not seem to have the same effect.

Table 3.13: Impulsive financial decision-making and the disposition effect

	DE	PGR	PLR
$1 \leq \text{factor score} < 2$	0.0636 (0.93)	0.2465*** (4.93)	0.1829*** (3.57)
$2 \leq \text{factor score} < 3$	0.0596* (2.01)	0.1686*** (8.38)	0.1090*** (4.36)
$3 \leq \text{factor score} < 4$	0.1467*** (6.60)	0.2288*** (10.75)	0.0821*** (5.26)
$4 \leq \text{factor score} \leq 5$	0.1219*** (6.00)	0.2049*** (10.51)	0.0829*** (6.48)

Note: This table reports subjects' mean *DE*, *PGR*, and *PLR* after placing them in four equally spaced buckets that classify them according to their score on the "impulsive financial decision-making" factor. The parentheses report the t -statistics for the null hypothesis that the measures are equal to zero. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.10$.

Lastly, we consider the fourth extracted factor, "impulsive financial decision-making," and its relation to the disposition effect. As Table 3.13 shows, more impulsive financial decision-makers seem to exhibit higher disposition measures (with

a mean DE of 0.1219; $p < 0.01$), than those who are less impulsive and hence more deliberate in their financial decision-making (with a mean DE of 0.0636; $p > 0.10$). When investigating the composition of the disposition measure, it can be seen that more impulsive subjects seem to have realized paper gains less readily (with a mean PGR of 0.2049 versus 0.2465, both with $p < 0.01$). However, the more substantial effect stems from their behaviour in the loss domain. Here, it seems that more impulsive decision-makers barely realize any losses (mean PLR of 0.0829, $p < 0.01$). Those who plan their financial decisions deliberately, though, realize a substantial proportion of their losses (mean PLR of 0.1829, $p < 0.01$), which, overall, leads them to exhibit a substantially smaller disposition measure.

Table 3.14: Mann-Whitney U-tests

		DE	PGR	PLR
<i>Factor 1</i>	Financial planning	3,578.5 (0.0900)	3,770.0 (0.2327)	3,277.5 (0.0164)
<i>Factor 2</i>	Anxiety	4,103.0 (0.1644)	4,033.5 (0.1228)	4,178.0 (0.2150)
<i>Factor 3</i>	Interest in financial matters	3,136.5 (0.2053)	2,845.5 (0.0440)	3,332.0 (0.4080)
<i>Factor 4</i>	Impulsive financial decision-making	2,988.5 (0.0229)	3,411.5 (0.2235)	3,292.5 (0.1304)

Note: This table summarizes the results of Mann-Whitney U-tests for the difference in mean DE , PGR , and PLR values between the high and low buckets for each factor separately. The top values represent the respective U - statistics and the p - values are reported in parentheses.

It thus seems that more impulsive financial decision-makers — who act spontaneously and intuitively with a short-term consumption preference — are more prone to the disposition effect. This difference is also statistically significant ($U = 2,988.5$, $p = 0.0229$). This observation could be explained by the postulation that more deliberate decision-makers are more inclined to consider the long-term implications of their actions. Hence, they realize that, in the long-term, it will be beneficial for them to hold on to gains while realizing losses. Still, it is particularly interesting to see that the Mann-Whitney U-tests reported in Table 3.14 suggest that these people will have to change their behaviour in the gain and loss domain simultaneously. This is because taken separately, the gain and loss realization behaviour of impulsive and deliberate decision-makers was not significantly different from each other ($U = 3,411.5$, $p = 0.2235$ and $U = 3,292.5$, $p = 0.1304$, respectively).

3.5 Conclusion

3.5.1 Summary and Implications

The aim of this research paper was twofold: First, we set out to investigate if US investors exhibit the same underlying financial attitudes and behaviour dimensions as those identified by Fünfgeld and Wang (2009) in the German-speaking region of Switzerland. Additionally, we wanted to test whether these dimensions exhibit a significant relationship with the disposition effect. Thereby, we implicitly tested whether the self-stated financial attitudes and behaviours correlate with actual behaviour, directly addressing the call for research in Fünfgeld and Wang (2009). Having analysed these issues in detail in section 3.4, we will now aggregate our findings in order to provide explicit answers to our research questions from section 3.2.5.

First and foremost, factor analysis revealed four factors that capture the financial attitudes and behaviours of US investors: “financial planning,” “anxiety,” “interest in financial matters,” and “impulsive financial decision-making.” Even though we employed a factor analysis instead of a principal component analysis to extract these factors, the resulting dimensions considerably overlap with the financial attitudes and behaviours identified by Fünfgeld and Wang (2009). More specifically, the “anxiety” and “interest in financial issues” factors are almost identical to those in the German-speaking region of Switzerland (even though we eliminated some items due to low factor loadings). Additionally, the other two dimensions are relatively similar to the remaining three factors that Fünfgeld and Wang (2009) extract. In particular, all dimensions are related to the tradeoff between short-term and long-term financial planning and decision-making. Hence, we can summarize these findings as follows:

Result 1 (R1): *While US investors do not exhibit the exact same underlying financial attitudes and behaviour dimensions as their counterparts in the German-speaking region of Switzerland, there is a significant overlap between the extracted factors in both geographies.*

Furthermore, we found that subjects in our experiment on average exhibited a positive disposition effect — here, males suffered from a slightly higher disposition effect than females did. With regards to the substantial heterogeneity that has been found in previous research but that has never really been discussed thus far, we also found that roughly one-quarter of participants showed a negative disposition effect. To investigate this phenomenon in more detail, we combined the analysis of the disposition effect with the investigation of financial attitudes and behaviours of

US investors. In particular, we found that subjects who score high on the “financial planning” dimension and low on the “impulsive financial decision-making” dimension exhibit lower disposition effects and vice versa. These investors seem to have in common that they focus more on the long-term implications of their decisions: either by comparing and calculating risks more attentively, or by being more deliberate in their financial decision-making processes. The dimensions “anxiety” and “interest in financial matters” do, however, not seem to impact subjects’ propensity to be affected by the disposition effect. Therefore, we can conclude:

Result 2 (R2): *Investors who score high on the “financial planning” dimension and low on the “impulsive financial decision-making” dimension exhibit lower disposition effects and vice versa. The remaining two dimensions do not possess a significant effect.*

3.5.2 Future Research

While the present research evidently shows that the financial attitudes and behaviour dimensions proposed by Fünfgeld and Wang (2009) are similar in the US and the German-speaking region of Switzerland, they are not exactly identical. Therefore, further research could investigate these dimensions in additional geographies in order to further assess their external validity. Seeing that Switzerland and the US can be seen as developed markets with relatively financially literate investors, it would be particularly interesting to expand the investigation to developing markets.

Additionally, we find that investors who think more about the long-term implications of their financial actions are less affected by the disposition effect. Thereby, we have shown that the self-stated financial attitudes and behaviour dimensions correlate with actual behaviour in an experimental asset market. However, we only focused our investigation on the disposition effect. Other financial biases or purely observational trading characteristics (such as trading frequency or trading performance) could also be investigated in future research undertakings. While the data collected as part of the present experiment could be used to investigate some of these ideas, we refrained from doing so in the above analysis as we feared that this would dilute the focus and contribution of our paper, which clearly lies on the investigation of investor heterogeneity with regards to the disposition effect.

Conclusion

The principal aim of this dissertation is reflected in its title: **“Understanding and Debiasing Investor Behaviour.”** This endeavour was motivated by several underlying developments. For example, financial markets in general have become ever more accessible to individual investors over the last decades. The Internet in particular has contributed substantially to increased stock market participation and, more recently, robo-advisors have lowered investment barriers for retail investors even further. Simultaneously, global pension systems have come under significant pressure. As a result, a shift from defined benefit to defined contribution schemes has occurred, which makes individuals ever more responsible for their future financial wellbeing. However, it is also well known that the average individual investor is subject to several behavioural and cognitive biases, which can adversely affect their financial decision-making abilities.

In light of these developments, Chapter 1, which is a direct proceeding of the VikoDiA project, reports the results of an experiment that tests individuals’ understanding of a hypothetical investment scenario. Here, the overall objective is to assess if individuals are well-prepared for the above-described developments. Therefore, the focus is on the risk and return parameters, which are arguably the most fundamental characteristics of any investment. The findings show that, overall, subjects do not seem to understand their investment very well. Most notably, especially adverse economic environments seem to make investors lose the understanding of their investment. Concurrently, we also show that adequate investment performance reporting is particularly important on digital surfaces. The experiment indicates that the newly developed universal framework of customer-centricity can provide considerable value in this regard. Overall, the chapter adds to the current discussion about the digitalization of financial advice and hopes to encourage further research and experimenting about related questions.

As an immediate result of these observations, which show that individuals encounter significant difficulties when trying to understand and evaluate their invest-

ment, Chapter 2 looks at one prominent behavioural bias in more detail. The decision to focus on the disposition effect was made deliberately for two reasons: First, it would be virtually impossible to consider all aspects of investor behaviour or even only the most pronounced biases at the same time. Secondly, the disposition effect is one of the most ubiquitous, robust, and well-studied phenomena that negatively affects investors' investment performance. In particular, it has been shown extensively that a wide variety of investors exhibits the disposition effect, whereas efforts to debias it have been limited in quantity, scope, and practicability thus far. Therefore, we investigate the influence of investment goals and their presentation format on the disposition effect in an experimental setting. In doing so, we find that providing investors with a specific investment goal that they are primed to achieve in the experiment significantly reduces their disposition effect. In fact, enhanced self-control and the refraining from mental accounting seem to cause these subjects to hold on to paper gains for longer. While their behaviour with regards to loss realization does not change, they exhibit a reversed disposition effect overall. However, aggregating their portfolio's performance in a single visual graphical representation does not have any significant effect.

