How Market Conditions Shape Investors' Behavior

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Zusammenfassung

Menschliches Verhalten auf Märkten wurde in den Wirtschaftswissenschaften lange Zeit durch die Schablone der Theorie der Effizienten Märkte betrachtet. Folgt man der strengen Auslegung dieser Theorie, verhalten sich Anleger auf Finanzmärkten grundsätzlich rational: Sie kalkulieren ein, dass alle relevanten Informationen im Marktpreis eines Vermögensgegenstandes bereits enthalten sind. Informationen zur vergangenen Entwicklung eines Marktes haben dementsprechend keinen Bezug zum zukünftigen Marktpreis. Die durch Finanzmarktblasen und ihr Platzen geprägte Aktienmarktentwicklung der letzten Jahrzehnte stellt allerdings in Frage, ob die vorausgesetzte rationale Erwartungsbildung der Anleger jederzeit erfüllt ist oder ob Anleger entgegen der Theorie Informationen aus der Vergangenheit in ihre Investitionsentscheidungen miteinbeziehen (z.B. als Trendfolger).

Meine vorliegende Dissertation ist dementsprechend durch die Fragestellung motiviert, welchen Einfluss die vorhandenen Marktbedingungen auf das Verhalten von Aktienmarkt-Investoren haben. Um diese Ausgangsfrage eingehend zu beantworten, beleuchten wir das Verhalten der Marktteilnehmer in Bezug auf das Aktienmarktumfeld anhand von 4 Kapiteln.

Im einleitenden Teil der Arbeit beschreibe ich die Schwierigkeiten der Theorie der Effizienten Märkte, scheinbar irrationales Verhalten von Anlegern vor dem Hintergrund eines sich wandelnden Marktumfeldes zu erklären. Um die Entscheidungsprozesse der Anleger dennoch nachvollziehen zu können, greifen wir auf die Verhaltensökonomie als alternativen Erklärungsansatz zurück.

Im zweiten Kapitel zeigen meine Kollegen und ich, dass Investoren in der Tat das zurückliegende Marktumfeld in ihre Anlageentscheidungen miteinbeziehen. Wir ermitteln, wie Gewinn- und Verlustmuster der vergangenen Tage die

Investitionsentscheidungen privater Aktienmarktanleger beeinflussen. Zwei markante Verhaltensmuster können wir auf dem betrachteten Markt feststellen: Zum einen lösen Aktienmarktmuster, die sich aus mehrheitlich positiven Tagen zusammensetzen, signifikant mehr Käufe und Verkäufe aus als Aktienmarktmuster mit mehrheitlich negativen Tagen. Zum anderen verkaufen Anleger nach mehrtägigen Aufwärtsbewegungen anteilig mehr Aktien als sie kaufen. Diese Ergebnisse widersprechen allerdings der Annahme effizienter Märkte, der zufolge Anleger vergangene Kursbewegungen nicht in ihre Entscheidungen miteinbeziehen. Um die Beobachtungen zu erklären, teilen wir die privaten Investoren in Aktienhalter (potentielle Verkäufer) und Aktieninteressenten (potentielle Käufer) ein. Wir nehmen an, dass beide Gruppen grundsätzlich unterschiedliche Bindungen sowie gegensätzliche Einschätzungen gegenüber den jeweiligen Aktien haben. Diese voneinander abweichende Wahrnehmung der Aktien wird durch unterschiedliche Muster am Aktienmarkt verstärkt und führt durch das daraus resultierende unterschiedliche Timing von Transaktionen zu den beobachteten Verhaltensweisen.

Um das beobachtete Verhalten einzuordnen, nutzen wir Ansätze aus der Verhaltensökonomie. Im 3. Teil der Arbeit zeigen wir, wie durch das Marktumfeld ausgelöste Emotionen das Erregungsniveau von Anleger steuern und damit deren Risikoneigung bei Anlageentscheidungen beeinflussen können. Wir entwickeln einen theoretischen Rahmen, der die im Investmentprozess vorhandenen Auslöser von Emotionen, wie die Entwicklung eigener Aktien und die allgemeine Aktienmarktumgebung, mit dem Risikoappetit von Anlegern verbindet. Unser Modell prognostiziert, dass Anleger mit einem hohen emotionalen Erregungslevel Aktien länger halten und damit höhere Risiken akzeptieren als weniger erregte Anleger. Besondere Bedeutung für die Entstehung emotionaler Erregung hat dabei die Entwicklung der unterschiedlichen Komponenten der Aktienmarktumgebung. Wir zeigen, dass bei paralleler Entwicklung des eigenen Portfolios und des allgemeinen Aktienmarkts starke Emotionen ausgelöst werden, die selbst dominante Verhaltensmuster wie den Dispositionseffekt auflösen können.

Allerdings sind Anleger den Marktbedingungen und daraus resultierenden Emotionen nicht hilflos ausgesetzt. Der 4. Teil der Dissertation zeigt, wie das Marktumfeld zwar das Investitionsverhalten beeinflusst, wie es Anlegern aber auch gelingt, durch Lernprozesse nachteilige Verhaltensweisen wie den Dispositionseffekt zu vermeiden − und zwar ebenfalls in Abhängigkeit vom Marktumfeld. So weisen wir nach, dass Investoren sowohl in Bullen- als auch in Bärenmärkten dem Dispositionseffekt unterliegen, dass diese Abweichung vom rationalen Verhalten aber während der Bärenmärkte wesentlich stärker ausgeprägt ist. Allerdings können wir während dieser Abschwungphasen auch die größten Lernerfolge bei Anlegern beobachten. Gründe für den schnelleren Lernerfolg in Bärenmärkten können sowohl die stärker negativen Auswirkungen des Dispositionseffektes als auch die schnellere finanzielle Rückkoppelung während dieser volatileren Phasen sein.

Damit zeigt auch dieses Ergebnis, dass die zurückliegende Marktentwicklung bei der Untersuchung des Anlegerverhaltens berücksichtigt werden sollte. Allerdings, und auch das ist ein Ergebnis der vorliegenden Arbeit, sind Anleger nicht nur Spielball dieser Marktbedingungen. Durch das Erlernen emotionaler Selbstkontrolle in schwierigen Marktphasen können sich Investoren ein Stück weit emotional unabhängig von der Marktentwicklung machen.

Stichwörter: Verhaltensökonomie, Bullen- und Bärenmärkte, Kapitalmarktentwicklung, Dispositionseffekt, Emotionen, Aktienmarktmuster, Lernverhalten, Entscheidungen am Finanzmarkt

Executive Summary

Human behavior in regard to financial issues has long been explained in the light of the efficient market hypothesis. Following the strict interpretation of this theory, investors in the financial markets act generally in a rational manner and take into account that all relevant information is already included in the market price of an asset. Accordingly, information from the past or the present does not affect future prices as all information is instantly incorporated. However, the reality looks somewhat different: the stock market performance of recent decades is characterized by the formation of financial market bubbles and their subsequent bursts. This development questions whether investors take the immediate reflection of all information in a market price for granted, as predicted by the efficient market hypothesis, or whether investors do consider the past market development (i.e. by following market trends) in their investment decisions.

My dissertation is therefore motivated by the question of how the existing market conditions may influence the behavior of stock market investors. To focus on the different perspectives of this question, I divide this work in four chapters, each of them dealing with another aspect of investors' behavior in regard to the market environment.

In the introductory chapter, I describe the difficulties of the efficient markets hypothesis in explaining the behavior of investors within a strictly rational frame. As an alternative to this approach, I exploit behavioral finance with its consideration of the diverse emotional constraints in the decision-making processes of market participants.

In Chapter 2, my colleagues and I show that investors actually do consider the previous market development for their upcoming investment decisions. We find two

striking trading patterns in the buy and sell behavior. First, stock market patterns with predominantly positive days trigger significantly more trades than patterns with negative days. Second, after recent upward movements, investors sell proportionally more stocks than they buy. These differences are robust after controlling for the amount of returns and thus only depend on the up-down pattern of the previous days. However, these findings contradict the assumption of efficient markets that investors do not include past price movements into their decisions. To explain these observations simultaneously, we divide traders into holders (i.e., potential sellers) and sideliners (i.e., potential buyers). We assume that both groups naturally have different levels of commitment, as well as contrary perceptions towards their respective shares, which significantly frame their transactional processes. Different frames are induced by different up-down constellations, leading to different timings of the trading decisions and finally to the observed trading patterns.

Behavioral finance with its consideration of emotions offers an alternative way to explain the deviations from the predicted rational investment behavior. In the third chapter, we offer an explanation for the consideration of the market environment by investors. We show how emotions, triggered by market related factors, are able to direct investors' levels of arousal and thereby can influence their risk appetites. We expound a theoretical framework that connects investment-related triggers of arousal, such as the performance of own stocks and the general market environment, with investors' risk appetite in the decision-making processes. Our model predicts that aroused investors accept higher risks by holding stocks longer in comparison to their less aroused peers. Our empirical results confirm a strong link between the arousing development of homogenously trending market determinants and an increased acceptance of risks.

Nevertheless, investors are not helplessly exposed to these market conditions and the resulting emotions. In the fourth chapter of this dissertation, we show how two extreme market environments, the bull and the bear market, affect the disposition effect and especially learning to avoid this behavioral bias. Our findings indicate that investors compare the current asset price with prices from the past and therefore are inclined to exhibit the disposition effect. They are subject to the bias in each market phase but with a far stronger propensity during the bear market. However, we show that investors also make the greatest progress in avoiding the disposition effect during this period. We attribute these improved learning results to the prompter feedback received during bear markets and the harsher financial consequences of the disposition effect at such times. The learning achievements identified can mainly be traced back to “learning by doing” and less to “learning about ability”. These results again suggest that future studies about investors’ behavior in the financial markets should consider the previous market environment as an important determinant. However, and this is also shown by the present work, investors are not merely the plaything of the different market conditions but are able to make themselves emotionally independent from market turmoil through the awareness of potential problems and the enhancement of emotional coping strategies.

Keywords: behavioral finance, bull and bear market conditions, disposition effect, market environment, emotions, stock market patterns, learning, decision-making in financial markets

Chapter 1

Introduction

1.1. The limitation of the efficient market hypothesis

Until two decades ago, the principle of efficient markets was widely accepted in economics. Supported by Fama's (1970) influential work, the rational, value-maximizing investor who operates in efficient capital markets became the starting point of almost any economic analysis. In these efficient markets, security prices reflect all available information − almost immediately and in an unbiased fashion. Information flows unimpeded and free of costs between all market participants in these model-like markets. All available information is immediately incorporated into the prices of securities. Thus, market participants take into account that they cannot achieve higher risk-adjusted returns than the overall market in the long term by using any available information. Accordingly, these investors use neither technical analysis, which is the study of past market prices, nor fundamental analysis, which is the evaluation of corporate key figures, to beat the market (Malkiel 2003). Over- and undervaluation of stocks does not exist either. Under these conditions, asset prices are not predictable but are subject to a random sequence of changes. This price trend, known as random walk, describes a sequence of random departures from previous price levels. Consequently, today's information is crucial only for today's pricing. For tomorrow's pricing, only the − unpredictable − news of tomorrow is of importance.

However, the stock market development of recent decades, with its investment bubbles and the subsequent bursting of these bubbles, has presented major challenges to the economics profession. This highly volatile stock market development does not indicate that a majority of investors forms rational expectations about the future development of stock prices (Shiller 2003), as predicted by the efficient market hypotheses. Indeed, it seems that investors systematically question the random walk of stock prices by using different sources of information to beat the market. One of these potential sources of information might be the past performance of stocks. Following the assumptions of the efficient market hypothesis, investors cannot realize an outperformance by evaluating the course of the price, as this information is easily observable by anyone and thus already incorporated into the price. However, if market participants with "irrational" expectation formation try to use information from a past pattern of the stock market development, their action should be counterbalanced by "rational" investors. Following the efficient market hypothesis, the majority of rational investors would take advantage of the fallacy and thus make the market efficient again in the sense that it reflects all information in an unbiased fashion. Investors behaving in an irrational and thus costly way should therefore sooner or later run out of funds and leave the market.

1.2. The introduction of the market environment as an important determinant of investors' behavior

In this dissertation, I aim to shed light on the impact that past stock market developments have on investors' decision-making processes. Following this introduction, I present three chapters on the relationship between distinct stock market environments and investors' trading decisions in respect to these environments.

In order to analyze the impact of the previous market development, we examine in the second chapter how past stock market prices affect the buy and sell decisions of private investors[1]. We focus on the last days before investors buy or sell a stock. Our main concern is the sequence of the daily stock development, i.e. whether a pattern consists of mostly positive or mostly negative days, or whether a pattern misses a clear trend. The efficient market hypothesis predicts that the reactions of investors should be independent in regard to the distinct day patterns. Thus, investors should buy and sell the same number of stocks, no matter what kind of past stock price pattern they are facing. However, our findings show a different picture, with investors adapting their sell and buy decisions in accordance to the preceding stock market environment. We find evidence that stock market patterns with

[1] This chapter is based on Muhl et al. (2017).

predominantly positive days trigger significantly more trades than patterns with negative days. Such an outcome is a violation of the efficient market hypothesis and raises the question of the importance of other factors in investors' decision-making processes.