In line with prior research, the findings in this experiment indicate that there is substantial heterogeneity with regards to the degree to which subjects exhibit a disposition effect. In fact, merely 60% of participants show a disposition effect at all. Hence, Chapter 3 sets out to investigate this heterogeneity in more detail by relating subjects' financial attitudes and behaviours to the disposition effect. We find that US investors' self-stated financial attitudes and behaviours can be captured by the following four dimensions: "financial planning," "anxiety," "interest in financial issues," and "impulsive financial decision-making." Upon closer inspection, we find that investors who score high on the "financial planning" dimension and low on the "impulsive financial decision-making" dimension exhibit lower disposition effects and vice versa. These investors seem to have in common that they focus more on the long-term implications of their decisions: either by comparing and calculating risks more attentively, or by being more deliberate in their financial decision-making processes.

In conclusion, this dissertation hence shines light on an important aspect of investor behaviour. First, it shows that investors often do not grasp even the basic characteristics of their investment. Furthermore, it illustrates a practical debiasing mechanism for the disposition effect and argues which types of investors could benefit from it in particular. Still, seeing that the scope was limited, future research will

have to investigate the concepts presented in this dissertation more broadly. For one, this dissertation focussed exclusively on the disposition effect. However, there are many more behavioural and cognitive biases that adversely affect investors' financial decision-making and performance. Using the approaches presented here, future research could examine which types of investors are particularly prone to these biases and subsequently design and test appropriate debiasing mechanisms.

Appendix A

Appendix to Chapter 1

A.1 Exemplary PDF Reports

[Positive Scenario, Page 1]

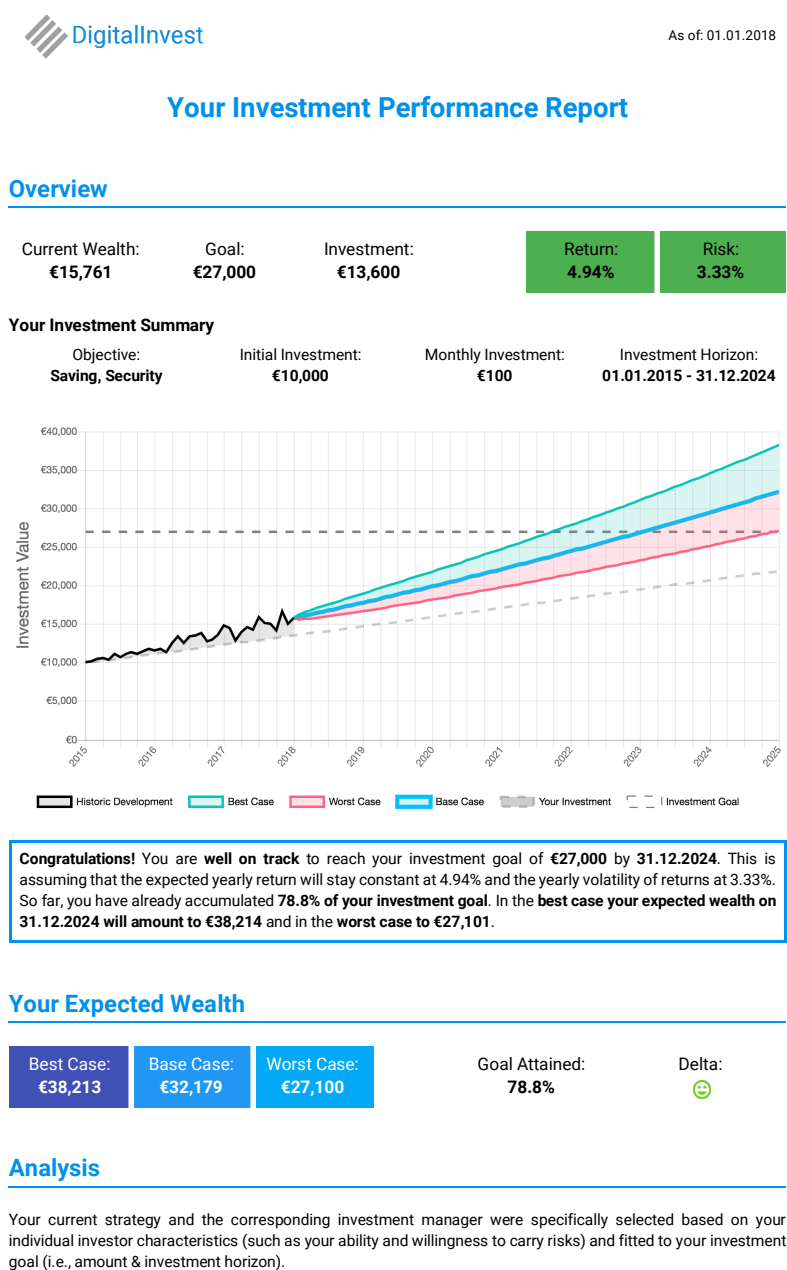


Figure A.1: Screenshot of the PDF investment performance report depicting the positive scenario (Page 1 of 6)

[Positive Scenario, Page 2]



As of: 01.01.2018

Below you can compare your investment strategy's historic (last year & lifetime) performance to a benchmark with similar investment parameters. As you can see, your investment has exhibited a **slightly lower return as compared to the benchmark**, yet it was also subject to **considerably less volatility**. This resulted in a **significantly better Sharpe Ratio** of 1.3 as compared to 0.63 for the benchmark.

Criterion	Your Strategy	Benchmark
Return	4.94%	5.6%
Risk	3.33%	7.9%
Sharpe Ratio	1.3	0.63
Omega	1.32	1.21

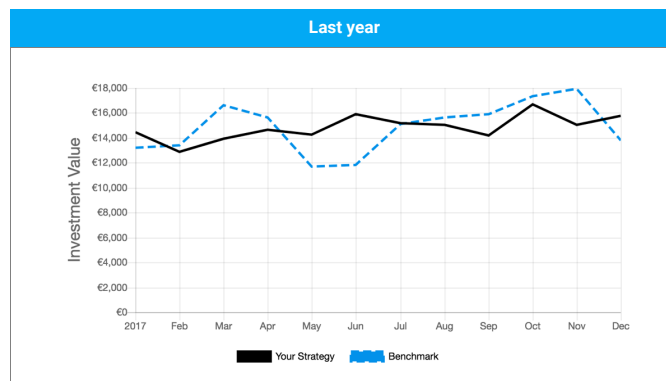
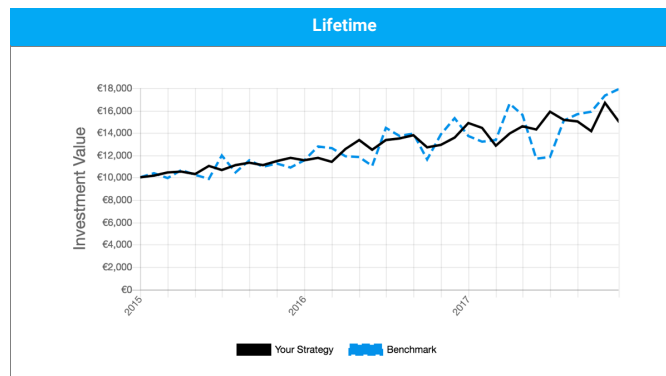


Figure A.2: Screenshot of the PDF investment performance report depicting the positive scenario (Page 2 of 6)

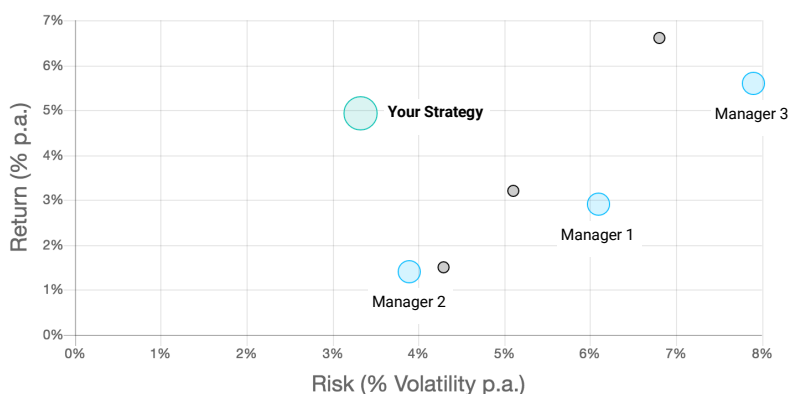
[Positive Scenario, Page 3]



As of: 01.01.2018

Comparison

The graph below shows the risk and return parameters of your strategy, other investment managers on the platform, and several private investors (grey) who have chosen to share their investment data with DigitalInvest. As you can see, your strategy exhibits the **lowest volatility amongst all other portfolios**. Increasing your expected return is only possible by increasing your risk exposure.



Criterion	Return	Risk	Sharpe Ratio	Omega	Comment
Your Strategy	4.94%	3.33%	1.3	1.32	Your current investment strategy.
Manager 1	2.90%	6.10%	0.37	1.12	In order to achieve the highest return while keeping the strategy's risk at a minimum, this investment manager employs a wide dispersion of capital across a variety of countries, regions, and industries. The equity share amounts to 50%.
Manager 2	1.40%	3.90%	0.20	1.05	This investment manager mainly targets those investors who wish to preserve their invested capital and are reluctant to taking on excessive risk. The equity share might amount up to 25%, so some fluctuations in wealth can be expected.
Manager 3	5.60%	7.90%	0.63	1.21	This investment manager has set up a strategy that is aimed at those investors whose primary goal is to preserve their invested capital but who are still open to some risk exposure and wish to benefit from international capital markets. The equity share is aimed to amount to 40-60%, so a certain degree of volatility can be expected.