To explain this deviation from the efficient market hypothesis, we analyze the motives of investors for their different reactions in regard to distinct market developments. We present our results in the third chapter[2]. Following the efficient market hypothesis, a majority of investors is considered as rational market participants. In this theory, irrational behavior is a marginal phenomenon that occurs only to a minority of investors. And these irrationally acting investors will leave the market in the long run due to a lack of success. The fact that bubbles occur time and again contradicts the supposed short-term self-regulation of efficient markets. A pivotal role in these market exaggerations is attributed to emotions − a term that was often described in the economic literature as a natural counterpart of rationality and which had no place in the efficient markets. However, emotions are ubiquitous and researchers recently noticed their importance, also in the financial markets (Fenton-O'Creevy et al., 2011; Lo & Repin, 2002; Wu et al., 2012). Following the new stream of research, emotions are an integral part of the everyday life of investors. In the third chapter, we show what role these emotions play in decision-making processes among investors. We introduce the missing theoretical framework that connects market-related emotional arousal with the risk taken by investors. This emotional arousal is triggered by the performance of own stocks and the general market environment, two factors that are strongly related to the past. Both factors individually have the potential to trigger emotions. Our empirical findings show, however, that the combined effects of both factors lead to the strongest emotions. Thus, we demonstrate that it is not only the latest news that is incorporated into the stock prices but also past stock (market) movements and their resulting emotions.

[2] This chapter is based on Muhl et al. (2018).

As highlighted in Chapter 3, in addition to the total stock market environment, the development of the own portfolio plays an important role for the decision-making process of investors. When looking at own shares, investors do not only base their evaluation of the stock on newly available information but often also on a comparison with a historical reference value. Following Shefrin & Statman (1985), this reference value is frequently the purchase price of the stock held. In Chapter 4, we show that this implicit comparison with a reference value from the past is able to trigger the disposition effect[3]. We also demonstrate how this behavioral bias is getting stronger or weaker in regard to the overall market environment. We focus on two extreme stock market environments − the bull and the bear market. While investors are continually prone to the disposition effect, the bull or bear market environment determines to which extent investors are inclined to this behavioral bias. However, investors are not entirely at the mercy of the stock market (and the portfolio) developments but have the ability to learn and thus to avoid certain harmful behavioral patterns. In Chapter 4, we also examine whether investors make learning advances and whether certain capital market developments facilitate these improvements. Our results confirm that although market participants show the strongest disposition effect during bear markets, their learning progress is also highly pronounced during these depreciating market phases. We attribute these stronger learning results to the higher financial pressure taking place during this market environment.

Altogether, the three following chapters confirm that investors incorporate information from past stock movements into their investment decisions. Investors gather information from the course of the general stock market development as well as information from the performance of their own portfolio. Both sources of information are not interpreted independently of each other but are considered together. One key mechanism to translate these different kinds of information is emotions. We assume that it is frequently the emotional reaction to a market or

[3] This chapter is based on Muhl and Talpsepp (2017).

portfolio movement that makes this information relevant for investors. In the case of the disposition effect, the emotional response on such a backward-looking investment behavior is often not beneficial for investors. However, our findings also show that this disadvantageous investment behavior is no natural law, as investors are capable of learning through the accumulation of experience. Through the process of learning, investors are able to improve their regulation of emotions − even with regard to past market movements. This shows that strict rationality, especially in dealing with financial issues, is by no means innate. However, it also implies that investors are not the plaything of the markets if they are able to mobilize the necessary resources to learn to avoid costly behavioral biases. Thus, investors are not born as the often idealized Homo Economicus but have (at least partially) the chance to develop their trading skills by steady experience as well as by hurtful incidents.

Chapter 2

Two Sides of Different Coins:

Stock Movement Based Trading Decisions of Small Private Investors

2.1. Introduction

Imagine the following investment situation: you want to buy a certain stock, but you would like to time your purchase well. So you wait a few days to see how the stock price moves. How would you react if your observed stock loses three days in a row? Maybe you would like to wait a little bit longer since you currently feel somewhat insecure about your purchase decision? Or how would you react if the same stock went up for three days in a row? Now, maybe you would buy that stock immediately to avoid missing the trend entirely?

These kinds of decision-making processes, which rely on the daily data of stock movements, seem very natural for private investors. However, the effect of up-down patterns on purchasing and selling decisions has not been, to the best of our knowledge, studied in the literature thus far. Even though previous research found empirical evidence that investors react to past returns, the extent to which daily stock market patterns have an impact on investors’ decisions has been largely neglected. This lack of research is all the more surprising as most investors are constantly confronted with the information of past market patterns. For instance, the short article from the local newspaper regarding whether the stock market yesterday had its fourth day of losses this week or the illustration of the recent market development through charts on various internet pages are only two examples of the omnipresence of past market movements. The frequent presence of these describing or visual references to recent developments suggests that investors derive benefit from it − considering it as a source of information. This conclusion would coincide with the findings of recent research (among others: Griffin et al., 2007; Mussweiler and Schneller, 2003) but contrasts sharply with the standard economic theory, which does not attach any importance to the past.

It seems that investors widely use information from past developments but interpret them in different ways. In order to understand why some private investors are buying stocks, while, at the same time, other investors are selling these stocks, it is important to comprehend the motivation of these investors for their respective transactions. Current research offers only insufficient explanations of this behavior. To fill this gap, we examine how small private investors change their buy and their sell behavior in regard to short term market up and downswings. In doing so, we rely on daily up-down patterns, which include the latest days before a transaction takes place. We believe that these last days before a trade is executed are important, as many investors do not trade stocks spontaneously, but rather pre-choose a potential stock and observe it for a certain time to pick an appropriate moment for trade execution.

Our results support existing findings that small private investors react to the stock market development by adjusting their trading behavior. However, our results differ from previous research in two points. First, the more a pattern consists of positive days and the less this pattern is interrupted by negative days, the more investors trade − which is true for purchases and for sales. In the case of predominately rising market patterns, this means that more investment decisions are triggered. This implies that a rising number of small private investors considers the stock price to be attractive (buyers), while, at the same time, a rising number of investors evaluates it as expensive (sellers). And second, although both the purchases and sales of small private investors are increasing, we find that they do not rise by the same level. While small private investors tend to sell relatively more stocks than they buy after positive market patterns, they purchase relatively more stocks following negative patterns. This behavior remains when we control for stock splits or different time periods.

Existing theories have severe difficulties in explaining this link between market patterns and trade volume in combination with the imbalanced transaction ratio. To solve this puzzle, we introduce an approach that does not require the same decision-making process for all investors, but rather places emphasis on the different perspectives on the buy and sell side of trading. We explain the contrary behavior of both sides with an asymmetric evaluation of the same market pattern. Due to the naturally diverging perceptions of a stock, investors' decisions are shaped by distinct framings. While buyers seek to own a stock and thus typically attribute a positive potential to it, sellers are in general willing to sell their stock and therefore attribute a rather low potential to it. The result of this positive (negative) framing is the interpretation of the stock market pattern from the respective perspective. These contrary views reinforce distinct behavioral mechanisms when purchasing and selling stocks. The stock-related framing strengthens (attenuates) the trading-related confidence, which leads to a rising (decreasing) trading activity on the buy and on the sell side.

This dichotomy of mindsets limits and also supplements the results of Barber and Odean (2008b), who found that private investors are net buyers following positive and negative one-day market shocks − which they attribute to private investors' tendency to attention-grabbing. In contrast, our results show that stock market patterns, which cover several days, do not necessarily trigger attention-induced trading, but rather a framed behavior that depends on the self-attribution as buyer or seller. Thereby, our study provides an important component in understanding the trading behavior of small private investors in regard to stock market situations that do not trigger attention-based behavior.

This paper is organized as follows: in the next section, we review the empirical findings of the relationship between the past stock market development and a possible change in trading volume, as well as its underlying theoretical explanations. In Section 2.3, we describe our data set and the methodology we employ. We report our empirical results in Section 2.4 and discuss them in Section 2.5. In Section 2.6, we conclude.

2.2. Current state of research

Standard economic theory suggests that prices at financial markets follow no specific pattern but rather develop in a random way. In his efficient market theory, Fama

(1965) described the successive changes of prices as independent, identically distributed random variables. As prices have no memory, investors cannot use past quotations to predict the future in any meaningful way. Rational actors − and in the economic standard theory, stock market investors are seen as such − do not need to take past prices into account.

This standard theory is in contrast to a range of empirical studies of recent years (Andreassen, 1988; Annaert et al., 2013; Nartea et al., 2017; Statman et al., 2006). According to these studies, it seems as if investors are likely to see a link between prices of the past and prices of the future. For instance, Statman et al. (2006) find evidence for a strong, positive correlation between past shocks in market return and market-wide trading activity. They observe a higher trading volume following the months after a bull market. In contrast, bear markets slow down trading activity in the following months considerably. The analysis of 46 global stock markets by Griffin et al. (2007) confirms a strong, positive relation between past market returns and trading volume. Investors increase trading activity significantly several weeks after positive return shocks, especially in developing countries.

However, Gallant et al. (1992) and Chordia et al. (2007) find slightly dissenting results. Both analyses confirm that investors react to long-term changes in market return but report increasing stock trading volume after very strong, as well as very weak, stock market developments. While Chordia et al. (2007) find that volume still increases more strongly following positive market shocks, Gallant et al. (1992) provide evidence for a fairly symmetric effect after price declines and price rises. Barber and Odean (2008) also analyze the reactions of investors after strong market movements but limit their research to notable one-day changes. Their outcome supports the results of Gallant et al. (1992) and Chordia et al. (2007) that investors react similarly to positive and negative stock market shocks even though Barber and Odean (2008b) refer only to the ratio of buy and sell transactions. They find evidence that private investors are net buyers of stocks that experience extreme one-day returns. This applies to stocks with a considerable, positive, as well as with a considerable, negative, development.

As empirical findings differ in regard to the relation between past market development and following transaction patterns, so do the theoretical explanations for this behavior. For Statman et al. (2006) and Glaser and Weber (2009), the main explanation of different reactions to bull and bear markets can be found in the overconfidence theory (see also Odean, 1998b; and Gervais and Odean, 2001). According to this theory, investors are getting more self-confident after strong, positive stock market developments. This translates into an underestimation of the future volatility of stock returns and, as a consequence, investors trade more frequently. Griffin et al. (2007) examine different approaches that try to explain why the return-volume relation is different across countries. The theory that is most consistent with their findings is investors' participation costs, as found by Allen and Gale (1994) and Brennan and Cao (1997).

Barber and Odean (2008) show that individual investors react similarly after positive and after negative one-day shocks, and thus offer another starting point for explaining the behavior following strong stock market changes. They argue that attention-based decision-making has implications on how private investors trade stocks. When choosing stocks, these private investors are confronted with a vast number of possible equities to buy. As alternatives are plentiful and search costs are high, attention-grabbing stocks offer a quick shortcut through this search dilemma. Barber and Odean (2008) argue that stocks which exhibit pronounced one-day shocks are able to catch the attention of private investors. Thus, stocks that show strong one-day gains and losses are more likely to be purchased by private investors the next day than stocks out of the limelight. In contrast, private investors do not face the same search dilemma when selling stocks. Because private investors do typically own only a small subset of all available market stocks, they can choose the stocks to sell in their portfolio by their preferences with only few search costs. The authors show that the simplification attempt of the human brain for purchase transactions and the technical limitation for sell transactions might be the reason for why private investors are net buyers of attention-grabbing stocks after severe one-day shocks.

However, neither the overconfidence theory nor the attention-grabbing are able to explain our results in full. While overconfidence might provide reasons for why private investors are trading more frequently after strongly rising markets, it fails to explain why we see net buying after negative patterns and net selling after positive patterns. The attention-based approach is predicting net buying in both cases with roughly the same number of executed trades for positive, as well as for negative, market patterns and, therefore, is also not able to account for our empirical results.

To solve the puzzle, our study differs from the above-mentioned papers in the following two dimensions: we determine the trading volume for sell and buy transactions, as well as the corresponding imbalance between both kinds of transactions. Measuring the absolute and the relative changes enables us to take a deeper look into the different behaviors of small private investors who purchase and small private investors who sell stocks and thus helps us to derive potential specifics in motivation, commitment and risk evaluation on each side. Most previous studies do not examine the partially inversed behavior of buyers and sellers and implicitly assume identical psychological processes for both investor groups. One paper that perceives the existence of differences between sellers and buyers is Barber and Odean (2008). However, they only acknowledge the existence of technical trading limitations, but fall short to highlight the behavioral issues behind the sell and purchase transactions.

Furthermore, we examine the stock market pattern of the last days before a transaction is released. We believe that many investors do not buy and sell stocks spontaneously, but that they already know some days before a transaction which stock they want to sell or buy. This means they have picked a certain stock and only wait for the right moment to start the transaction. The seemingly right moment could be indicated by a certain up-down pattern. This sustained decision-making process, which probably lasts for several days, contrasts the view of Barber and Odean (2008), who limit their research to very significant changes at the last day before a transaction occurs. Their perspective of the investment decision neglects any timing aspect of trading and emphasizes only the selection issue. An additional advantage of day-to-day patterns might be the incorporation of further information into the decision-making process − at least in the eyes of small private investors. Barber and Odean (2008) focus only on the latest stock market development, which might consider the most prominent day in private investors' minds, but misses to cover the short-term trend. For example, a one-day gain of 1.5 percent might not be particularly remarkable for investors; however, four days in a row with 1.5 percent gains might arouse a more distinct interest. Thus, our work combines the examination of multi-day market patterns and the buy-sell trading-contrast in order to obtain a full understanding of the trading behavior of small private market participants.

2.3. Data set and methodology

Our analysis is based on a data set provided by the Taiwan Stock Exchange (TWSE). It covers all orders submitted to the TWSE from January 2001 to December 2006. During this time, roughly 4.7 billion stocks had changed ownership. The huge number of transactions allows us to draw reliable conclusions regarding the trading patterns of investors.

The available data include the aggregated number of bought and sold stocks for each day during the above-mentioned period, and can be divided into three subgroups of market participants. We are able to analyze the number of traded stocks for institutional investors as well as for small and large private investors. According to the numbers provided by the TWSE, around 20 percent of the exchanged stocks are traded by institutional investors. Of the remaining 80 percent, 15 percentage points of stocks are traded by large private investors who have an annual trading volume of more than 20 million US-Dollar. With such a high turnover, we believe this subgroup of affluent investors is more probably seeking professional financial assistance and is more likely to have better access to valuable information than other private investors. Our focus is thus on the small and medium size private investors (hereinafter referred to as small private investors in contrast to large private investors) that account for roughly 65 percent of all stocks traded. We believe that this group of investors has most probably less professional advice than their institutional and large private counterparts. Also, the access to stock market related information is more limited in this investor subgroup due to financial and time restrictions.

Our analysis considers only transactions in stocks. Other financial instruments that could be used for hedging or diversification purposes are only taken into account when the underlying stock was traded at the stock exchange.

The TWSE sets the price of the Taiwan Capitalization Weighted Stock Index (TAIEX), which covers nearly all of the stocks traded in Taiwan. Over the covered period of six years, the TAIEX realized a positive average annual return of nearly eight percent. Despite this relatively moderate annual return, the Taiwanese stock market index was subject to large price changes during this period, with a low of 3,446 points and a high of 7,824 points. This changing environment provides additional explanatory power to the results of our analysis, as we are able to take investors' behavior during different market conditions into account.

We use the TAIEX as a benchmark for the general development of Taiwanese stocks. As it represents the average development of all Taiwanese stocks, the TAIEX could serve as a proxy for the average development of individual stocks. When stating a positive or negative day at the stock market, we are referring to the TAIEX closing price of a certain trading day in comparison to the closing price of the previous trading day. For calculating the average number of buy and sell transactions in regards to a certain pattern, we set t_0 as trade execution day. The days before t_0 form the stock market pattern for which we examine the impact on the number of traded stocks at t_0. We focus in this paper on the effect that the price movement of the most recent days (t_{-1} to t_{-3}) has on small private investors' decisions at t_0. We do not consider the stock market information of t_0, as the number of buy and sell decisions on this day affects the stock prices on the very same day.

To determine a potential transaction imbalance, we use three-day patterns. For each pattern, we calculate the imbalance as:

$$TI_p = \frac{\frac{\sum_{i=1}^{k_p} B_i}{n_p}}{\sum_{p=1}^{f} \frac{\sum_{i=1}^{k_p} B_i}{n_p}} - \frac{\frac{\sum_{i=1}^{k_p} S_i}{n_p}}{\sum_{p=1}^{f} \frac{\sum_{i=1}^{k_p} S_i}{n_p}}$$

where k_p is the number of different stocks that could be traded after pattern p, B_i is the number of purchases of stock i one day after pattern p ends, S_i is the number of sales of stock i one day after pattern p ends, n_p is the number of times a certain pattern occurs and f is the number of different patterns. For each pattern, we calculate the share of buy and the share of sell transactions that are executed the day after the pattern. These pattern-specific buy and sell ratios cover all trades over the whole period of six years. To identify pattern-dependent transaction imbalances (TI_p), we subtract the share of sold stocks after pattern p from the share of bought stocks after the very same pattern. If small private investors buy more stocks than they sell after a certain pattern, we get a positive transaction imbalance. In case small private investors are inclined to sell more stocks, we get a negative transaction imbalance.

2.4. Results

In the following, we examine the reaction of Taiwanese small private investors to past day-to-day market movements. First, we focus on the relation between different patterns and their effects on the frequency of trading. In a subsequent step, we examine the transaction imbalance after different types of market patterns. Finally, we test the robustness of our results for different time periods and for stock splits.

2.4.1. The impact of stock market patterns on trading activity

If investors react to past market patterns, this is likely to have an effect on the number of trades executed. Our results in Table 2.1 confirm a distinct difference between three-day stock market patterns with predominantly positive days and three-day patterns with predominantly negative days. While primarily positive days trigger the purchase and sale of more stocks, a sequence of primarily negative days causes fewer transactions.

Table 2.1: Average buy and sell transactions of Taiwanese small private investors after three-day patterns

buy transactions			sell transactions		
three-day pattern	average number of bought shares	frequency of the pattern	three-day pattern	average number of sold shares	frequency of the pattern
+ + +	2,551,156,442	194	+ + +	2,732,066,180	194
+ + -	2,305,278,537	179	- + +	2,339,840,661	179
- + +	2,194,416,351	179	+ + -	2,307,569,030	179
+ - +	2,132,678,201	184	+ - +	2,219,806,024	184
- + -	1,975,771,359	193	- + -	1,938,692,891	193
+ - -	1,963,608,621	188	+ - -	1,870,435,764	188
- - +	1,809,992,962	189	- - +	1,831,091,520	189
- - -	1,754,815,168	180	- - -	1,637,885,028	180

The table presents the average number of bought and sold shares of Taiwanese small private investors after each three-day pattern. The first character indicates a positive (+) or negative (-) whole day development of day t_{-3}, the second character indicates the whole day development for day t_{-2} and the third character indicates the whole day development for day t_{-1}. The table also presents the frequency of these patterns during the period from January 2001 to December 2006.

We see the strongest discrepancy between the patterns of three days with gains (+ + +) and three days with losses (- - -). After the pattern + + + (with the first character indicates a positive (+) or negative (-) whole day development of day t_{-3}, the second for day t_{-2} and the third for day t_{-1}), investors buy, on average, 69 percent and sell 60 percent more stocks compared to after the pattern - - -. After alternating market patterns without a distinct up or downward trend, investors tend to release only an average number of buy and sell transactions as can be seen for the patterns + - + and - + -. Employing the Tukey's range test confirms the significant difference between predominantly positive and negative stock market patterns.

In conclusion, our results indicate that investors are more willing to trade after patterns with predominantly positive days.

2.4.2. The stock market pattern and the transaction imbalance

In the last subsection, we outlined that the stock market pattern of previous days has an impact on the propensity to trade. In general, the more positive days a pattern has, the more small private investors are willing to trade. This applies to the number of bought, as well as for the number of sold, stocks, but does not account for potential differences between the sell and the buy behavior. To test for these differences, we search for a potential transaction imbalance by comparing the proportional number of bought and sold stocks after identical day patterns. As every sell transaction is mirrored by a buy transaction at the stock market, each transaction imbalance at the small private investors' level has to be balanced by buy and sell transactions of institutional investors.

Table 2.2 shows the ranked transaction imbalance for all three-day patterns. After market patterns with a primary upward trend, small private investors sell more stocks than they buy, as indicated by the negative transaction imbalance. In comparison, a range of mostly negative days at the stock market induces small private investors to buy proportionally more stocks than to sell.

Table 2.2: Buy-sell transaction imbalance of Taiwanese small private investors after three-day patterns

three-day pattern	buy-sell transaction imbalance
+ + +	-0.9%
- + +	-0.7%
+ - +	-0.4%
- - +	0.0%
+ + -	0.1%
- + -	0.4%
+ - -	0.7%
- - -	0.8%

This table presents the buy-sell transaction imbalance of Taiwanese small private investors during the period from January 2001 to December 2006. A positive transaction imbalance indicates that small private investors buy more stocks than they sell after the respective pattern. In the case of a negative transaction imbalance, small private investors are inclined to sell more stocks than they buy after the respective pattern.

On the basis of the ranking in Table 2.2, we could establish the following two general rules in regard to the transaction imbalance:

Rule 1) The more positive days a pattern has, the more likely investors sell more stocks than they buy.

Applied to the three-day patterns, this means that, after a pattern of three straight days of gains, more stocks are sold, on average, than after a three-day pattern with only two days of gains. This first rule is further specified by a second rule:

Rule 2) Days closer to the trade execution day have a higher impact.

Thus, days directly ahead of the transaction day are substantially more important in comparison to more distant days. The interaction of both rules can be seen in Table 2.2. We use the stock market patterns - - -, + - - and - + - as examples to illustrate the mechanism. On the top of the transaction imbalance is pattern - - -, which can be traced back to Rule 1. As it includes the most negative stock market days of all patterns, it has the highest ratio of bought stocks in comparison to sold stocks. The second highest ranked pattern with a positive imbalance is + - -. As this pattern has only two days with negative stock market development, the transaction imbalance is lower than for pattern - - -. In order to rank the patterns + - - and - + -, Rule 2 can be implemented. As both patterns have the same number of days with positive stock market development, only the distance between the positive stock market day and the day of trade execution is different. As - + - has a positive market development in t_{-2} (compared to t_{-3} for pattern + - -), this pattern triggers proportionally more buy transactions, which results in a lower transaction imbalance. Hence, applying these rules allows us to predict if small private investors are net buyers or net sellers in the stock market.

2.4.3. The robustness of the observed behavioral patterns

So far, we have presented the results only for three-day patterns. In order to be able to generalize the statements from the previous section, the observed behavioral patterns should also be visible for other time intervals. Similar to the three-day pattern, we examined two-day and four-day patterns. The results are shown in condensed form in Table 2.3 and Table 2.4.

We observe roughly the same behavior in investors for two-day and for four-day patterns as for three-day patterns. Again, small private investors increase their trading after predominantly positive days. The same results apply for the transaction imbalance where we are able to deploy both rules from 2.4.2 for two-day patterns and with slightly less accuracy also for four-day patterns. We thus can confirm the rules derived from three-day patterns for other multi-day patterns which underlines their robustness.

Table 2.3: Average number of transactions and buy-sell imbalance of Taiwanese small private investors after two-day patterns

buy transactions		sell transactions		buy-sell transaction imbalance	
two-day pattern	average number of bought shares	two-day pattern	average number of sold shares	two-day pattern	transaction imbalance in percent
+ +	2,379,959,455	+ +	2,543,839,993	+ +	-1.6%
+ -	2,134,324,544	+ -	2,116,189,743	- +	-0.4%
- +	1,969,172,812	- +	2,022,843,447	+ -	0.5%
- -	1,861,481,388	- -	1,756,688,122	- -	1.5%

The table presents the average number of bought and sold shares of Taiwanese small private investors after each two-day pattern during the period from January 2001 to December 2006. The first character indicates a positive (+) or negative (-) whole day development of day t_{-2} and the second character indicates the whole day development for day t_{-1}. The table also presents the transaction imbalances for the respective two-day patterns.

To analyze if the results of Section 2.4.2 are stable over different stock market environments or whether the observed differences cluster during a certain long-term market trend, we split up the data into two distinct periods. We divide the entire time period of six years into a volatile phase with a slightly negative stock market development (January 2001 to April 2003) and a phase with a long stable stock market upswing (May 2003 to December 2006). Again, we calculate the number of sell and buy transactions and the transaction imbalances for each three-day pattern for each of the two subperiods. The results of the two periods do not differ from each other significantly and thus indicate a similar behavior of investors regardless of the broader development of the stock market.

Table 2.4: Average number of transactions and buy-sell imbalance of Taiwanese small private investors after four-day patterns

buy transactions		sell transactions		buy-sell transaction imbalance	
four-day pattern	average number of bought shares	four-day pattern	average number of sold shares	four-day pattern	transaction imbalance in percent
+ + + +	2,621,148,939	+ + + +	2,801,807,921	- + + +	-0.5%
+ + + -	2,576,393,496	- + + +	2,660,871,486	+ + + +	-0.4%
- + + +	2,479,705,767	+ + + -	2,572,680,808	- - + +	-0.4%
+ - + +	2,317,210,815	+ - + +	2,458,294,838	+ - + +	-0.3%
+ + - +	2,285,245,339	+ + - +	2,377,512,619	+ + - +	-0.2%
+ - + -	2,132,000,783	- - + +	2,196,525,732	- + - +	-0.2%
+ + - -	2,050,115,793	+ - + -	2,115,054,452	+ - - +	0.0%
- - + +	2,045,850,210	- + - +	2,055,090,247	- - - +	0.0%
- + + -	1,991,699,789	- + + -	2,000,933,720	- + + -	0.0%
- + - +	1,973,330,302	+ + - -	1,968,042,379	+ + + -	0.1%
- + - -	1,892,219,208	+ - - +	1,895,708,383	+ - + -	0.1%
+ - - +	1,867,777,818	- - + -	1,799,889,810	- - + -	0.2%
- - + -	1,852,813,016	- + - -	1,789,886,616	+ + - -	0.3%
+ - - -	1,800,603,552	- - - +	1,758,488,303	- + - -	0.4%
- - - +	1,745,066,157	+ - - -	1,687,970,199	+ - - -	0.4%
- - - -	1,710,033,122	- - - -	1,588,900,630	- - - -	0.4%

The table presents the average number of bought and sold shares of Taiwanese small private investors after each four-day pattern during the period from January 2001 to December 2006. The first character indicates a positive (+) or negative (-) whole day development of day t_{-4} and the following characters indicate the whole day development for the days t_{-3}, t_{-2} and t_{-1}. The table also presents the transaction imbalances for the respective four-day patterns.