Figure A.3: Screenshot of the PDF investment performance report depicting the positive scenario (Page 3 of 6)

[Positive Scenario, Page 4]

 DigitalInvest As of: 01.01.2018

DigitalInvest Tips & Tricks

 DigitalInvest explains

Goal-based investing

Goal-based Investing

A relatively new approach to wealth management that emphasizes investing with the objective of attaining specific life goals. Goal-based investing (GBI) involves a wealth manager or investment firm's clients measuring their progress towards the specific life goals such as saving for children's education or building a retirement nest-egg, rather than focusing on generating the highest possible portfolio return or beating the market.

Consider an investor who is looking forward to retirement within a year, and who therefore cannot afford to lose even 10% of his or her portfolio. If the stock market plunges 30% in a given year and the investor's portfolio is down "only" 20%, the fact that the portfolio has outperformed the market by 10 percentage points would offer scant comfort.

Goal-based investing aims to get around this drawback of the traditional investment approach, which generally focuses on outperforming the market while staying within the investor's threshold for risk. Instead, it uses individual asset pools with an investment strategy that is tailored to the client's specific goals. Thus, if a client's main goals are to save for imminent retirement and fund the college education of her young grandchildren, the investment strategy would be more conservative for the former and relatively aggressive for the latter. As an example, the asset allocation for the retirement assets might be 10% equities and 90% fixed-income, while the asset allocation for the education fund may be 50% equities and 50% fixed-income.

The two biggest advantages of goal-based investing, according to their proponents, are - (i) it increases clients' commitments to their life goals by enabling them to gauge tangible progress towards their goals, and (ii) it reduces negative behavioral biases such as impulsive decision-making and overreaction.

Goal-based investing grew in popularity in the years after the Great Recession of 2008-09, as scores of investors realized the extent to which the attainment of personal goals could be affected by a severe bear market. Millions of hapless investors witnessed their net worth plunge dramatically as a result of the global recession that triggered declines of more than 50% in most major markets, as well as the steep correction in U.S. housing prices.

Adapted from: <https://www.investopedia.com/terms/g/goalbased-investing.asp>

 DigitalInvest explains the

Sharpe Ratio

The Sharpe Ratio

The Sharpe ratio is the average return earned in excess of the risk-free rate per unit of volatility or total risk. Subtracting the risk-free rate from the mean return, the performance associated with risk-taking activities can be isolated. One intuition of this calculation is that a portfolio engaging in "zero risk" investment, such as the purchase of U.S. Treasury

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Figure A.4: Screenshot of the PDF investment performance report depicting the positive scenario (Page 4 of 6)

[Positive Scenario, Page 5]



As of: 01.01.2018

bills (for which the expected return is the risk-free rate), has a Sharpe ratio of exactly zero. Generally, the greater the value of the Sharpe ratio, the more attractive the risk-adjusted return.

The Sharpe ratio has become the most widely used method for calculating risk-adjusted return; however, it can be inaccurate when applied to portfolios or assets that do not have a normal distribution of expected returns. Many assets have a high degree of kurtosis ('fat tails') or negative skewness. The Sharpe ratio also tends to fail when analyzing portfolios with significant non-linear risks, such as options or warrants. Alternative risk-adjusted return methodologies have emerged over the years, including the Sortino Ratio, Return Over Maximum Drawdown (RoMaD), and the Treynor Ratio.

Modern Portfolio Theory states that adding assets to a diversified portfolio that have correlations of less than 1 with each other can decrease portfolio risk without sacrificing return. Such diversification will serve to increase the Sharpe ratio of a portfolio.

Sharpe ratio = (Mean portfolio return - Risk-free rate)/Standard deviation of portfolio return

The Sharpe ratio is often used to compare the change in a portfolio's overall risk-return characteristics when a new asset or asset class is added to it. For example, a portfolio manager is considering adding a hedge fund allocation to his existing 50/50 investment portfolio of stocks and bonds which has a Sharpe ratio of 0.67. If the new portfolio's allocation is 40/40/20 stocks, bonds and a diversified hedge fund allocation (perhaps a fund of funds), the Sharpe ratio increases to 0.87. This indicates that although the hedge fund investment is risky as a standalone exposure, it actually improves the risk-return characteristic of the combined portfolio, and thus adds a diversification benefit. If the addition of the new investment lowered the Sharpe ratio, it should not be added to the portfolio.

The Sharpe ratio can also help explain whether a portfolio's excess returns are due to smart investment decisions or a result of too much risk. Although one portfolio or fund can enjoy higher returns than its peers, it is only a good investment if those higher returns do not come with an excess of additional risk. The greater a portfolio's Sharpe ratio, the better its risk-adjusted performance. A negative Sharpe ratio indicates that a risk-less asset would perform better than the security being analyzed.

Adapted from: <https://www.investopedia.com/terms/s/sharperatio.asp>



Behavioral Finance

Who Is Richard Thaler, Economics Nobel Prize Winner?

Richard Thaler, the father of behavioral economics, has been awarded the 2017 Nobel Memorial Prize in Economic Sciences, it was announced Oct. 9, 2017. As a founding economist in the behavioral finance field, he largely counters the belief of the efficient market hypothesis (EMH), heralded by economists of the neoclassical tradition. He argues that instead of individuals acting in rational and efficient form, there exist deviations where human agents act with fallibility.

The area of behavioral finance had only begun to emerge in the mid-80s. Behavioral finance argued there was a descriptive model of rationality. Instead of considering investors acting in a cold, irrational way, Thaler argues that investors act under the influence of behavioral biases often leading to decidedly less than optimal decisions.

A number of central ideas emerged early in his career that resisted assumptions in economics. For example, he wrote on "the endowment effect" to explain how individuals place a higher value on something they own than if the identical item was someone else's. This phenomenon challenges the rational economic view. Moreover, this departure can be explained by our acute aversion to loss.

Perhaps most strikingly, Thaler's research on prospect theory offered a new way of understanding how individuals react to the financial markets. Here, he takes a closer look at human decision-making. Essentially, he shows how individuals make decisions based on framing, or the context that the decisions are placed within. Thaler argues that prospect theory is perhaps one of the most important tools for behavioral economists.

Figure A.5: Screenshot of the PDF investment performance report depicting the positive scenario (Page 5 of 6)

[Positive Scenario, Page 6]



As of: 01.01.2018

One part of prospect theory is loss aversion, where the pain of loss is almost twice as powerful as an equal amount experienced from gains.

When it comes to retirement savings, Thaler has also conducted research that uses behavioral economics and psychology. Recognizing that the savings rate in the U.S. is declining, through the shift in many employers offering defined contribution plans instead of defined benefit plans, they acknowledged that the middle class will have to bear more weight in planning for retirement. "As we've switched over from defined benefit plans to defined contribution plans, we've turned over responsibility for enrollment and contribution decisions to individuals, many of whom don't have expertise in this area," says Thaler. Thaler and Shlomo Benartzi created a plan that allows employees to increase their contribution amount as their wages increase over time. In the program's first implementation, the average savings rate of the participants tripled over 28 months, from 3.5 percent to 11.6 percent.

Richard Thaler's work in the behavioral finance field seeks to unpack and explain how individuals can improve their decision making with regards to asset allocation, viewing the financial markets, looking at opportunities for investment, and retirement savings plans. His research seeks to understand the errors entrenched in individuals and applies a model that reflects the way individuals act on an empirical basis.

Adapted from: <https://www.investopedia.com/articles/investing/102715/richard-thaler-founding-father-behavioral-finance.asp>

Figure A.6: Screenshot of the PDF investment performance report depicting the positive scenario (Page 6 of 6)

[Negative Scenario, Page 1]



As of: 01.01.2018

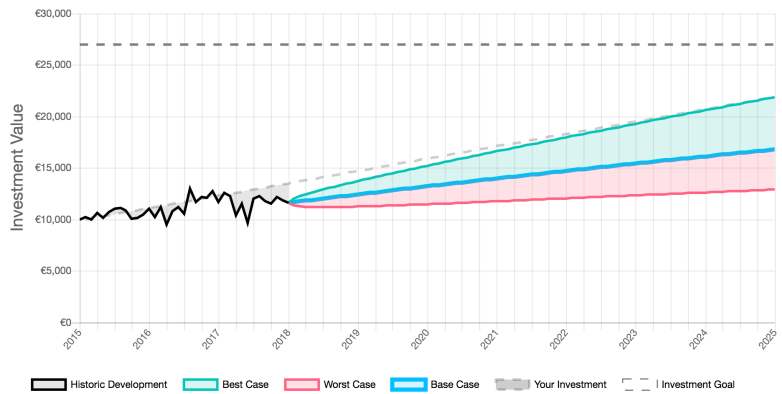
Your Investment Performance Report

Overview

Current Wealth: €11,606	Goal: €27,000	Investment: €13,600	Return: -3.09%	Risk: 5.15%
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Your Investment Summary

Objective: Saving, Security	Initial Investment: €10,000	Monthly Investment: €100	Investment Horizon: 01.01.2015 - 31.12.2024
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Attention! We currently project that you will not be able to reach your investment goal of €27,000 by 31.12.2024. This is assuming that the expected yearly return will stay constant at -3.09% and the yearly volatility of returns at 5.15%. So far, you have only accumulated 58.0% of your investment goal. Even in the best case your expected wealth by the end of the investment period will amount to €21,886, which is still less than your total investment by that time. We strongly recommend that you inspect the investment report in great detail and consider making adjustments to your current strategy.

Your Expected Wealth

Best Case: €21,886	Base Case: €16,792	Worst Case: €12,889	Goal Attained: 58.0%	Delta: ☹️
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Analysis

Your current strategy and the corresponding investment manager were specifically selected based on your individual investor characteristics (such as your ability and willingness to carry risks) and fitted to your investment goal (i.e., amount & investment horizon).

Figure A.7: Screenshot of the PDF investment performance report depicting the negative scenario (Page 1 of 6)

[Negative Scenario, Page 2]



As of: 01.01.2018

Below you can compare your investment strategy's historic (last year & lifetime) performance to a benchmark with similar investment parameters. As you can see, the **benchmark has consistently outperformed your investment strategy**. This also resulted in **significantly worse Sharpe and Omega Ratios** for your strategy.