Furthermore, it might be possible that the effect of up-down patterns is just an artifact of the overall return a stock experiences. In this case, only the daily returns would have an impact on the transaction imbalance with no effect left for the up-down patterns. We test the impact of the return amplitudes by controlling for daily returns in a regression with the transaction imbalance as dependent variable. Table 2.5 shows that the return is very likely to affect the transaction imbalance. However, many patterns remain significant, which indicates that the up-down patterns play a role regardless of the extent of the stock market's gain or loss. We got similar results for two-day patterns and four-day-patterns.

Table 2.5: Results of the regression on the buy-sell transaction imbalance of three-day patterns

independent variable	estimate	t	pr(>|t|)
intercept	0.013	2.868	**
pattern + + +	-0.025	-3.470	***
pattern + + -	-0.008	-1.126	
pattern + - +	-0.023	-3.371	***
pattern + - -	-0.001	-0.116	
pattern - + +	-0.027	-3.913	***
pattern - + -	-0.004	-0.685	
pattern - - +	-0.013	-1.995	*
return t_{-1}	-0.905	-6.625	***
return t_{-2}	-0.190	-1.393	
return t_{-3}	-0.095	-0.696	

The dependent variable is the buy-sell transaction imbalance of Taiwanese small private investors after three-day patterns during the period from January 2001 to December 2006. The transaction imbalance of three-day patterns is reported in Table 2.2. The independent return variables are calculated for the end of day stock market development of the TAIEX. We use the average number of traded shares for the different patterns. When stating ***, **, * and ., we denote significance at 0.1%, 1%, 5% and 10%, respectively.

In a further robustness test, we analyze if stock splits have an impact on our transaction imbalance results. As we only focus on the number of traded stocks, a stock split and thus a change in available stocks could change the interpretation of the transaction imbalance if small private investors predominantly buy or sell after such technical stock events. In the observed period, more than 2,000 stock splits were executed at the TWSE. With such a high number of stock splits it seems within the realms of possibility that these events can affect our results. To rule out that stock splits have an immediate effect on investors' behavior, we discard all transactions of these concerning stocks from our data set ten trading days before and after a stock split occurs. We then calculate the transaction imbalance for the data set without stock splits. The outcome does not differ substantially from our previous results. We still see the behavioral trading pattern we have described in Section 2.4.2.

In conclusion, our robustness tests show that the results are stable in regard to different market environments or technical issues like stock splits. Furthermore, the behavior can be observed not only after three-day patterns but also after two-day and four-day patterns. Thus, our tests confirm the observed investment related behavior of Taiwanese small investors.

2.5. Discussion

Our results from Section 2.4.2 show primarily two findings. First, small private investors react with different behavior to certain stock market patterns. The examined Taiwanese small private investors trade more after predominantly positive market patterns and reduce trading after negative market patterns. This observation is true for stock purchases, as well as for stock sales. A second finding includes the differences between the execution of purchases and sales. While proportionally more stocks are sold than bought after patterns with mostly up days, patterns with mostly down days result in a disproportionally large share of purchases. In the following, we try to explain this behavior by dividing small private investors into either a buy or a sell side.

To understand why some small private investors are buying stocks, while, at the very same time, others are selling the same stocks, it is necessary to understand the underlying motivation of these transactions. As described in Section 2.2, the existing literature provides only approaches that present investors as uniform actors, no matter whether they act on the buy or sell side. In contrast, our study divides investors into two groups: investors who own a certain share and want to sell it (hereafter referred to as holders) and investors who do not already own a certain share but potentially want to acquire it (hereafter referred to as sideliners)[4]. Both groups have in common that they wait for “the right moment” to start their transaction. Thus, these investors have already decided to buy or sell a certain stock and are waiting for an appropriate signal. And this signal might be found by some investors in the past market movement − the stock market pattern. The psychological dynamics triggered by these patterns are, however, very different for holders and sideliners (as they result in buy or sell transactions) and strongly depend on the perception of the respective stock. These differences in the stock perception frame investors’ decision-making processes and thus trigger a range of different behavioral mechanisms.

Holders already own a stock and are looking for a favorable moment to sell it. These investors have decided to release their shares because they anticipate a disadvantageous further development for them. Unlike investors who make a sell decision and immediately vend their stock, holders have come to a general sell decision but have not yet determined a precise time to sell; instead they wait for an advantageous opportunity to sell their shares. And this opportunity might be offered by a stock market pattern with predominantly positive days. In such a case, it seems

[4] In addition, there are investors who already own a certain share and want to reorder it plus institutional investors, which absorb the imbalance of stocks sold and bought between private investors.

that holders mostly do not believe in a further continuation of the upward trend as their general perception of the share is negative ("This low potential stock has already run well the last four days. There will probably be a counter-reaction soon."). The positive days that have passed since the sale decision do not necessarily contradict the initial skepticism towards the share, but rather promote a swift sale since the upward trend may be considered unjustified and a mean reversion is soon expected. In the opposite case of a pattern with mostly negative days, holders might regard this development as a confirmation of their unfavorable perception of the stock. However, they do not want to sell after a series of bad days because this would imply that they are having made a poor decision. As the stock could have been sold for a higher price before the range of negative days, the decision of not selling the stock could finally feel like a mistake. Instead, holders believe / hope again in a small short-term mean reversion and thus do not sell the stock directly after the negative trend ("After four negative days, it is very likely that at least a positive day will come next."). Thus, after patterns with predominantly positive, as well as with predominantly negative, days, holders bet on a trend reversal that resembles the gambler's fallacy bias[5].

Similar to the holders, we also assume that the sideliners in most cases do not spontaneously decide to purchase a stock, but that many of their trades follow a monitoring process. But unlike the investors at the sell side, we believe sideliners are more likely to follow market trends, and thus to mirror the hot (cold) hand fallacy called behavior[6]. In general, buyers have a rather positive view on the share they want to purchase. These investors usually believe in the potential of their chosen stock, otherwise they would not be willing to acquire it. Accordingly, after a pattern with mostly positive days, they feel reaffirmed in their decision to buy stocks. This reaffirmation of their trading idea fosters the confidence in their own trading skills.

[5] The gambler's fallacy is a logical misconception that is based on the idea that a random event becomes more likely if it has not occurred for a long time.

[6] The hot (cold) hand fallacy describes the erroneous belief that the continuation of a trend has a higher probability, though the sequence of the single elements is random.

Furthermore, the simple occurrence of rising markets makes small private investors prone to a market-induced overconfidence (Statman et al., 2006; Glaser and Weber, 2009). This is particularly noticeable for the investor subgroup of sideliners who are positive about their share and are only looking for a confirmation of their decision. As a result, after mostly positive patterns, sideliners underestimate the future stock market volatility, which stimulates them to purchase more stocks. Additionally, the rising buying activity after positive market patterns might be also supported by regret aversion. Investors (who are already willing to purchase stocks) feel a kind of regret, after a chosen and monitored but yet-to-be bought stock achieved gains. In order to avoid further regret when stocks continue to rise, they start buying. Altogether, these different processes encourage sideliners to buy more stocks after several positive days. On the other side, after patterns with predominately negative days, the sideliner’s positive perception towards the share does not match the declining market development. Further, the market-related confidence level is likely to be low after these patterns (Statman et al., 2006; Glaser and Weber, 2009), which could lead to an overestimation of the future stock market volatility. Combined, these factors result in fewer share purchases of sideliners.

In addition, it should be noted that the two perspectives of holders and sideliners affect the average small private investor with a different intensity. The commitment of holders is rather high, since these investors already own stocks and any change at the stock market generates real profits and real losses in their portfolio. For sideliners, the pain after missed gains might feel less intense since “only” potential profits and losses vanish. Hence, holders who suffer from real losses might feel a stronger pressure to fall back to their respective trading behavior. We believe that this explains in large parts why holders dominate the market towards the sideliners. Thus, after patterns with predominantly rising days, holders create an oversupply of stocks within the subgroup of small private investors and, after patterns with predominantly falling days, they create an undersupply of stocks. In the following, we present three basic stock market scenarios that show how market patterns potentially affect the behavior of holders and sideliners:

Situation I − the stock market pattern consists of predominantly negative days: After market patterns with mostly negative days, the willingness of sideliners to buy stocks is low, as they are trend followers due to the market-related low level of self-confidence and the conflict between buy decision and market development. At the same time, fewer shares are offered by holders, since these investors are less inclined to separate themselves from shares that have lost several days in row due to their hope in short-term trend reversion. The result is fewer trades after weak trading days. If we take a look at the proportion between the purchases and sales of small private investors, we see − due to the higher commitment of holders − that there are significantly fewer stocks sold than bought.

Situation II − the stock market pattern consists of predominantly positive days: Our results show that the average holder is more inclined to sell stocks after patterns with predominantly positive days. As holders do not believe in a trend continuation of their "poor" stock and instead expect a market reversal, they are more willing to sell their shares. On the buy side, sideliners are getting more self-confident due to a consistent development of expectation and market trend and a generally positive market environment. Additionally, they fear that they will miss the up-trend entirely. These investors are therefore more willing to enter the market after positive days. Although purchases and sales are growing strongly after positive patterns, there is nevertheless a proportional overhang in sales. Hence, more small private investors are willing to sell shares than to buy, which might be a consequence of the higher commitment of holders.

Situation III − the stock market pattern consists of days with alternating direction: In the case of short-term market trends that cannot be clearly attributed to a rising or falling pattern, the stock market development does not provide a clear impulse for investors who are waiting to buy or sell their shares. Thus, this market situation triggers only an average number of trades with roughly the same ratio of purchases and sales.

In conclusion, the entire transaction mechanism is based on an insider-outsider mechanism of holders and sideliners, triggered by certain market pattern constellations. In contrast to the flashy singular events studied by Barber and Odean (2008), the market patterns examined in this paper do not consist of isolated trading sessions, but rather of a range of related days which are not necessarily striking developments in terms of daily returns. Our results indicate that these market patterns do not generally attract a pronounced attention-based behavior. The observed Taiwanese small private investors release more transactions only after positive patterns, but do not show such increased trading activity after strongly negative patterns, as would be expected by Barber and Odean (2008). We thus believe that our investors are primarily not acting on the basis of attention, but rather on market patterns that trigger different reactions to contrary framed investors at the buy and sell side. The consideration of the mentally opposite perspectives of holders and sideliners in regard to a stock could help to understand why both groups are confronted with the same initial stock market situation, but choose diametrically different actions.

2.6. Conclusion

The efficient market theory assumes that investors make their purchase and sell decisions on the basis of new additional information. In our paper, however, we can show that this new information is not the only source for small private investors' trading decisions. On the basis of our Taiwanese stock market data, we find evidence that, in the case of buy and sell decisions, investors also take account of past stock price patterns. We show that the more positive a past market pattern is, the more it encourages small private investors to trade stocks. This applies to purchases and to sales. After a rather negative pattern, the observed small private investors released significantly fewer trades. We can thus confirm the long-term observations of Statman et al. (2006) that the past stock market development has a strong impact on the decisions of private stock market investors. Additionally, we examine the buy-sell ratio after these up-down patterns to find further evidence for differing reactions to the patterns. Again, we see differences with regard to the various patterns. While small private investors execute more sell than buy trades after patterns with predominantly positive days, we measure the opposite behavior after mainly negative patterns. This observed behavior is robust under different conditions and for multi-day patterns. We do not see any changes in the buying and selling during different market environments or for the exclusion of stock splits.

Our findings suggest that patterns do have an impact on the trading behavior of small private investors. However, no existing theory is able to explain this behavior since, after certain patterns, small private investors increase the number of sell transactions while, at the very same time, other small private investors increase the number of buy transactions. To solve the puzzle, we introduce an approach that regards purchases and sales as two separate decision-making processes which should not be considered from the same behavioral perspective. We have thus divided all trading small private investors into holders and sideliners. Due to different perceptions towards the respective share, the transactions on the buy side (sideliners) and on the sell side (holders) are oppositely framed. These distinct frames induce different interpretations of the same market pattern. This has, among other things, implications for the confidence level in regard to buy and sell decisions. This difference in framing explains why the same patterns trigger different decisions. Additionally, the commitment of small private investors is an important issue to factor in. While holders are highly committed by owning stocks and thus realizing real profits and losses, sideliners are only confronted with paper profits and losses.

Our findings restrict, but also supplement, the results of Barber and Odean (2008), who attribute the increased trading after positive and negative one-day return shocks to an attention-grabbing mechanism. The price patterns examined in this paper, however, generate no such attention, but are perceived only by those who have become aware of the stock anyway − because they either own or want to buy. We show that patterns − even when consisting of a distinct noticeable trend − trigger a different behavior of small private investors by activating opposite transaction frames for buyers and sellers.

In conclusion, this paper examines a little recognized field in economic research − the inclusion of past price patterns into trading decisions by small private investors. The fact that small private investors seem to react strongly to the past stock market environment shows the substantial role that this information plays for this investor subgroup. Accordingly, it would be important to understand the exact motivation of small private investors, especially in times when increased responsibility for old-age provision is placed on small private investors in many countries. A deeper understanding of the minds of these investors could ultimately help to provide private investors with more effective tools to cope with the challenges of long-term asset management.

Chapter 3

The Arousal-Risk Mechanism:

How Emotions Guide Investors' Risk Appetite

3.1. Introduction

Emotions are an integral part of our lives. Instead of a complex cost-benefit analysis, we often use the emotional shortcut in daily life decision-making processes. In an intricate environment, emotions help us to not get stuck in the thicket of manifold options. As Fenton-O'Creevy et al. (2011) put it, "emotion is central to our cognitive functioning". But this support comes with a price. Whenever we become overwhelmed by our own emotions, there is a real risk of inappropriate reactions − reactions that might have been different in a calm state of mind. Over the last decades, an increasing number of economic, psychological and neuroscientific research has attempted to decode how emotions influence the decision-making process (Ackert et al., 2003; Forgas, 1995; Kamstra et al., 2003). The focus of this research was often on the valence dimension of emotions.

Arousal, as a second dimension of emotions, was often overlooked in this debate. Even in the financial market context − an environment where intense emotions are commonplace (Lo & Repin, 2002) − a comprehensive analysis of arousal and its impact on decision-making is missing so far. This study tries to reduce the gap by adding the arousal as a further determinant of investors' attitudes towards risk.

In our study, we build on the work of Mano (1994) and Leith & Baumeister (1996), who found experimental evidence for the risk-related impact of arousal. We expand their studies to the financial market environment. For this purpose, we develop a theoretical framework for the relationship between emotional arousal and investors' attitudes towards risk which we term the arousal-risk mechanism. To validate this theoretical mechanism, we take advantage of our comprehensive data set, which covers all transactions in the Estonian stock market.

We argue that there are mainly two determinants that trigger trading-related arousal − the market frame and the portfolio setting. The market frame covers the broader stock market environment and causes initial emotions. The portfolio sentiment, which includes the emotions evoked by own assets, adds to the already existing emotions of the market frame. If both determinants elicit similar emotions, they can reinforce each other to a high level of arousal. We believe that such a high state of arousal induces two interwoven processes. First, the brain focuses only on high priority goals. Second, these goals are no longer embedded in a well-balanced strategy that considers constraints like elaborate risk management. As a result, the goal of earning money is left without regard to any pre-defined risk limits.

Our empirical findings support the arousal-risk mechanism. If investors are exposed to synchronous market determinants that trigger a high level of arousal, they hold their stocks longer and sell them less frequently and thus accept a higher level of risk in their portfolio. Depending on the strength of the underlying market frame and portfolio setting, this mechanism can even inhibit the widespread disposition effect. In contrast, if market frame and portfolio setting trigger opposing emotions, investors incur fewer risks.

The organization of the paper is as follows: Section 3.2 provides a short literature overview of the role of emotions and arousal in decision-making. On the basis of this overview, we derive the arousal-risk mechanism in Section 3.3. In the proceeding section, we describe our data set and explain the method we use to exploit it. In Section 3.5, we conduct an empirical analysis to show the implications of the arousal-risk mechanism for investors in the Estonian stock market. We finally conclude the paper in Section 3.6.

3.2. Decision-making and emotions − current state of research

By investing in the stock market, most investors have an explicit goal: earning money. For a long time, this goal was pursued by rational and perfectly unemotional decisions − at least in the eyes of many economists. The central paradigm for this model was the efficient market hypothesis with the guiding principle that human behavior is based on pure logic. Investors act as individuals who maximize their own expected utility in efficient markets where, according to Fama (1991), all available information is already reflected by the prices.

During the last decades, the efficient market hypothesis was challenged by increasing empirical evidence that investors do not behave in the predicted rational manner (Huberman & Regev, 2001; Kahneman & Tversky, 1979; Shefrin & Statman, 1985; Shiller, 2005). The realization that investors consistently exhibit irrational behavior made behavioral finance a new strand of research that connects psychological and economic insights. An increasing part of this research deals with emotions. However, although emotions are an important aspect of the human psyche, their emergence, interaction and impact are still not fully understood (Ackert et al., 2003). Even a commonly accepted definition of emotions has been missing up until now. Forgas (1995) describes emotions as an affective state that is intense and short-lived with a definite cause and a cognitive basis. In contrast, Frijda (2008) argues that emotions do not necessarily need cognitive work, but can be evoked without any cognitive processing before and even against rational beliefs. A more common understanding exists about the affective state, which is used as a generic label for the aggregate of emotions within a person (Forgas, 1995) and which can be considered as a primarily two-dimensional construct of valence and arousal (Russel, 1980). While valence reflects the evaluation of the affect (pleasant or unpleasant), arousal characterizes its strength (high or low emotional state).

For a long time, emotions were primarily seen as a disruptive force for elaborate decision-making (Shiller, 2005) and the central process of thinking was even seen as completely apart from any emotion (Fenton-O’Creevy et al., 2011). But recent research contests this view. Ackert et al. (2003) evaluate different neurobiological studies and conclude that emotions are able to improve decision-making. Emotions help the individual to come to a decision when a situation calls for it. Instead of getting overwhelmed by possibilities and details, emotions are speeding up the decision-making process by allowing the individual to focus on the most salient and urgent aspects. Following Lo & Repin (2002), emotions substantially reduce the costs of deliberation and thus enable an individual to handle a vast number of cues.

However, it is not only the occurrence of emotions itself but also their extent that has a huge impact on decisions. Kaufman (1999) argues that extreme states of arousal, such as no arousal at all or a very high level of arousal, contribute to bounded rationality. While the absence of arousal entails that too little energy is devoted to the gathering of information and to the actual problem solving, a state of very high arousal blocks out rational considerations of benefits and costs (Lo et al., 2005). However, arousal affects not only the quality of the decision-making process. According to the research of Leith & Baumeister (1996), Ditto et al. (2006) and Figner & Weber (2011), arousal is a considerable determinant for the risk attitude of individuals as well. We examine this relationship between arousal and risk in detail in Section 3.3.3.

Most research focuses only on the valence dimension of emotions. Isen et al. (1978) and Wright & Bower (1992) find that positive emotions are associated with optimistic decision-making and negative emotions lead to more pessimistic choices. However, there exists conflicting evidence regarding how the valence of individuals affects their risk appetite. Isen & Geva (1987) report that people who are in a good mood (positive valence) tend to be more risk-averse than those who are in a neutral mood. Additionally, higher risk-taking is found for negatively framed situations in comparison to those which are positively framed (Mittal & Ross, 1998). In contrast, Kuhnen & Knutson (2011) suggest that investors who are negatively framed by losses might have a reduced willingness to accept risks. In accordance with this result, Thaler & Johnson (1990) find that an induced history of success generates a positive frame that leads to higher risk-taking in gambling experiments. Criticizing all these valence-based approaches, Lerner & Keltner (2000) propose a more subtle differentiation between emotions. They develop an emotion-specific model that takes into account that emotions can evoke different risk attitudes, even though they share the same valence.

Many of the experimental results described above lack a mechanistic account of how emotions affect the decision-making process. New findings in neuroscience can provide some answers in this respect. For example, (Kuhnen & Knutson, 2011) found that parts of the brain, which have been identified as a source of emotions, are also engaged in the processing of information and in the selection of risk. In particular, two components of the limbic system have been found to be involved in decision-making: the nucleus accumbens (NAcc) and the anterior insula. The NAcc is situated along the reward approach system and is activated during the reception of pleasure and in anticipation of monetary gains (Peterson, 2007). An activation of the NAcc is also associated with risk-seeking behavior (Knutson et al., 2008). The localization of negative emotions is more difficult because the corresponding processes take place in several regions within the limbic system. A crucial part of this system is the anterior insula, which is activated in the anticipation of physical pain and shows a strong response in expectation of aversive visual stimuli (Kuhnen & Knutson, 2005). Additionally, in their clinical study, Paulus et al. (2003) find that the activation of the anterior insula precedes a risk-averse behavior. A possible explanation for this reaction might be that individuals confronted with adverse stimuli adopted a successful survival strategy by taking fewer risks and by withdrawing from unpleasant situations. When transferring these results to a financial market situation, an activation of the NAcc or the anterior insula due to changes in the own portfolio or in the market environment can imply an adjustment in investors' risk attitudes.

3.3. The theoretical framework of the arousal-risk mechanism

On the basis of the general understanding of emotional decision-making, which we introduced in the previous section, we develop a simple model of how different investment-related factors affect the decision-making process through the emergence of emotions. We point out how the two stock market-related determinants − portfolio setting and market frame − are able to affect investors’ risk attitudes. We first describe both factors and explain the way in which they have an impact on the arousal of investors. In a second step, we draw a link between investors’ affective state and their risk appetite and thus introduce the arousal-risk mechanism.

3.3.1. Portfolio setting and market frame as determinants of investment-related emotions

A crucial determinant of stock investors’ behavior is the performance of the assets that they hold (Fenton-O’Creevy et al., 2012), hereinafter referred to as portfolio setting. This development of own stocks can be directly translated into financial losses or gains by investors. Depending on the personality of the investor, a range of different emotions can be evoked by the respective portfolio setting. This link between the performance of assets and investors’ behavior is already an integral part of the prospect theory of Kahneman & Tversky (1979). A key point of their theory is the orientation on a reference price for an asset. Based on this reference price, investors evaluate their own financial assets. If the asset price moves away from the reference price, different emotions can be released. While losses are able to trigger negative emotions, rising prices cause feelings that are positive (Fenton-O’Creevy et al., 2011; Lo et al., 2005; Wu et al., 2012). The bigger the portfolio losses or the portfolio gains are, and thus the bigger the gap to the reference price, the stronger the corresponding sensations that investors are confronted with evolve (Steenbarger, 2004).

So far, most studies that analyze the various behavioral biases in financial markets consider primarily the valuables held by investors and thus only focus on the portfolio setting (Feng & Seasholes, 2005; Odean, 1998a; Shefrin & Statman, 1985). In contrast to this one-dimensional perspective, we believe that the emotions of investors are determined by (at least) two stock market-related factors: the performance of own stocks, described above as portfolio setting, and the overall situation in the stock market, hereafter referred to as market frame. The market frame comprises the development of the general stock market environment and the overall response of market participants in regard to this development. This includes, among other factors, the development of benchmark indices, the corresponding economic media coverage or even the exchange of opinions in financial market blogs in the internet. Pronounced market up and down-swings like the bull and bear market are the two extremes on the scale of the market frame. According to Cohn et al. (2012) and Nofsinger (2012), both market trends are able to create a sentiment that directly affects investors' emotional state. Although the performance of investors' own stocks has a decisive impact on their sentiment, the market frame creates the overall setting in which investors make financial market decisions. And this setting is able to influence the trading behavior as it confronts investors who try to form an opinion about their own portfolio with the market sentiment. Accordingly, investors do not decide and trade in a vacuum, but rather in a trading environment that constantly provides them with a large range of data, analyses and opinions. Although all investors at a certain stock market are confronted with roughly the same market frame, every investor transmits this determinant in line with personal factors like experiences, personality and current state of mind. Thus, the rise of emotions and their handling depends to a certain extent on individual emotional competences (Fenton-O'Creevy et al., 2012).

The following example illustrates the interaction between market frame and portfolio setting. An investor holds a stock that trades above the reference price and which could thus be sold with a gain. Without considering the market environment, the development of the stock is the only external source of information for decision-making and it is so far the only exogenous stock market determinant that has been considered by most studies. By taking the market conditions into account, we add a further determinant of investors' decision-making process. For instance, during a bear market with high volatility and a panic sell-off, our investor is probably exposed to another market sentiment than he would be during a substantial market rally. In a serious market downturn, he is most likely confronted with a strong negative sentiment. Even if we assume that his stock is not affected by the market turmoil, the panic in the market makes our investor feel uncomfortable. His stock has not moved substantially but emotions like fear might spread in his head as he is afraid that his stock will also be affected by an ongoing market sell-off. This means that, regardless of the performance of his stock, the investor is facing emotions induced only by the market frame. Hence, only following the market frame could be sufficient enough to raise emotions. However, combined with changes in the portfolio setting, the emotional state of investors can reach even higher levels.

3.3.2. The different sources of market determinant-related emotions

According to studies from Engelberg & Sjberg (2006) and Lee et al. (2009), people dealing with monetary issues seem to be not always the predictable, mathematically calculable actors described in theory, but rather humans driven by emotions. The occurring emotions are often released through individual involvement. The higher the personal stake in a relevant issue is and the more significance is ascribed to this issue, the more intense emotions occur (Ladouceur et al., 2003; Wulfert et al., 2008). Accordingly, the stock market, as a place with high individual involvement, is able to release a wide range of different emotions through the following trading-related factors:

Market frame − emotions through past experiences: Potent sources of emotions are the investors' own trading histories. Most investors have observed various market phases before. Those who are more experienced have also gone through a number of different market conditions while being invested in stocks. This experience plays a weighty role when investors are again confronted with a similar market frame. However, the situation in the market does not have to be exactly the same. To subconsciously recall past events, it can be sufficient when certain key stimuli (for example a sharp market downturn following a long appreciation period) remind investors of the former market constellation (Henson, 2003). The perception of these stimuli might activate emotions that are associated with the initial market movement. Current market movements act therefore as a trigger to recall past experiences and associated emotions.

Market frame − emotions through social exchange: Besides references to past experiences, the market frame can also evoke emotions by exogenous sentiment transmitted via social contacts. Investors are usually not entirely separated from any social interaction. Most professional traders are constantly exposed to the opinions of fellow traders i.e. colleagues. It is even more often than not the essence of their job to evaluate and interpret all kinds of information, such as economic data or rumors, in order to come to decisions. Even private investors have access to certain financial information or have the opportunity to share views with acquaintances. The result is not only an exchange of objective information, but also a circulation of opinions, which could include a transfer of emotions.

Market frame − medially transmitted emotions: Following Tetlock (2007), it is not only the fluctuations of the broad stock market that affects investors' actions, but the medial response resulting from these fluctuations. Thus, a high degree of media pessimism or optimism is able to induce a shift in investors' moods. By consuming media with a pessimistic view on the stock market, investors might re-examine their own position and approach the pessimistic perception to a certain degree. But even supposedly neutral information, like the announcement that Warren Buffett buys or sells a certain stock, is able to raise certain emotions (Hirshleifer & Hong Teoh, 2003).