Criterion	Your Strategy	Benchmark
Return	-3.09%	5.6%
Risk	5.15%	7.9%
Sharpe Ratio	-0.72	0.63
Omega	0.97	1.21

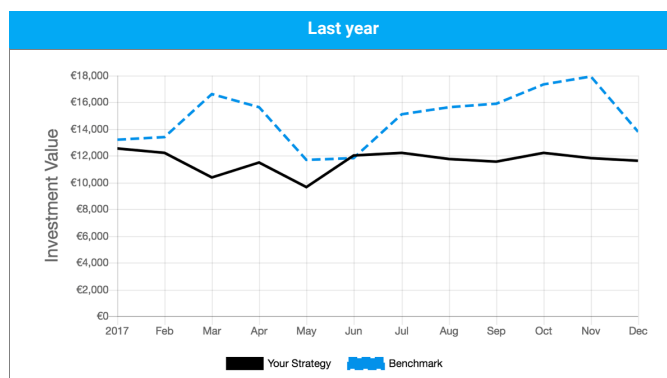
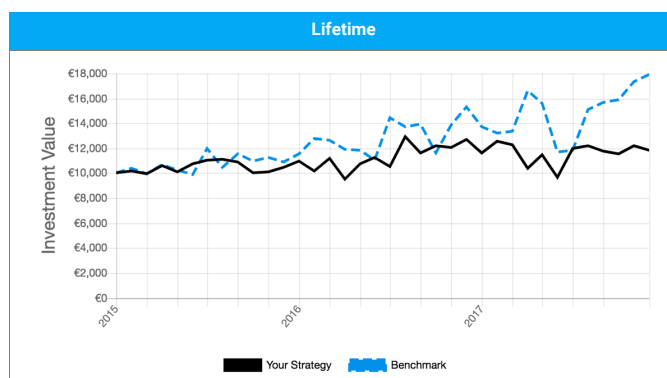


Figure A.8: Screenshot of the PDF investment performance report depicting the negative scenario (Page 2 of 6)

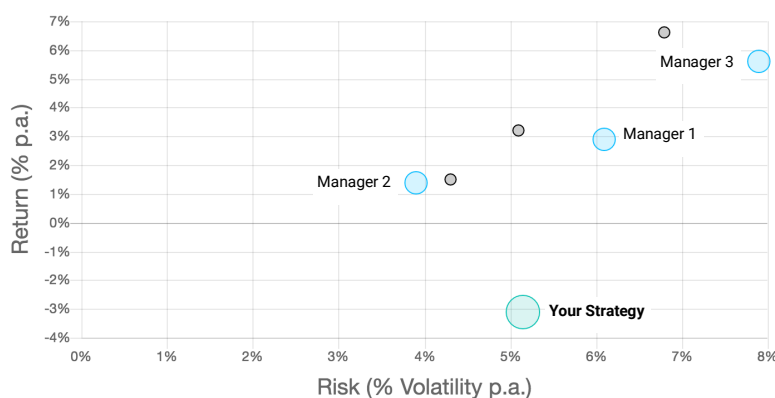
[Negative Scenario, Page 3]



As of: 01.01.2018

Comparison


The graph below shows the risk and return parameters of your strategy, other investment managers on the platform, and several private investors (grey) who have chosen to share their investment data with DigitalInvest. As you can see, your strategy exhibits the **lowest return amongst all other portfolios**. In fact, it is the **only portfolio that reports a negative return** over its lifetime. We strongly recommend that you consider adapting your current strategy. Otherwise, you risk not meeting your investment goal!




Criterion	Return	Risk	Sharpe Ratio	Omega	Comment
Your Strategy	-3.09%	5.15%	-0.72	0.97	Your current investment strategy.
Manager 1	2.90%	6.10%	0.37	1.12	In order to achieve the highest return while keeping the strategy's risk at a minimum, this investment manager employs a wide dispersion of capital across a variety of countries, regions, and industries. The equity share amounts to 50%.
Manager 2	1.40%	3.90%	0.20	1.05	This investment manager mainly targets those investors who wish to preserve their invested capital and are reluctant to taking on excessive risk. The equity share might amount up to 25%, so some fluctuations in wealth can be expected.
Manager 3	5.60%	7.90%	0.63	1.21	This investment manager has set up a strategy that is aimed at those investors whose primary goal is to preserve their invested capital but who are still open to some risk exposure and wish to benefit from international capital markets. The equity share is aimed to amount to 40-60%, so a certain degree of volatility can be expected.

Figure A.9: Screenshot of the PDF investment performance report depicting the negative scenario (Page 3 of 6)

[Negative Scenario, Page 4]


As of: 01.01.2018


DigitalInvest explains

Goal-based investing

Goal-based Investing

A relatively new approach to wealth management that emphasizes investing with the objective of attaining specific life goals. Goal-based investing (GBI) involves a wealth manager or investment firm's clients measuring their progress towards the specific life goals such as saving for children's education or building a retirement nest-egg, rather than focusing on generating the highest possible portfolio return or beating the market.


Consider an investor who is looking forward to retirement within a year, and who therefore cannot afford to lose even 10% of his or her portfolio. If the stock market plunges 30% in a given year and the investor's portfolio is down "only" 20%, the fact that the portfolio has outperformed the market by 10 percentage points would offer scant comfort.

Goal-based investing aims to get around this drawback of the traditional investment approach, which generally focuses on outperforming the market while staying within the investor's threshold for risk. Instead, it uses individual asset pools with an investment strategy that is tailored to the client's specific goals. Thus, if a client's main goals are to save for imminent retirement and fund the college education of her young grandchildren, the investment strategy would be more conservative for the former and relatively aggressive for the latter. As an example, the asset allocation for the retirement assets might be 10% equities and 90% fixed-income, while the asset allocation for the education fund may be 50% equities and 50% fixed-income.

The two biggest advantages of goal-based investing, according to their proponents, are - (i) it increases clients' commitments to their life goals by enabling them to gauge tangible progress towards their goals, and (ii) it reduces negative behavioral biases such as impulsive decision-making and overreaction.

Goal-based investing grew in popularity in the years after the Great Recession of 2008-09, as scores of investors realized the extent to which the attainment of personal goals could be affected by a severe bear market. Millions of hapless investors witnessed their net worth plunge dramatically as a result of the global recession that triggered declines of more than 50% in most major markets, as well as the steep correction in U.S. housing prices.

Adapted from: <https://www.investopedia.com/terms/g/goalbased-investing.asp>


DigitalInvest explains the

Sharpe Ratio

The Sharpe Ratio

The Sharpe ratio is the average return earned in excess of the risk-free rate per unit of volatility or total risk. Subtracting the risk-free rate from the mean return, the performance associated with risk-taking activities can be isolated. One intuition of this calculation is that a portfolio engaging in "zero risk" investment, such as the purchase of U.S. Treasury

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Figure A.10: Screenshot of the PDF investment performance report depicting the negative scenario (Page 4 of 6)

[Negative Scenario, Page 5]



As of: 01.01.2018

bills (for which the expected return is the risk-free rate), has a Sharpe ratio of exactly zero. Generally, the greater the value of the Sharpe ratio, the more attractive the risk-adjusted return.

The Sharpe ratio has become the most widely used method for calculating risk-adjusted return; however, it can be inaccurate when applied to portfolios or assets that do not have a normal distribution of expected returns. Many assets have a high degree of kurtosis ('fat tails') or negative skewness. The Sharpe ratio also tends to fail when analyzing portfolios with significant non-linear risks, such as options or warrants. Alternative risk-adjusted return methodologies have emerged over the years, including the Sortino Ratio, Return Over Maximum Drawdown (RoMaD), and the Treynor Ratio.

Modern Portfolio Theory states that adding assets to a diversified portfolio that have correlations of less than 1 with each other can decrease portfolio risk without sacrificing return. Such diversification will serve to increase the Sharpe ratio of a portfolio.

Sharpe ratio = (Mean portfolio return - Risk-free rate) / Standard deviation of portfolio return

The Sharpe ratio is often used to compare the change in a portfolio's overall risk-return characteristics when a new asset or asset class is added to it. For example, a portfolio manager is considering adding a hedge fund allocation to his existing 50/50 investment portfolio of stocks and bonds which has a Sharpe ratio of 0.67. If the new portfolio's allocation is 40/40/20 stocks, bonds and a diversified hedge fund allocation (perhaps a fund of funds), the Sharpe ratio increases to 0.87. This indicates that although the hedge fund investment is risky as a standalone exposure, it actually improves the risk-return characteristic of the combined portfolio, and thus adds a diversification benefit. If the addition of the new investment lowered the Sharpe ratio, it should not be added to the portfolio.

The Sharpe ratio can also help explain whether a portfolio's excess returns are due to smart investment decisions or a result of too much risk. Although one portfolio or fund can enjoy higher returns than its peers, it is only a good investment if those higher returns do not come with an excess of additional risk. The greater a portfolio's Sharpe ratio, the better its risk-adjusted performance. A negative Sharpe ratio indicates that a risk-less asset would perform better than the security being analyzed.

Adapted from: <https://www.investopedia.com/terms/s/sharperatio.asp>



Behavioral Finance

Who Is Richard Thaler, Economics Nobel Prize Winner?

Richard Thaler, the father of behavioral economics, has been awarded the 2017 Nobel Memorial Prize in Economic Sciences, it was announced Oct. 9, 2017. As a founding economist in the behavioral finance field, he largely counters the belief of the efficient market hypothesis (EMH), heralded by economists of the neoclassical tradition. He argues that instead of individuals acting in rational and efficient form, there exist deviations where human agents act with fallibility.

The area of behavioral finance had only begun to emerge in the mid-80s. Behavioral finance argued there was a descriptive model of rationality. Instead of considering investors acting in a cold, irrational way, Thaler argues that investors act under the influence of behavioral biases often leading to decidedly less than optimal decisions.