Market frame − emotions through general market movements: In their physiological study on professional traders, Fenton-O'Creevy et al. (2012) find that the overall stock market development has measurable implications for investors' affective states. In particular, pronounced periods of appreciation and depreciation have a strong impact on market participants (Kim & Wei, 2002; Kim & Nofsinger, 2007; Cohn et al., 2015). While bear markets most likely elicit emotions with adverse valence, bull markets evoke positive emotions. In addition, also major short-term market events and the associated risks are able to release powerful emotions, even if investors are not directly affected. By measuring the physiological characteristics of professional securities traders, like skin conductance or blood volume pulse, Lo & Repin (2002) confirm that even the most experienced market participants exhibit strong emotional responses to relevant market events. Here, not only the actual risk of a stock plays an important role for the emergence of emotions, but also the perceived risk, which can be different among investors (Wang, 2011).

Portfolio setting − emotions through financial involvement: Changes in the own wealth are a powerful tool to move investors' emotional status (Taneja, 2012). Trading stocks implies decisions with directly quantifiable consequences for each action. Investors who hold stocks are thus exposed to a permanent adjustment of their asset values. Each up or down in the stock market can be directly translated into (unrealized) gains and losses. While gains naturally activate positive emotions, losses trigger negative ones (Fenton-O'Creevy et al., 2011; Locke & Mann, 2005; Steenbarger, 2004). And the larger a financial change is, the stronger the feelings that occur (Wulfert et al., 2008). Thus, the constant change in portfolio wealth works as a major catalyst for investment-related emotions (Fenton-O'Creevy et al., 2012; Kuhnen & Knutson, 2011; Lo et al., 2005).

Portfolio setting − emotions through trading availability: Additional emotions can be triggered by the possibility to step into action and change the current status by placing new orders. This anticipation of action and the (assumed) possibility of permanent opportunities are able to put pressure on investors and to intensify emotions in regard to the investment process (Tomaka et al., 1993). Thus, even in moments when investors are only thinking about trading issues, they can be exposed to a constant flow of emotions (Lo & Repin, 2002).

Emotions through issues unrelated to the stock market: Emotions that tend to affect decisions are not always directly related to the decision itself. For example, Saunders (1993) finds a relationship between weather induced mood and equity returns at the New York Stock Exchange. Other research verifies a link between stock pricing and the personal well-being (Fenton-O'Creevy et al., 2011), the human biorhythms (Kamstra et al., 2003) or important sports events (Boyle & Walter, 2003). All of these studies show that unrelated everyday issues are able to evoke emotions that might affect trading decisions. This misattribution of emotions seems to be a steady factor in the life and work of investors. As the sources of emotions are infinitely diverse, they affect all investors in every possible mood and at any time. However, in a study with as many investors and with a long observation period as ours, we assume that determinants like market frame and portfolio setting play the dominant role.

3.3.3. Similar emotions reinforce the level of arousal

In the previous subsection, we pointed out how portfolio setting and market frame are able to release feelings. In the following, we describe a simple model of how these market determinants affect the level of arousal.

According to Lucey & Dowling (2005), emotions interfuse decision-making at different steps. Our model of aroused decision-making reflects this multi-level interaction and builds on the risk-as-feelings approach of Loewenstein et al. (2001). From their work, we are able to see that the processes of cognitive evaluation and emotional reaction are mutually interacting with each other. We use the above-derived emotional determinants, market frame and portfolio setting, as exogenous factors in the decision-making process, as can be seen in Figure 3.1. Both variables influence the cognitive evaluation, as well as the emotional reaction, as indicated by Processes 1 and 2. The strength of the emotional reaction depends on the conditions we discussed in Section 3.3.2. However, the emotional reaction serves also as a source of information for cognitive processes (Xie et al., 2011). And the stronger the emotional reaction is, the more it affects the cognitive evaluation of investors (Bower, 1981; Isen et al., 1978), as indicated by Process 3. On the other hand, emotions can be evoked as a reaction to cognitive evaluations as well (Process 4). Based on cognitive processes, new insights that are able to trigger emotions may arise. In sum, the cognitive evaluations and the emotional reactions are two operations that are deeply interrelated (Loewenstein et al., 2001) but influence the decision-making process in distinct ways. While the emotional reactions directly determine the level of arousal, the cognitive evaluation has only an indirect impact on the arousal through Process 4. This distinct impact on the arousal level has crucial implications for the decision-making process.

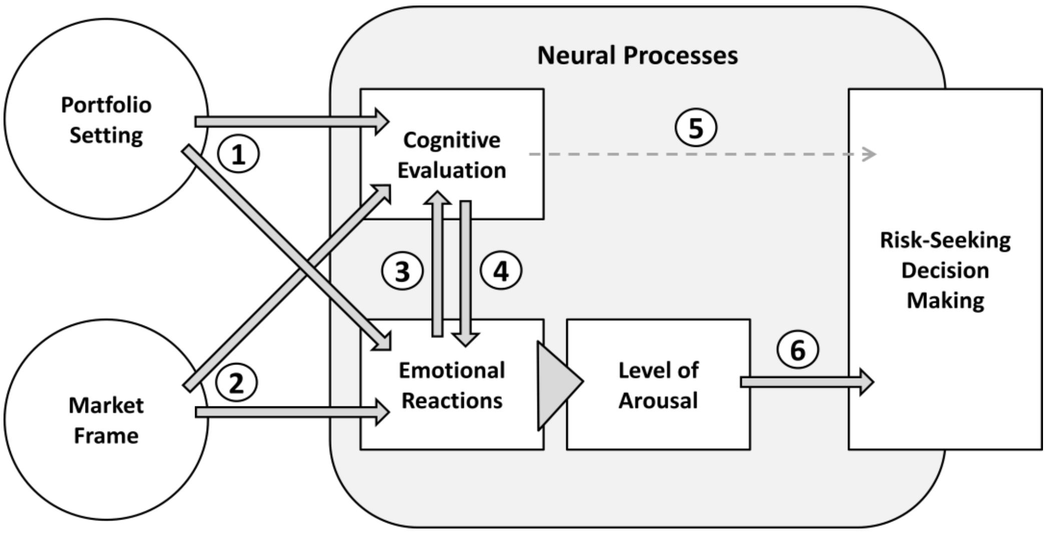

Figure 3.1: A simple model of the decision-making process under high arousal

The figure shows a simplified model of the mode of action between the two market-related determinants of emotions, the corresponding arousal and the initiated risk attitude of investors in the case of high arousal. The numbers 1 to 6 illustrate the different processes related to emotional decision-making.

Most decisions cause only few emotions and thus have a low potential of arousal. These decisions account for the majority of daily life choices and are solved by mainly cognitive processes with only minor intervention of emotions (Forgas, 1995).

In contrast, decision-making involving very intense emotions is largely determined by the level of arousal (Process 6), with only little room for impact from the cognitive evaluation (Process 5). Thus, whether or not the decision-making is predominantly driven by cognitive processes or emotional reactions is decided by the intensity of a person's arousal (Forgas, 1995). And this intensity is determined by the combined quantity, magnitude and direction of emotions investors are facing (Wulfert et al., 2008). To categorize and compare the different emotions, investors make use of the underlying appraisal tendencies of the emotions, such as attentional activity, pleasantness or control. Thus, even when emotions share the same valence (like fear and anger), they are different in terms of their appraisal tendencies. And the more homogenous investors' appraisal tendencies are, the more likely the corresponding emotions will reinforce each other and raise a higher level of arousal.

Before evaluating the stocks they hold, investors are often already emotionally biased by the market frame. Additionally, investors who take their own portfolio into consideration can release further powerful emotions. These portfolio setting emotions are stronger than the already existing emotions from the market frame. However, they are valued in light of the present market frame derived sentiment. While the market frame has already induced emotions which lead to a certain level of arousal, the emotions of the portfolio setting are able to further enhance this level, if both factors have the same appraisal tendencies. For example, an investor who is confronted with a strong bear market is negatively framed by the difficult environment and fears of a further deterioration in market conditions. After looking into his portfolio with stocks in the red, additional emotions of fear appear because he starts to be afraid of losing money. As the separate emotions triggered by both market determinants are already highly arousing and have similar appraisal tendencies, they are aggregated to very intense emotions of fear. The investor is now subject to an extreme state of arousal. In contrast, if the stocks of the investor are not following the downward trend, but rather trade with a gain, the positive excitement from the portfolio setting encounters the market frame emotion of fear. As both emotions do not have similar appraisal tendencies, they do not reinforce each other − with the effect that the investor’s level of arousal is lower than in the situation described before.

3.3.4. The level of arousal as determinant of investors’ risk attitude

After deriving the market-related level of arousal, we now explain its implications on the risk attitude of investors.

The arousal evoked by market frame and portfolio setting has a strong impact on the risk investors accept. A range of experimental studies confirms the importance of arousal for decision-making in regard to the level of risk. Figner & Weber (2011) point out that the accepted level of risk depends on the extent of affect that is induced by a broader environment in their experiments. This causal relationship between affect and risk is also found by Leith & Baumeister (1996). In their six experimental studies about emotions with a negative valence, they observe that participants with a high level of arousal took significantly more risks. Low aroused persons were far less inclined to assume the same risks. Ditto et al. (2006) verify the link between arousal and risk-taking in two experiments that target emotions with positive valence. By dividing participants into one group that was aroused by visceral cues and one control group, they observed that aroused persons tended to be less cautious and accepted higher risks. In two further experiments with lottery and insurance-like designs, Mano (1994) also confirms a positive correlation between risk and arousal. While participants in an aroused state were willing to pay more for lotteries, their propensity to invest in insurances against losses dropped considerably. These results were observed independently from the valence of the induced mood. Thus, Mano’s (1994) findings extend the evidence that a high level of arousal entails a risk-seeking behavior, no matter if the test subjects experienced positive or negative related arousal. We term this relation between heightened arousal and strong risk appetite the arousal-risk mechanism.

Research on the relationship between arousal and risk is still in its infancy but recent studies in the areas of neuroscience and psychological economics could provide some helpful insights to explain the arousal-risk mechanism. Kuhnen & Knutson (2011) point out that the affective state of a person is generated in the same brain areas that are relevant for the level of risk in decision-making. Not only do these areas of the brain within the limbic system generate emotional reactions and guide our instinctive actions; they also process incoming information. The system is responsible for vital human needs (eating, reproduction, prevention of sudden risks) and controls the fight/flight reactions in cases of danger. When confronted with a highly arousing situation, the limbic system gives priority to automatic emotional responses and blocks operations that demand elaborate cognitive processes (Frijda, 2008; Shiv et al., 2005). Following Mano (1994), this leads to a restriction of attentional capacity and noticeably reduces the number of considered options. The brain is forced to focus on only a few relevant options to come to rapid decisions (Shiv et al., 2005). To operate efficiently, the brain does not only oust secondary cognitive processes, but also works in a goal-oriented way (Fenton-O'Creevy et al., 2011). As a result, secondary aims or auxiliary conditions like risk assessment are subordinated to the main target.

When we transfer these complex processes to the stock market, we expect a similar mechanism for investors with a high level of arousal. In their clinical study, Lo et al. (2005) argue that thoughtful decision-making in the stock market involves higher brain functions such as logical thinking, long-term planning, encoding information and comparing different investment alternatives. However, we believe that in an aroused situation, all of these operations are interrupted. On the one hand, the goal of earning (or not losing) money is elevated to top priority. On the other hand, this goal is no longer embedded in a long-term strategy that takes all risks into consideration. All a priori defined trading strategies that aim to implement a balanced strategy with effective risk management are impeded by the focus on this one objective. Consequently, investors with high arousal focus almost entirely on the aspect of (re-)gaining money rapidly and let any prudent risk management of their portfolio slide. Thus, we suppose that, by paying less attention to lower ranked safety issues, highly aroused investors raise the risk profile of their trading behavior.

In conclusion, most decisions in daily life are taken under a low level of arousal. This involves decisions that relate to familiar everyday activities or tasks with low complexity (Forgas, 1995). These decisions are mainly solved by cognitive processes with only little impact of emotions. Accordingly, the risk accepted should be relatively well-suited. A different mechanism is activated for states of high arousal. For these decisions, cognitive processes are only secondary to emotions. Due to the restriction of attentional capacity, the main goal is pursued without consideration of lower ranked (safety) targets or other elaborate constraints. In the investment context, this means that investors accept a substantially higher portion of risk in the decision-making process when aroused.

3.4. Data set and methodology

3.4.1. Data set

Our data are provided by Nasdaq OMX Baltic and cover all transactions of the OMX Tallinn stock index (OMXT) during the period January 1st, 2004 to October 30th, 2010. As OMX Baltic is the only stock exchange in Estonia, the OMXT comprises the complete trading record of Estonian stocks for domestic and foreign investors. In total, we exploit over 410,000 single trades, executed from more than 27,000 different accounts. The information for each trade consists of trading-related data like account-ID, security number, transaction date and stock price.

The data set offers a number of advantages over data used by similar research. As the data enable us to analyze all transactions in a country, we avoid the problem of investor preselection by using data from a specific brokerage firm. This ensures representative results without any demographic groups being over or underrepresented. Additionally, the large number of trades, as well as the long observation period, helps us to produce reliable outcomes. Possible caveats are the missing of asset classes other than stocks and the limitation to Estonian equities.

The data set from the OMXT covers a period of almost seven years. During this time, the index more than doubled its initial value with an average annual return of more than 12.5 percent. However, the development of the OMXT was not as straight as the positive annual return might suggest. Investors were confronted with diverse market backgrounds such as the global financial crisis in the years 2007/2008 and the subsequent economic recovery. To take these severe changes into consideration, we split the data into bull and bear market periods. Following the approach of Pagan & Sossounov (2003), we apply the term bull market for an appreciation of the OMXT of more than 20 percent that lasts a time span of at least several months. In contrast, a phase of stock prices falling more than 20 percent over several months is regarded as a bear market period. In line with this view, we have identified two bull markets and one bear market in our data set. Bull period A starts in January 2004 and ends in July 2007. This long appreciation phase is followed by the relatively short but pronounced bear market in period B until March 2009. The second bull market in period C starts in March 2009 and lasts until October 2010.

3.4.2. Methodology and data setup

To measure the likelihood that investors sell their stocks, we use the survival analysis. This method has the benefit of taking the price path into consideration, and thus of giving more robust results by exploiting all available data. We follow Feng & Seasholes (2005), who first used survival analysis to examine the disposition effect and who provide a comprehensive summary of the approach. As a specification of survival analysis, we apply the Cox proportional hazard model. This model allows us to measure the probabilities at which investors are selling their stocks at a certain time.

The basic Cox model with fixed covariates can be expressed as:

$$h(t, p, X) = p\lambda t^{p-1}\exp(X\beta + \epsilon_t)$$

In this model, the hazard rate h of selling a stock at time t is the product of the baseline hazard $p\lambda t^{p-1}$ and the term $\exp(X\beta + \epsilon_t)$. The baseline hazard, with parameter p and the constant of integration λ can be interpreted as the probability of a stock being sold when the covariates become zero. The second term incorporates the regression coefficient β and the covariate X, which represents fixed independent variables such as the Trading Gain Indicator (TGI) or the Trading Loss Indicator (TLI). These variables help us to quantify the disposition effect and are described in-depth below. To estimate the covariates, we use maximum likelihood estimation. We only report the hazard ratios of the coefficients which are equal to $\exp(\beta)$. They can be regarded as the ratio of the hazard rate of one group to the hazard rate of a second group.

To compile a stock portfolio with a starting position for each investor, we follow the approach applied by Shapira & Venezia (2001). For every bull and bear period, we define a position as opened when a buy order was executed after the starting date of the period, and as closed when the whole position is sold. All stocks bought before the respective starting date are discarded from the portfolio since we do not know their purchase prices. Subsequent buy and sell orders are considered as a single buy or sell order. The volume-weighted average purchase price is used as reference price for each position. After a stock has been bought, we generate a holding position for each stock until the stock is completely sold. This holding position includes the variables TGI and TLI, which signal whether the position trades with a gain (TGI=1; TLI=0) or with a loss (TGI=0; TLI=1). If the daily low of a position is above the reference price, we count this as a day with a gain because an investor could have sold his position only with a positive nominal profit. In contrast, when the daily high of a position is below the reference price, we count this as a day with a loss. In case a position is entirely closed, we measure the gain or the loss by comparing the reference price with the actual sell price. In summary, we calculated daily holding positions for each investor and each position, which included altogether nearly 35 million observations.

3.5. Empirical results and their interpretation

After describing the theoretical framework of the arousal-risk mechanism, this section demonstrates its implications for investors in the financial markets on the basis of our dataset. So far, researchers found evidence for a link between arousal and risk in experiments only. We show that the arousal-risk mechanism exists for stock market investors as well. Since we cannot directly measure the level of investors' arousal, we use the market-related determinants of investors' emotions and the outcomes of their investment decisions that are affected by these emotions as proxies.

The stock market continuously requires decisions between alternatives that imply different levels of financial risks. To measure the risks investors are taking, we focus on the duration they hold their stocks. For example, investors who sell more stocks during volatile markets, and who have shorter average holding periods, show a more cautious behavior than investors who hold on to their stocks during the same period. Thus, each day investors keep their stocks can be regarded as an acceptance of risk, as the stock price can change to the disadvantage of the investor. In contrast, investors who sell their stocks obtain a clear financial outcome with no risk left. In this respect, the hazard ratios of the covariates TGI/TLI are able to reflect the risk attitude of investors. A hazard ratio above one means that investors are more likely inclined to limit the risk and sell stocks. In contrast, a hazard ratio below one characterizes a low propensity to sell stocks. Therefore, every shift in the hazard ratios can be interpreted in regard to the risk investors find acceptable.

To identify the shift of risk under different investment conditions, we first determine the average propensity to sell stocks for investors in the Estonian stock market. Over the entire period, investors who hold stocks with losses (TLI) have a weighted average hazard ratio of 0.59. To provide an understanding of the extent of bias, we can deduce that it is 41 percent less likely that investors sell a stock with a loss than a stock that trades at the purchase price. On the other hand, the average hazard ratio for stocks with a gain (TGI) is 1.68 and thus considerably above one. Hence, stocks with a gain have a 68 percent higher chance to be sold than stocks at the purchase price. Both results are significantly different from one which signals that investors are changing their sell behavior when the stock price moves away from the purchase price.

Such behavior of risk-avoidance in the territory of gains and risk-seeking in the territory of losses is known as the disposition effect. The bias describes a behavior of asymmetric risk evaluation. While investors lower the risk with gains by selling stocks quickly, they accept more risk when confronted with losses by holding on to decreasing stocks. As investors at the Estonian stock market are, on average, prone to this behavioral bias over the entire period, a deviation in the magnitude of the disposition effect can be regarded as a change in risk handling.

In the succeeding Subsection 3.5.1, we show the impact of different market frame designs to the risk attitude of investors. In Subsection 3.5.2, we find evidence that different intensities of the portfolio setting evoke additional emotions that change investors’ risk appetite and are even able to prevent the disposition effect.

3.5.1. The risk attitude in dependence on the market environment

We divide the entire period of almost seven years into bull and bear markets to examine the impact of different market environments to investors’ risk attitudes. For bull and bear markets, we calculate the hazard ratios for winning and losing stocks and are thereby able to analyze four different starting points for investment decisions.

Bear market: Investors in bear market B exhibit a hazard ratio of 0.45 for stocks with a loss (TLI), as indicated in Table 3.1. The result is significantly below the hazard ratio of one. This means that investors who are confronted with declining equity markets sell their stocks in the negative territory 55 percent less often than stocks that trade at the purchase price. This is a far weaker propensity to launch a sell order than for the whole period. In contrast, investors with gaining stocks (TGI) during a bear market show a pronounced tendency to sell their stocks quickly with a hazard ratio of 2.17. Thus, the probability to execute a sell order for stocks with a gain is more than two times stronger than for stocks at the purchase price. Summarizing the hazard ratios for TLI and TGI, investors show a higher risk-seeking for losses and a stronger risk-adversity for profits in bear market B in comparison with the entire seven years during which we monitor the Estonian stock market, a result that was already found by Muhl & Talpsepp (2017) in regard to the learning progress of investors.

The reason for the exhibited risk attitude can be found in the constellation of the general market environment and the personal investment performance. In a bear market, investors are confronted with a broad front of declining stock prices over a longer period of time, which increases the likelihood of pessimistic media coverage. Thus, the overall market frame evokes most likely negative emotions with a certain level of arousal (Cohn et al., 2012; Tetlock, 2007). Additionally, if investors also incur losses with the stocks they hold, the negative emotions already obtained from the market frame are amplified by adverse emotions from the portfolio setting. Together, both factors have a mutually reinforcing effect that leads to a more intense arousal. This state of high arousal lets investors accept higher risks.

Although confronted with a bear market as well, investors with stocks in the positive territory show a deviant behavior. They are facing the same pessimistic big picture as other investors, but benefit from the positive development of their own stocks. We thus expect emotions with contrary appraisal tendencies. Negative emotions triggered by the market frame encounter positive emotions caused by the portfolio setting. Such a conflicting investment picture does not enhance investors' arousal. The result is a higher risk aversion and thus a higher propensity of investors to sell their stocks during bear markets.

Bull market: During the two bull markets in period A and C, investors show similar risk patterns. For stocks with losses, we observe hazard ratios of 0.65 (period A) and 0.63 (period C). Both numbers indicate a considerably higher propensity to sell stocks in comparison to the bear market phase. The hazard ratios of investors selling a stock with a gain are 1.53 and 1.5, respectively. Again, the results are significantly different from one. This means that investors act more risk-averse in losses and accept higher risks in gains, which results in a reduction of the disposition effect during rising markets. However, investors are still prone to this bias, albeit to a much smaller extent than in the bear market period.

During a bull market, equity prices rise on a broad front for a longer period of time. The overall market sentiment is euphoric and also backed by optimistic media coverage. This promising market frame is able to evoke positive emotions. Investors who are participating in the bull market with their own rising stocks release positive emotions due to the portfolio setting, in addition to the positive emotions supported by the market frame. Because both factors induce emotions with similar appraisal tendencies, investors experience a kind of elation. The consequence of these strong emotions is a high arousal that induces investors to accept more risks. Hence, compared to declining markets, stocks are held for a longer period of time.

A different pattern can be observed for investors during bull markets with stocks in the negative terrain. Positive emotions from the market frame encounter negative emotions from the own portfolio. Such emotions with contrary appraisal tendencies do not mutually reinforce each other. Accordingly, these only slightly aroused investors sell their stocks more quickly.

Table 3.1: Hazard ratios during bull and bear periods

	TGI			TLI		
	Haz. Ratio	Z-stat.	Sign.	Haz. Ratio	Z-stat.	Sign.
Bull Market A	1.53	47.9	***	0.65	-49.3	***
Bear Market B	2.17	55.1	***	0.45	-56.9	***
Bull Market C	1.50	32.5	***	0.63	-36.1	***

The table above presents the hazard ratios for investors in the Estonian stock market. The results were already found by Muhl & Talpsepp (2017) in regard to the learning progress of investors. We report results for the different sub-periods that are divided by bull and bear market trends. The Trading Gain Indicator (TGI) represents hazard ratios for stocks with a gain and the Trading Loss Indicator (TLI) represents hazard ratios for stocks with a loss. A hazard ratio less than one indicates that investors have a lower propensity to sell a stock, while a hazard ratio above one suggests a higher propensity. The term *** denotes significance from one at 0.1%.

In summary, the results for the bull and bear market support the theoretical framework that we expounded in Section 3.3. If emotions from both market-related determinants coincide, investors accept higher risks and stay longer in the stock market. This behavior can boost, as well as ease, the disposition effect − depending on the market environment. We thus emphasize that the market frame has a huge impact on risk attitude by raising or decreasing the level of risk investors are willing to accept.

3.5.2. Investors' risk attitude in dependence on the strength of the portfolio setting

In the following, we demonstrate that not only the direction, but also the strength of the portfolio setting matters for the decision-making process. Supported by findings of Steenbarger (2004) and Wu et al. (2012), we assume that a bigger difference to the reference price (purchasing price) is able to evoke more emotions than a smaller gap. We divide the losses and gains of stocks into three categories: small losses/gains (with a difference of between 0.1% to 19.9% of the purchase price), medium losses/gains (20% to 49.9%) and large losses/gains (> 50%). Instead of distinguishing only between losses and gains, we can now track investors' behavior for six different states in the portfolio setting.

Bear market: Table 3.2 and 3.3 show investors' sell and buy behavior during bull and bear markets in regard to the extent of losses and gains. During the strong depreciation phase in period B, investors with small gains have still a comparably moderate hazard ratio of 1.9. For large gains, the hazard ratio increases to a hazard ratio of 3.14. Hence, for profits of more than 50 percent, investors show an inclination to sell the stock that is three times higher than for stocks at the purchase price. For losing stocks, we see the opposite behavior, with the highest hazard ratio for small losses and the lowest hazard ratio for large losses. All results are significantly different from one.

The exhibited hazard ratios indicate two different behavioral patterns. While investors reduce the risks and sell their stocks more, the higher are their gains and they act increasingly risk-seeking for higher losses. Accordingly, investors demonstrate the highest disposition effect for large gains and large losses. The force behind this behavior is the strong arousal potential of heavy losses and large gains. Investors who suffer from declining markets by own stock losses additionally encounter a negative sentiment from the market environment. The higher the losses are, the more arousal they evoke and thus the more risk investors accept. Investors with the biggest minus show the least inclination to reduce the risk and to sell their stocks. Again, we observe an opposite pattern for stocks with gains during the bear market. Because of conflicting emotions due to the beneficial portfolio setting and the negative market frame, the arousal of investors is not remarkably elevated. Consequently, investors with the highest gains act rather risk-averse and sell their stocks more quickly.

Table 3.2: Hazard ratios for stocks with different profit levels

	TGI small gain	TGI medium gain	TGI large gain
Bull Market A	1.33 *(36.2)* ***	1.09 *(8.6)* ***	0.93 *(-6.7)* ***
Bear Market B	1.90 *(42.4)* ***	3.02 *(32.4)* ***	3.14 *(24.4)* ***
Bull Market C	1.44 *(33.9)* ***	1.02 *(1.2)*	0.87 *(-10.6)* ***

The table above presents hazard ratios for the average investor who owns stocks with a gain. Results are divided by bull and bear market trends and by different magnitudes of the gain. Profits are categorized into small gains (0.1% to 19.9%), medium gains (20% to 49.9%) and large gains (> 50%). A hazard ratio less than one indicates that investors have a lower propensity to sell a stock, while a hazard ratio above one suggests a higher propensity. Z statistics are shown in parentheses and ***, **, * and . denote significance from one at 0.1%, 1%, 5% and 10%, respectively.