A number of central ideas emerged early in his career that resisted assumptions in economics. For example, he wrote on "the endowment effect" to explain how individuals place a higher value on something they own than if the identical item was someone else's. This phenomenon challenges the rational economic view. Moreover, this departure can be explained by our acute aversion to loss.

Perhaps most strikingly, Thaler's research on prospect theory offered a new way of understanding how individuals react to the financial markets. Here, he takes a closer look at human decision-making. Essentially, he shows how individuals make decisions based on framing, or the context that the decisions are placed within. Thaler argues that prospect theory is perhaps one of the most important tools for behavioral economists.

Figure A.11: Screenshot of the PDF investment performance report depicting the negative scenario (Page 5 of 6)

[Negative Scenario, Page 6]



As of: 01.01.2018

One part of prospect theory is loss aversion, where the pain of loss is almost twice as powerful as an equal amount experienced from gains.

When it comes to retirement savings, Thaler has also conducted research that uses behavioral economics and psychology. Recognizing that the savings rate in the U.S. is declining, through the shift in many employers offering defined contribution plans instead of defined benefit plans, they acknowledged that the middle class will have to bear more weight in planning for retirement. "As we've switched over from defined benefit plans to defined contribution plans, we've turned over responsibility for enrollment and contribution decisions to individuals, many of whom don't have expertise in this area," says Thaler. Thaler and Shlomo Benartzi created a plan that allows employees to increase their contribution amount as their wages increase over time. In the program's first implementation, the average savings rate of the participants tripled over 28 months, from 3.5 percent to 11.6 percent.

Richard Thaler's work in the behavioral finance field seeks to unpack and explain how individuals can improve their decision making with regards to asset allocation, viewing the financial markets, looking at opportunities for investment, and retirement savings plans. His research seeks to understand the errors entrenched in individuals and applies a model that reflects the way individuals act on an empirical basis.

Adapted from: <https://www.investopedia.com/articles/investing/102715/richard-thaler-founding-father-behavioral-finance.asp>

Figure A.12: Screenshot of the PDF investment performance report depicting the negative scenario (Page 6 of 6)

A.2 Scenario & Instructions

Scenario

DigitalInvest is an online platform that allows you to find an investment manager who will invest money on your behalf in order to help you achieve a specific goal over a certain investment period. For this experiment, please imagine that you invested €10,000 on the platform three years ago (i.e., on 01.01.2015). Each month, you invest an additional €100 directly from your salary. So far, you have hence invested €13,600 in total. Your goal is to accumulate a total of €27,000 over ten years (i.e., by 31.12.2024).

Instructions

This study consists of two parts:

1. You will be asked to put yourself in the position where you have invested €10,000 with an investment manager via the online platform DigitalInvest three years ago. Today, you want to check how your investment is doing. You decide to log on to the DigitalInvest platform where you will be shown an investment performance report. It is very important to you that you reach your investment goal as specified above, so please review the report in great detail. You will be asked specific questions about the report in the next part, so please make sure that you have carefully studied all available information.
2. After 7 minutes you will automatically be redirected to a questionnaire which will ask a series of questions about the investment performance report. If you believe that you have studied the report in the appropriate amount of detail in less than 7 minutes, you can proceed to the questionnaire by clicking the “Finish Experiment” button on the next screen.

We ask you to work carefully on both parts of the study and to give spontaneous, honest answers to all questions! Please click the “Start Experiment” button below in order to start the experiment.

Thank you for your participation!

A.3 Technical Appendix

A.3.1 Objective

This appendix aims to document the case scenarios that provide the underlying data for the performance reporting experiment as part of the VikoDiA project. The aim of said experiment is to investigate under which circumstances investors feel particularly well informed about their investment, how their perception of expected risk and return changes, and which behavioural intentions arise after the inspection of a particular investment performance report.

In order to address these research questions, subjects will be shown a specific investment report. The performance of the investor’s current strategy and the performance and historic development of other investors and investment managers shown there will be drawn exactly from real-life portfolios and investment strategies. This is so that cases can be constructed which put subjects in a specific investment situation as it is suspected that subjects will react differently across the two scenarios (positive and negative).

Generally, participants in the experiment will be asked to imagine they had invested €10,000 with an online investment platform three years ago. Subjects in the first condition will then be shown an investment performance report that depicts a case where they are likely to achieve their investment objective (€27,000) over the pre-specified period of time (over the next seven years, such that the investment period amounts to ten years in total). On the other hand, some subjects will be shown an investment performance report where they are presented with a scenario in which it is unlikely that they will achieve their investment goal over said time frame.

Hence, the the combination of scenarios and investment performance reports shown as part of the experiment that will constitute the six experimental conditions will look as follows:

		Investment Report Version		
		Static	Interactive	Assisted
Scenario	Positive	Condition 1	Condition 3	Condition 4
	Negative	Condition 2	Condition 4	Condition 6

Table A.1: Summary of experimental design including scenario and investment report version definition

Therefore, the following data is needed as inputs for the planned experimental conditions:

- Simulated development of the investment of €10,000 from January 2015 to January 2018. This simulated path will be shown in the investment performance report as the historic development of the investment. In both, the positive and negative scenarios, the investor invests an additional €100 per month by default. Hence, this monthly add-on has to be considered as well. Only one historic path will be simulated per scenario.
- Simulated developments of the portfolio value as of January 2018 until December 2029.¹ For the future development, the 2.5%, 50%, and 97.5% percentiles were calculated such that the expected future development will be within said funnel in 95% of all cases.

As a general note, all cases were constructed in a way such that the input parameters could easily be adapted. This was necessary in order to calculate the data arrays for the simulation which is included in Conditions 3-6, where the investor can “simulate” the effect of a change in the investment parameters² on their expected future performance. The following graph shows the complete positive scenario that was constructed on the basis of the parameters specified for a time horizon of ten years:

¹ Note that the scenario was calculated for a longer time horizon than necessary for the experiment such that the experimental setup could easily be adapted.

² The following investment parameters can be changed: one-time add-on investment (€0, €1,000, €2,000, €3,000); monthly add-on (€0, €100, €200, €300); investment horizon (December 2024, December 2025, December 2026).

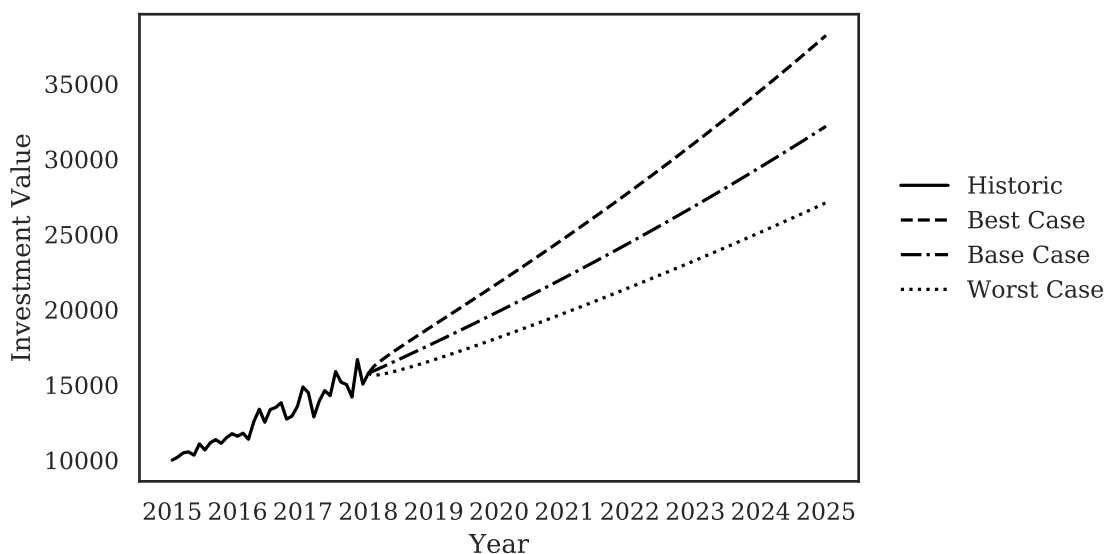


Figure A.13: Example data for the positive scenario

A.3.2 Case Definition

This section will briefly document all 5 investment cases and their input parameters. All scenarios were constructed based on a combination of historic risk (annualized volatility of returns, σ_{yearly}) and return (annualized, μ_{yearly}) parameters extracted from real life funds over an observation period of at least two years.³ The origin of said historic risk-return parameters is indicated in the column “Based on,” whereas the column “Description” briefly presents the main argument as to why the specific scenario was constructed in such a way and why it was included in the investment report.

³ Note: The data for the positive and negative scenario stems from November 2017, whereas all other risk and return combinations stem from performance reports dated July 2017.

Name	μ_{yearly}	σ_{yearly}	Based on	Description
Positive	4.94%	3.33%	3 Banken Long Term Eurobond- Mix	Data scenario constructed in a way such that it is likely that the investor will reach their investment goal in the pre-specified period of time.
Negative	-3.09%	5.15%	3 Banken EM- Core Convertibles Global	Data scenario constructed in a way such that it is unlikely that the investor will reach their investment goal in the pre-specified period of time.
Manager 1	2.90%	6.10%	AKTIV Port- folio Balance Benchmark	Constructed in a way such that it exhibits less return but more volatility than the Base scenario and hence should be less preferable.
Manager 2	1.40%	3.90%	AKTIV Portfolio Stabilität Bench- mark	Constructed in a way such that it exhibits less return than the Base scenario at a comparable level of volatility.
Manager 3	5.60%	7.90%	AKTIV Portfolio Balance	Constructed in a way such that it exhibits more return and more volatility than the Base scenario.

Table A.2: Summary of all scenarios including main parameters

As can be seen in the table above, the five scenarios were constructed in a way such that they are sufficiently different from each other. Therefore, it was not regarded necessary to include further scenarios. However, it was considered in the construction of these cases that an investor should only be shown those investment managers and their strategies that are suitable to their individual investment profile. Hence, only those funds were included that can be attributed to risk class 3 or 4 according to the risk classification of the Committee of European Securities Regulators (CESR). According to said methodology, volatilities are matched with risk classes in accordance with the following framework:

Risk Class	Volatility Intervals	
	equal or above	less than
1	0.0%	0.5%
2	0.5%	2.0%
3	2.0%	5.0%
4	5.0%	10.0%
5	10.0%	15.0%
6	15.0%	25.0%
7	25.0%	

Table A.3: Risk class definition based on volatility intervals according to CESR

A.3.3 Assumptions

All scenarios underlie certain assumptions that made their construction somewhat more feasible. The main assumptions shall be summarized here so that the origin of the data is easily comprehensible. The general input parameters — that are valid for all cases — were set as follows:

Parameter	Value
Initial investment	€10,000
Monthly add-on investment	€100
Investment goal	€27,000
Investment start	01.01.2015
“Today”	01.01.2018
Investment horizon	until 31.12.2024
Data simulation	until 31.12.2029
r_f	0.6155%

Table A.4: Summary of main input parameters for case definition

Furthermore, the following assumptions were made:

- The simulation of historic and future developments of the initial investment were calculated on a monthly basis. The monthly return and volatility parameters were calculated from the yearly risk and return parameters (μ_{yearly} and σ_{yearly}) provided in Table A.2.

- The monthly-add on is invested at the end of each month.
- An additional add-on investment can be made at the end of the 36th month (i.e., at the end of December 2017), which will be added onto the current value of the investment as of 01.01.2018 and hence serves as the new basis for the future simulations.
- The return of the risk-free asset (r_f) used for the calculation of the Sharpe Ratio and the target return for Omega was calculated as the arithmetic average of annualized monthly returns of the Euro OverNight Index Average (EONIA) over the period November 2007 to November 2017. The data was accessed via Deutsche Bundesbank.⁴ Data for December 2017 was not available yet at the time of construction of the scenarios.

A.3.4 Case Construction and Formulae

Monthly return and volatility

Using the provided annual return, the monthly return used for further calculations was determined according to the following formula:

$$\mu_{monthly} = \frac{\mu_{yearly}}{12} \quad (\text{A.1})$$

Correspondingly, the monthly volatility of returns was calculated as:

$$\sigma_{monthly} = \frac{\sigma_{yearly}}{\sqrt{12}} \quad (\text{A.2})$$

Note here that for reasons of simplicity, no distinction was made between historic and future risk and return parameters. This decision was made because the data calculated here merely serves the purpose to make the scenarios more realistic such that truthful and realistic responses can be elicited from the experiment's participants.

⁴ See: <https://www.bundesbank.de/>

Case calculation

In general, the investment value in period T was calculated according to the following formula:

$$\begin{aligned}
 & W_0 e^{[(\mu_{monthly} - \frac{\sigma_{monthly}^2}{2})T + z\sigma_{monthly}\sqrt{T}]} \\
 & + w_1 e^{[(\mu_{monthly} - \frac{\sigma_{monthly}^2}{2})(T-1) + z\sigma_{monthly}\sqrt{T-1}]} \\
 & \quad \quad \quad + \dots \\
 & + w_{T-1} e^{[(\mu_{monthly} - \frac{\sigma_{monthly}^2}{2})(1) + z\sigma_{monthly}\sqrt{1}]} \\
 & \quad \quad \quad + w_T
 \end{aligned} \tag{A.3}$$

Here, W_0 refers to the initial investment, in this case €10,000, whereas w_T is the monthly add-on investment. In our case, the monthly add-on is constant at €100 per month over the entire investment horizon.

Using the formula above, the historic path was first calculated for each scenario. Note that all scenarios were based on a different sequence of random numbers and hence the corresponding z values also differed across the scenarios. The output of this historic simulation, i.e., the investment value as of January 2018 was then used as an input parameter for the future simulation. Afterwards, the same formula was used to calculate the the 2.5%, 50%, and 97.5% quantiles. The corresponding z values were calculated using the “=NORMINV(quantile;0;1)” formula in Microsoft Excel. Overall, the simulations lead to the following data:

	Base	Bad	M1	M2	M3
Parameters					
Initial Investment			— €10,000 —		
Investment as of 01.01.2018			— €13,600 —		
Investment Goal			— €27,000 —		
Historic					
Value 01.01.2018	€15,671	€11,606	€13,218	€13,193	€13,813
Future Simulation					
2.5% quantile	€27,101	€12,889	€18,424	€19,037	€20,062
50% quantile	€32,180	€16,792	€25,224	€23,271	€30,144
97.5% quantile	€38,214	€21,886	€34,548	€28,451	€45,318

Table A.5: Summary of data resulting from historic and future simulation for all scenarios

Sharpe Ratio and Omega

In addition to the historic risk and return parameters and the historic, as well as expected future, development of the investment, all performance reports also contained information about the Sharpe Ratio and Omega. These were calculated according to the following formulae:

$$S_r = \frac{\mu_{yearly} - r_f}{\sigma_{yearly}} \quad (\text{A.4})$$

$$\Omega = \frac{\int_{r_f}^{+\infty} (1 - F(x)) \, dx}{\int_{-\infty}^{r_f} F(x) \, dx}. \quad (\text{A.5})$$

Where $F(x)$ = cumulative density function of returns

A.4 Questionnaire

[Part 1]



Question 1

The following questions relate to the initial investment, not the investment cases you (might have) simulated or adopted.

	I fully disagree			I fully agree		
This investment bears a high risk of losing money or of missing personal investment objectives (downside risk).	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I feel uncertain, as I feel uninformed and incompetent about the investment (ambiguity).	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
This investment also entails good chances to realise higher, above-average returns (upside risk).	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Regarding this investment, I reckon there will be significant performance variations over time (volatility).	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

Question 2

Please estimate the investment's average rate of return per year (time horizon: the next few years):
On average ____% per year.

Question 3

I would describe this investment report as:

	not at all applies			very much applies		
Informative	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Intelligent	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Knowledgeable	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Resourceful	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Useful	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Helpful	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

Figure A.14: Screenshot of the questionnaire that succeeded the experiment (Part 1 of 4)

[Part 2]

Question 4

I feel informed about:

	completely disagree				completely agree			
What the investment is all about.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
What the investment can mean for me.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
What the investment is really like.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
The overall quality of the investment	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Objective characteristics of the investment	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Parts of the investment that are relevant to my needs.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
What it is really like to have made the investment.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
The extent to which the investment meets my requirements.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

Question 5

I would like to receive more information about...

	strongly disagree				strongly agree			
...my investment manager.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
...the activity of other investors and investment managers on the platform.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
...the historic performance of my investment.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
...the future (expected) performance of my investment.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
...the current state of my investment (e.g., asset allocation, profit/loss per position, ...).	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
...general market news (e.g., market performance, new investment strategies, ...).	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
other: <input type="text"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

Question 6

I would like to receive the information mentioned above...

	strongly disagree				strongly agree			
...by calling my investment manager directly.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
...from my investment manager via email.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
...by meeting with my investment manager in person.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
...on the platform directly, without having to ask for it explicitly.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
...by visiting an offline event / seminar.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
...by setting up a request for my investment manager to call me with the desired information.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
other: <input type="text"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

Figure A.15: Screenshot of the questionnaire that succeeded the experiment (Part 2 of 4)

[Part 3]

Question 7

Please evaluate the following statements:

	1				5
How do you assess your investment knowledge? (1 = I have very small knowledge; 5 = I have a lot of knowledge).	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Please evaluate to what extent you have already gained investment experience (1 = I am very inexperienced; 5 = I am very experienced).	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I know a lot about investing money (1 = I fully agree; 5 = I fully disagree).	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I am very inexperienced in investing money (1 = I fully agree; 5 = I fully disagree).	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

Question 8

Financial investments are personally relevant to me.

strongly disagree strongly agree

Question 9

Suppose you had €100 in a savings account and the interest rate was 2 percent per year. After 5 years, how much do you think you would have in the account if you left the money to grow:

- more than €102
- do not know
- less than €102
- refuse to answer
- exactly €102

Imagine that the interest rate on your savings account was 1 percent per year and inflation was 2 percent per year. After 1 year, would you be able to buy:

- less than today with the money in this account?
- more than today with the money in this account?
- refuse to answer
- exactly the same as today with the money in this account?
- do not know

Figure A.16: Screenshot of the questionnaire that succeeded the experiment (Part 3 of 4)

[Part 4]

Do you think that the following statement is true or false? "Buying a single company stock usually provides a safer return than a stock mutual fund."

do not know

false

true

refuse to answer

Demographic Questions

Please select your gender:

male

female

prefer not to say

Please state your current age in years:

Please select your highest education degree to date:

Graduate degree

Some college

College graduate

Some graduate work

High school or less

Please select the title that best describes your current status of employment:

Secretarial

Graduate Student

Part-time employment

Undergraduate Student

Professional

Educational (Professor, Research Assistant, ...)

Technical, Maintenance & Skilled Crafts

Other

Figure A.17: Screenshot of the questionnaire that succeeded the experiment (Part 4 of 4)

Appendix B

Appendix to Chapter 2

B.1 Stock Price Developments

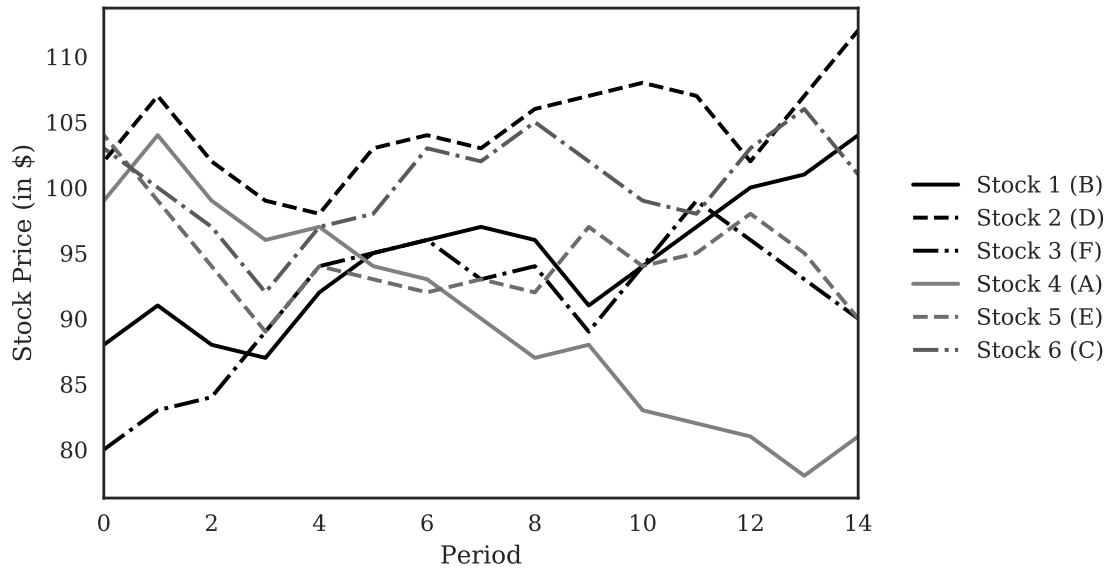


Figure B.1: Simulated stock price development over time

Note: The graph shows the simulated price development of all six stocks. The prices were determined randomly once before the start of the data collection period according to the process described in section 2.3.1. Consequently, all participants were shown the same price developments.

B.2 Trading Interface Screenshots



Figure B.2: Screenshot of all trading interfaces by condition

Note: This figure shows screenshots of the trading interface for all four experimental conditions. Note that, depending on the specific condition, subjects are reminded about their investment goal and are provided with a graph that depicts their aggregate portfolio performance by period.

B.3 Instructions

[Page 1]

Welcome!

About this experiment

Welcome to this experiment about stock market decision-making. If you decide to participate, you will find detailed instructions on the next screen. At the end of the experiment, you will also be asked to answer a few questions. Please answer all questions truthfully — there is no right or wrong answer.

Compensation

Your compensation will depend on the quality of decisions you make during the experiment. You will initially be endowed with \$10,000, which you can invest over 14 periods.

At the end of the experiment, your payoff will amount to \$4.50 plus 0.25% of your increase in total assets. I.e., if your total final assets amount to \$11,000, you will receive a flat fee of \$4.50 plus \$2.50 ($\$11,000 - \$10,000 = \$1,000 * 0.25\% = \2.50). Hence, you would receive \$7 in total.

Thank you for your participation!

[Page 2]

Instructions

Description

This experiment consists of 14 periods. At the start of the experiment, you will be endowed with \$10,000. You will have the possibility to trade six distinct shares (A-F) starting in period 0. In periods -3 to -1, you are asked to observe prices — but you cannot trade any shares yet.

Share price development

The starting prices in period -3 are determined randomly. Prices subsequently change according to the following two processes in each period:

- First, it will be determined whether a stock will exhibit a price in- or decrease. The probabilities of in- or decreases are distinct for each share and do not change over time. You do not know which share (A-F) is associated with which of the following probabilities:

Number of shares on the market	Probability of price increase	Probability of price decrease
1	65%	35%
1	55%	45%
2	50%	50%
1	45%	55%
1	35%	65%

- Second, the magnitude of the price in- or decrease will be determined. Prices either change by \$1, \$3, or \$5 with the same probability. Again, the magnitude of price changes is completely independent.

In other words, price changes do not depend on your or others' trading decisions. Instead, they follow a random process.

Trading

On the next screen, you will see a trading interface that will look similar to this:

[Trading interface adopted according to experimental condition]

At the top of the page, the current trading period will be displayed. Remember, you cannot trade during the first three periods. The bar below shows how much of your total assets you currently hold in cash and in shares. No interest will be paid on the amount you hold in cash.

The graph entitled "Share prices" displays the historic price development of all shares (A-F). Using your mouse cursor, you can investigate these developments in more detail.

Buying shares

Lastly, you will see a row for each share. If you click on the "buy" button, you will receive one of the respective shares and its current price will be deducted from your cash balance. You cannot buy any shares if you do not have the appropriate cash balance — i.e., borrowing money is not possible in this experiment.

Selling shares

If you click on “sell,” you will sell one share at the current price and the proceedings will be added to your cash balance. If the current price is above (below) the weighted average purchase price, the sale will be counted as a realized gain (loss). You cannot sell shares you do not own — i.e., short-selling is not allowed in this experiment.

When you are content with all your trading decisions for the current period, you can click on the “Next period” button to receive new prices. In period 14, the button’s label will change to “Continue.” If you click on it you will be redirected to a short questionnaire.

Goal

[Control Condition]:

The goal of this experiment is to invest in the shares such that you maximize your wealth over the 14 trading periods. Remember, your compensation will depend on your performance in the experiment as well.

[Goal Condition]:

Please imagine that your goal is to invest in the shares such that you reach your investment goal of at least \$11,000 by the end of the 14th period. Remember, your compensation will depend on your performance in the experiment as well.

[Graph Condition]:

The goal of this experiment is to invest in the shares such that you maximize your wealth over the 14 trading periods. Remember, your compensation will depend on your performance in the experiment as well.

[Goal & Graph Condition]:

Please imagine that your goal is to invest in the shares such that you reach your investment goal of at least \$11,000 by the end of the 14th period. Remember, your compensation will depend on your performance in the experiment as well.

B.4 Questionnaire

[Part 1]



Question 1

Please evaluate the following statements:

	1	2	3	4	5
How do you assess your investment knowledge? (1 = I have very small knowledge; 5 = I have a lot of knowledge)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Please evaluate to what extent you have already gained investment experience (1 = I am very inexperienced; 5 = I am very experienced)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I know a lot about investing money (1 = I fully disagree; 5 = I fully agree)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I am very inexperienced in investing money (1 = I fully agree; 5 = I fully disagree)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

Question 2

Suppose you had \$100 in a savings account and the interest rate was 2 percent per year. After 5 years, how much do you think you would have in the account if you left the money to grow:

- more than \$102
- exactly \$102
- do not know
- less than \$102
- refuse to answer

Imagine that the interest rate on your savings account was 1 percent per year and inflation was 2 percent per year. After 1 year, would you be able to buy:

- refuse to answer
- do not know
- exactly the same as today with the money in this account
- less than today with the money in this account
- more than today with the money in this account

Do you think that the following statement is true or false?

"Buying a single company stock usually provides a safer return than a stock mutual fund."

- false
- do not know
- true

Figure B.3: Screenshot of the questionnaire that succeeded the experiment (Part 1 of 2)

[Part 2]

Question 3

How do you feel about yourself right now?

extremely negatively extremely positively

Question 4

Please state on a scale between 1 (no rejoice) and 10 (strong rejoice) how much rejoice you felt when you owned shares which had increased in value compared to the previous period.

no rejoice strong rejoice

Please state on a scale between 1 (no regret) and 10 (strong regret) how much regret you felt when you owned shares which had decreased in value compared to the previous period.

no regret strong regret

In my personal life, investments are personally relevant to me.

strongly disagree strongly agree

Question 5

Please select your gender

female

male

Please state your current age in years:

Why did you choose to participate in this experiment?

Please use the slider below to indicate your motivation for participation in this experiment.

money fun/leisure

The goal I was provided with at the start of the experiment was to...

maximize my wealth.

accumulate \$10,000 by the end of the 14th trading period.

accumulate \$11,000 by the end of the 14th trading period.

none of the above.

Figure B.4: Screenshot of the questionnaire that succeeded the experiment (Part 2 of 2)

Appendix C

Appendix to Chapter 3

C.1 Instructions

[Page 1]

Welcome!

About this experiment

Welcome to this experiment about stock market decision-making. If you decide to participate, you will find detailed instructions on the next screen. At the end of the experiment, you will also be asked to answer a few questions. Please answer all questions truthfully — there is no right or wrong answer. Your MTurk survey code will be shown on the second page of the questionnaire.

Compensation

Your compensation will depend on the quality of decisions you make during the experiment. It is your task to make buying and selling decisions such that you maximize your total assets by the end of the experiment. You will start the experiment with \$350 in experimental currency to invest.

At the end of the experiment, your payoff will amount to \$2.00 plus 1% of the your total assets. I.e., if your total final assets amount to \$350, you will receive a flat fee of \$2.00 plus \$3.50. Hence, you would receive \$5.50 in total.

Thank you for your participation!

[Page 2]

Instructions

Description

This experiment consists of 100 periods. At the start of the experiment, you will be endowed with \$350 in experimental currency. You will have the possibility to trade three distinct stocks (A-C) starting in period 9. In periods 0 to 8, you are asked to observe prices — but you cannot trade any stocks yet. In period 0, you must buy one unit of each stock for a price of \$100, leaving you with \$50 in cash.

Market design

In each period, you will be shown two distinct screens: a price update and a trading screen. First, a random stock will be picked on the price update screen and you will be provided with information on how its price has changed (the price change dynamics will be explained below). This screen will be displayed for three seconds only. Next, another stock will be randomly selected (this could but does not have to be the same stock as before) and you will be asked if you want to buy the stock, sell the stock, or do nothing.

At any point in time, you can own up to one unit of each stock. Short-selling is not allowed, while your cash balance can be negative. Notice, however, that a negative cash balance will decrease your total assets and thereby negatively affect your compensation at the end of the experiment.

Stock price development

Each stock can either be in a good or a bad state (note that this state can be different for all stocks). In the good state, the stock's price increases with 55% probability and decreases with 45% probability. In the bad state, however, its price increases with only 45% probability and decreases with 55% probability. At the beginning of the experiment, each stock is randomly allocated to the good or bad state with equal probability. The stock price changes are summarized in the table below:

Probability	Good state	Bad state
Price increase	55%	45%
Price decrease	45%	55%

If the price increases, it can increase by \$5, \$10, or \$15, with equal probability. If the price decreases, it can decrease by - \$5, - \$10, or - \$15, also with equal probability. After the price change has been calculated, it will be determined whether a stock will stay in the good (bad) state or switch to the bad (good) state. With 80% probability the state will stay the same, with 20% probability it will change for the next period. The table below summarizes these probabilities:

State	Good tomorrow	Bad tomorrow
Good today	80%	20%
Bad today	20%	80%

Trading

On the next screen, you will see a trading interface that will look similar to this:

[Screenshot of the trading interface, see Appendix C.2]

At the top of the screen, the current trading period will be displayed. Remember, you cannot trade during the first 8 periods. You will also be shown the current and historic prices in a chart on the top left-hand side and the value and quantity you currently hold in each of the stocks or in cash on the right-hand side.

Goal

The goal of this experiment is to invest in the shares such that you maximize your total assets over the 100 trading periods. Remember, your compensation will depend on your performance in the experiment as well.

C.2 Trading Interface Screenshots



Figure C.1: Screenshot of the initial trading interface in period 0

Note: This screenshot depicts the initial trading interface in period 0. All subjects are asked to buy one unit of each stock (A, B, and C) for \$100 before they can proceed.

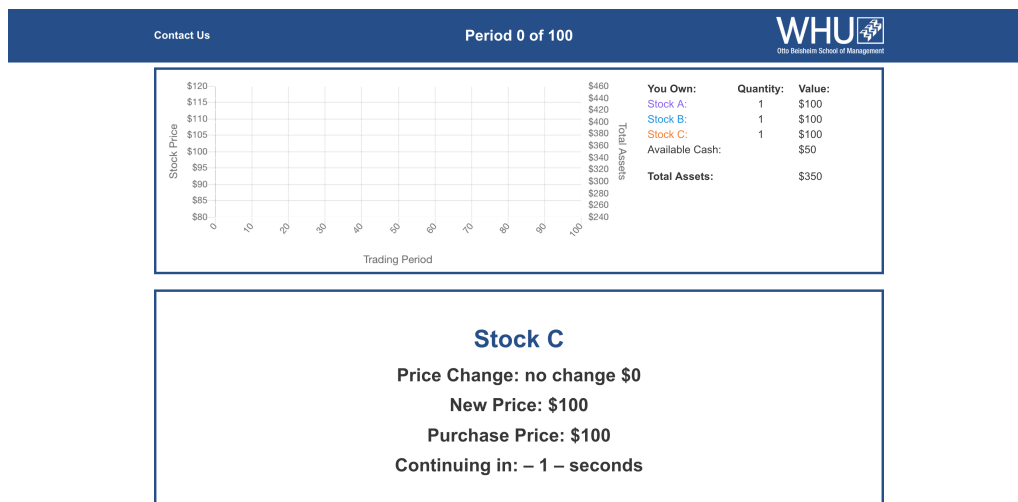


Figure C.2: Screenshot of the price update interface

Note: This screenshot shows the price update screen, which was always shown for three seconds. It shows the randomly picked stock (in this case, stock C), the price change, new price and, if the subject currently owns the selected stock, its purchase price.

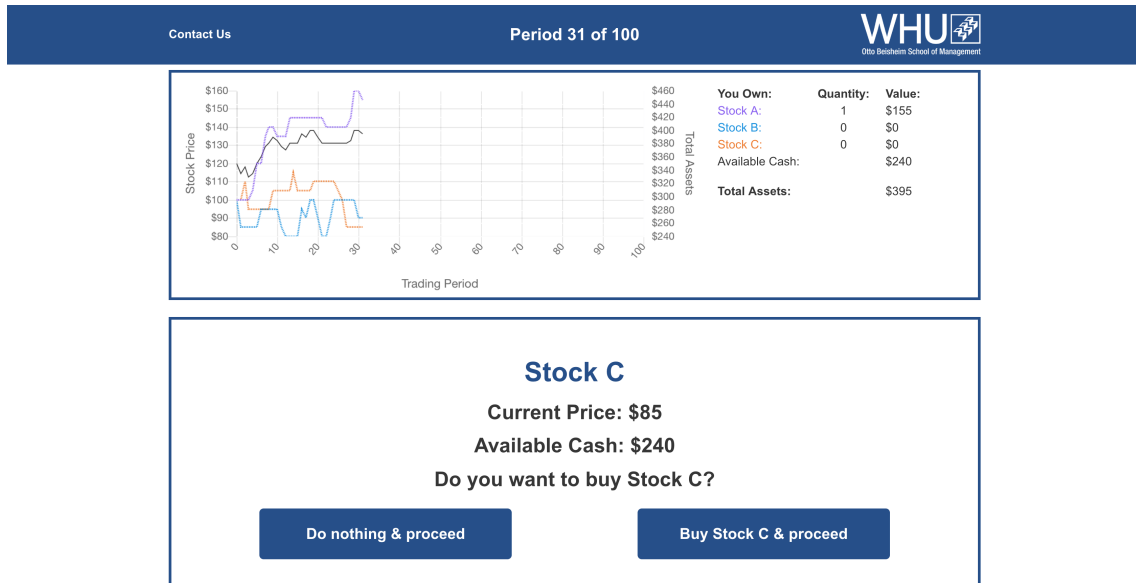


Figure C.3: Screenshot of the trading interface

Note: This screenshot displays the trading interface. It shows the randomly selected stock (in this case, stock C), its current price and the subject's available cash. Because the subject currently does not own the selected stock, they can either buy stock C or do nothing and proceed to the next price update screen. The subject's current holdings are displayed in the top right-hand corner. On the left, a graph is shown that displays the historic price development of all three stocks, as well as the development of total assets over time.

C.3 Questionnaire

[Part 1]



Please answer all questions on this page truthfully and remember that there is no right or wrong answer. You will receive your MTurk survey code on the next page.

Question 1

Please evaluate the following statements:

	1	2	3	4	5
How do you assess your investment knowledge? (1 = I have very small knowledge; 5 = I have a lot of knowledge)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Please evaluate to what extent you have already gained investment experience (1 = I am very inexperienced; 5 = I am very experienced)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I know a lot about investing money (1 = I fully disagree; 5 = I fully agree)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I am very inexperienced in investing money (1 = I fully agree; 5 = I fully disagree)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

Question 2

Suppose you had \$100 in a savings account and the interest rate was 2 percent per year. After 5 years, how much do you think you would have in the account if you left the money to grow:

refuse to answer

do not know

exactly \$102

less than \$102

more than \$102

Imagine that the interest rate on your savings account was 1 percent per year and inflation was 2 percent per year. After 1 year, would you be able to buy:

exactly the same as today with the money in this account

do not know

less than today with the money in this account

more than today with the money in this account

refuse to answer

Do you think that the following statement is true or false?

"Buying a single company stock usually provides a safer return than a stock mutual fund."

true

do not know

false

Figure C.4: Screenshot of the questionnaire that succeeded the experiment (Part 1 of 4)

[Part 2]

Question 3

Please state your accordance with each of the statements below from (1) "absolutely" to (5) "absolutely not":

	(1) absolutely	(2)	(3)	(4)	(5) absolutely not
Special offers can entice me into buying.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I do not complain very often, even if I have reason to do so.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I feel annoyed when things don't go my way.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I get unsure by the lingo of financial experts.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I find it hard not to have some money away for a rainy day.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I am anxious about financial and money affairs.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I like to join conversations about financial matters.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I enjoy reading about the results of product comparisons.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
After making a decision, I am anxious about financial and money affairs.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I read the business section of the newspaper attentively.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
	(1) absolutely	(2)	(3)	(4)	(5) absolutely not
I spend money when I am unhappy or frustrated.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I compare and calculate risks.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
To care for the future is essential for me.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Even on large purchases, I tend to spend spontaneously.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I tend to postpone financial decisions.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
At the end of the day, I decide intuitively in financial affairs.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I enjoy spending money more than saving.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

Question 4

How do you feel about yourself right now?

extremely negatively extremely positively

Figure C.5: Screenshot of the questionnaire that succeeded the experiment (Part 2 of 4)

[Part 3]

Question 5

Please state on a scale between 1 (no rejoice) and 10 (strong rejoice) how much rejoice you felt when you owned shares which had increased in value compared to the previous period.

no rejoice strong rejoice

Please state on a scale between 1 (no regret) and 10 (strong regret) how much regret you felt when you owned shares which had decreased in value compared to the previous period.

no regret strong regret

In my personal life, investments are personally relevant to me.

strongly disagree strongly agree

Question 6

Please select your gender:

- female
- male

Please state your current age in years:

Please select the highest level of education you have completed:

- Secondary school
- Apprenticeship
- High school diploma
- University degree

Figure C.6: Screenshot of the questionnaire that succeeded the experiment (Part 3 of 4)

[Part 4]

Please select the category which best describes your current profession:

- white collar/clearical
- managerial/administrative
- blue collar/craftsman
- services/sales
- professional/technical
- unemployed


Are you currently in possession of stock(s) or stock fund(s)?

- no
- yes

Why did you choose to participate in this experiment?

Please use the slider below to indicate your motivation for participation in this experiment.

money fun/leisure



The magnitude of stock price changes was:

- \$0, \$5, or \$10
- \$5, \$10, or \$15
- \$1, \$5, or \$10
- none of the above.

Figure C.7: Screenshot of the questionnaire that succeeded the experiment (Part 4 of 4)

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