Bull market: The hazard ratios for investors with gains during both rising stock markets are reported in Table 3.2. While investors who hold stocks with small gains show hazard ratios of 1.33 and 1.44, investors with medium gains are able to reduce the propensity to sell significantly. However, the lowest propensity to sell is measured for investors holding stocks with large gains with hazard ratios of 0.93 and 0.87, respectively. Table 3.3 presents the results for losing stocks. Investors with small and medium losses show hazard ratios well below one. This stands in contrast to the sell behavior for stocks with large losses, with hazard ratios of 2.02 and 1.41, respectively.

Again, the driver of this trading behavior can be found in the interaction between portfolio setting and market frame. The favorable market frame releases positive emotions. If positive emotions from the own gaining stocks add to these market frame emotions, the arousal level rises. Investors with the largest gains develop the highest arousal level and are therefore willing to accept the biggest risks. This is reflected by the hazard ratios below one for large gains that underline a behavior of holding stocks longer. A contrary risk attitude during bull markets is adopted by investors with losses. Investors with the most serious losses show the lowest propensity of accepting risks. As the emotions that developed through market frame and portfolio setting are opposite, investors' levels of arousal, and hence their risk appetites, are low.

Table 3.3: Hazard ratios for stocks with different loss levels

	TLI small loss	TLI medium loss	TLI large loss
Bull Market A	0.75 *(-30.8)* ***	0.48 *(-39.1)* ***	2.02 *(35.3)* ***
Bear Market B	0.85 *(-11.7)* ***	0.77 *(-17.6)* ***	0.68 *(-21.9)* ***
Bull Market C	0.67 *(-29.5)* ***	0.68 *(-14.8)* ***	1.41 *(13.3)* ***

The table above presents hazard ratios for the average investor who owns stocks with a loss. Results are divided into bull and bear market trends and different magnitudes of the loss. Losses are categorized into small losses (0.1% to 19.9%), medium losses (20% to 49.9%) and large losses (> 50%). A hazard ratio less than one indicates that investors have a lower propensity to sell a stock, while a hazard ratio above one suggests a higher propensity. Z statistics are shown in parentheses and ***, **, * and . denote significance from one at 0.1%, 1%, 5% and 10%, respectively.

In conclusion, additionally to the direction of emotions, their magnitudes are important as well. The stronger portfolio gains or losses occur, the more extreme are its effects to investors' arousal, when the market frame evokes similar emotions. The high arousal that has already evolved due to similar appraisal tendencies measured in Section 3.5.1 is further strengthened by the pronounced emotions evoked by the portfolio setting. The combination of bull markets and large stock losses or large stock gains is even able to eliminate the disposition effect as investors under these conditions act even risk-seeking in gains and risk-averse in losses. In summary, our results provide empirical evidence for the arousal-risk mechanism.

Although the data from the Estonian stock market confirms our theoretical framework of the arousal-risk mechanism, further explanations for the behavior of the examined investors are possible. For example, a mismatch of the development of the general stock market and the own portfolio stocks can be perceived by investors as a more risky situation than synchronous trends and thus, trigger more stock sales to reduce the portfolio risk. However, such a risk-related assumption misses to explain, why the inclination to sell stocks decreases in case of a combination of a bearish market and held stocks with a loss, when the perception of risk should be the highest (Lo et al., 2005). The same problem arises for attention based approaches that predict higher sell activity for diverging trends. Following this explanation, a bullish stock market and large own stock gains would not draw much attention of investors − an assumption that would contradict previous empirical studies like Fenton-O'Creevy et al. (2011).

3.6. Conclusion

So far, in the search for determinants of investors' risk attitudes, economists and psychologists focused mainly on the valence of emotions. In this paper, we shed some light on a long neglected impact factor of financial risk-taking: the level of arousal. On the basis of existing psychological and neuroscientific research, we developed a theoretical framework for the link between arousal and financial risk-taking.

Our work builds on a range of psychological experiments such as those from Mano (1994) and Leith & Baumeister (1996), who found evidence that financially induced arousal has a substantial impact on the risk attitude of participants. The more aroused those participants were, the higher the level of accepted risk. To explain these experimental outcomes, we exploited the neuroscientific findings of decision-making processes. As emotions are generated in the same brain regions that are relevant for the level of risk in the decision-making process, strong emotions are able to override simultaneous cognitive processes and force the brain to focus on the most salient options (among others Kuhnen & Knutson (2011). This suppression of elaborate thinking favors two interconnected processes. On the one hand, the neuronal system supports goals that are deeply rooted in the subconscious. On the other hand, these goals are no longer embedded in a well-balanced strategy that considers predetermined constraints, as these processes need cognitive operations. As a result, investors who are highly aroused accept higher risks.

In the financial market context, we identified two determinants of arousal − the market frame and the portfolio setting. While the market frame primes investors with a certain sentiment, the portfolio setting elicits the pivotal emotions. However, in our model, it is not only the emotions solely triggered by the market frame or by the portfolio setting but their mutual interaction that affects the investors' behavior. If market frame and portfolio setting evoke emotions with similar appraisal tendencies, the portfolio setting reinforces the initial emotions from the market frame. Consequently, investors experience a state of high arousal. In contrast, if both market factors cause emotions that are not compatible to each other, the level of arousal is considerably lower. Following existing experimental research, we assumed that investors, who are severely aroused by these homogenous emotions, accept higher risks. We termed this connection between the emotion-based arousal and the risk attitude the arousal-risk mechanism.

We found evidence for the arousal-risk mechanism in our Estonian stock market data. To demonstrate the relevance of the market-related determinants of arousal, we split the entire period into bull and bear markets (market frame) and divided the stocks held by each investor into stocks with losses or gains (portfolio setting). Using survival analysis, we examined how long investors were willing to hold their stocks under the different combinations of market frame and portfolio setting. We found that investors' propensity for keeping their stocks longer and, thus, for accepting higher risks rises significantly when the market-related determinants indicate high arousal. This means that investors are more inclined to hold on to their stocks when own losses encounter a bear market or when portfolio gains hit a distinct bull market. To verify whether or not higher losses/gains affect the risk attitudes of investors, we examined the impact of different magnitudes of the portfolio. Our analysis showed that larger own losses (gains) in combination with a bear market (bull market) induce a stronger risk-acceptance. For pronounced levels of emotions, the resulting handling of risk is even able to suppress the disposition effect.

To sum it all up, certain constellations of market-related determinants are able to put investors under enormous emotional pressure. The high arousal resulting from this pressure can be one reason for the poor portfolio performance of investors as described by Kaufman (1999) and Lo et al. (2005). Fenton-O'Creevy et al. (2011) found that trading experience can significantly decrease the level of market-related arousal by improving the effectiveness of the own emotional control mechanism. However, to prevent that trading novices have to go the whole costly way of stock market experience, it might be beneficial, to offer them some kind of emotional education. This education should put special emphasis on the possibly extreme arousal in consequence of market turbulences or severe changes within the own portfolio. With such lessons in mind, investors are hopefully more aware of the emotional pitfalls of trading and are able to better master the ups and downs in the financial markets.

Chapter 4

Faster Learning in Troubled Times:

How Market Conditions Affect the Disposition Effect

4.1. Introduction

The well documented disposition effect describes the behavior of investors in selling winning stocks too quickly and holding losing stocks too long. Different studies have proven its disadvantageous nature (Goulart et al., 2015; Odean, 1998a; Seru et al., 2010). Consequently, learning to avoid the disposition effect would be beneficial for investors. However, the ever-changing nature of the market environment provides a challenging setting for improving the trading behavior. In this context, we focus on how market conditions affect learning in regard to the disposition effect.

In the financial markets, pronounced market swings related to various crises and the subsequent recoveries seem to be the rule rather than the exception. Hence, the market environment with its ups and downs in share prices creates a constantly changing frame in which investors act. A broad range of studies verifies (among others: Guidolin & Timmermann, 2005; Kim & Nofsinger, 2007; Leal et al., 2010; Necker & Ziegelmeyer, 2016) that the market environment affects the behavior of market participants. Following Kim & Nofsinger (2007), investors exhibit "some striking differences in investing behavior between the bull and the bear market". However, the existing analyses observe a distinct behavior between the different market phases but miss to explain how investors are able to cope with the challenges of the respective market environment. This paper will fill the gap by examining the learning behavior under the different market conditions in regard to the disposition effect.

To examine if learning in the disposition effect is dependent on the market conditions, we are able to exploit an extensive dataset of investors who traded on the Estonian stock exchange during the years 2004 to 2010. These data allow us to distinguish between market environments with pronounced appreciation and depreciation phases.

Our results give evidence for the relevance of market conditions for investors' learning behavior. We find a pronounced propensity to the disposition effect for the average investor over the entire period of almost seven years. Whereas inexperienced investors show a high level of the bias, investors with increasing experience can gradually attenuate the disposition effect. Thus, our findings indicate learning, a result that is supported by the earlier studies by Feng & Seasholes (2005) and Seru et al. (2010) but contradicts the outcome of Koestner et al. (2012).

To identify the impact of the market environment on investors' learning behavior, we divide the dataset into bull and bear periods. We find a strong inclination to the disposition effect in each of the distinct market periods as well. However, during the bear market the disposition effect of investors is considerably higher, opposing the results of Leal et al. (2010). These differences between the market phases do also occur for the learning progress. We provide first evidence that investors are able to reduce the disposition effect to a greater extent during bear markets than during bull markets, in case they are able to accumulate enough experience. We believe that the reasons for this stronger learning progress are prompter feedback and harsher financial consequences during bear markets. Furthermore, we find evidence that "learning by doing" is more important than "learning about ability", which stands in contrast to the outcome of Seru et al. (2010). The results lead to our final conclusion that research that ignores the different market conditions will miss an important explanatory source of investors' learning behavior.

The organization of the paper is as follows: Section 4.2 gives a short overview of literature on the disposition effect and learning in financial markets. In the next section, we describe our dataset and explain the calculation method used. In Section 4.4, we present the outcomes for the attenuation of the disposition effect, which we discuss in Section 4.5. We conclude the study with a summary in Section 4.6.

4.2. Disposition effect and learning − the current state of research

The behavioral pattern of selling rising stocks too early and selling decreasing stocks too late is a well observed bias in financial markets and was termed the disposition effect by Shefrin & Statman (1985). Since Shefrin & Statman (1985), several other studies have shown that investors are prone to the disposition effect. The first who performed a significant empirical analysis on individual trade histories was Odean (1998a) in his study of discount brokerage clients in the USA. Odean (1998a) demonstrates that individual investors in the United States prefer to sell winners and to hold losers, except for December, when tax motivated selling predominates. The disposition effect is also confirmed by Weber & Camerer (1998) in an experimental setup with students. Trading six different stocks, the participants showed a strong disposition effect for stocks in positive and negative territory. Shapira & Venezia (2001) analyze the behavior of individual and institutional investors in Israel. The authors observe a tendency towards the disposition effect for both investor subgroups, though with a much stronger bias for individual investors. Similar results are obtained by Grinblatt & Keloharju (2001) and Barber et al. (2007) who also distinguish between different investor types. Their analyses of the Finnish and Taiwanese stock markets confirm a weaker or no disposition effect for institutional investors. Dhar & Zhu (2006) find also evidence for a different inclination to the disposition effect among investors. Using socio-economic variables as proxies for investor literacy, they observe a much weaker propensity for the bias for wealthier individuals. Again, investors exhibit the weakest bias during the tax relevant month of December. In summary, these studies confirm investors’ general tendency for the disposition effect although with varying extent for different subgroups and time periods.

In our study, we are also asking for temporal differences concerning the disposition effect. While Odean (1998a) and Fu & Chen (2012) emphasize tax saving or seasonal momentum as reasons for temporarily differing magnitudes of the disposition effect, our work addresses the market conditions. Most studies that focus on investors' behavior do not take the market environment into consideration and hence fail to explain the impact of this important external factor on investors' trading decisions. Studies that do include the market environment observe distinct behavior patterns during different market phases (Chiang et al., 2011; Cohn et al., 2015; Kim & Nofsinger, 2007). An approach used by Kim & Nofsinger (2007) is the division of the market into appreciating and depreciating phases, a concept we are also following. After splitting their data into bull and bear markets, Kim & Nofsinger (2007) find that Japanese individual investors prefer riskier stocks during bear markets and that this choice leads them to underperform. Kim & Wei (2002) show that traders employ other trading styles during bull than during bear markets. Cohn et al. (2015) conduct a controlled experiment with financial professionals to explore, how the market environment affects individual risk-taking. They observe that bull and bear markets have a pronounced impact on the behavior, as these market phases directly affect participants' trading preferences. Guidolin & Timmermann (2005) point out that the market environment also plays an essential role in investors' strategic asset allocation. They find evidence that the occurrence of bull and bear markets greatly affects the optimal choice of bonds and stocks.

Leal et al. (2010) and Cheng et al. (2013) analyze the direct impact of the market conditions on the disposition effect. Both studies notice a significant influence of bull and bear markets on the bias but come to dissenting results. Using only aggregated data from the Portuguese stock market, Leal et al. (2010) measure the highest bias for the period with increasing stock prices. Contrary results are found by Cheng et al. (2013) who examine the relationship between the disposition effect and gender and age for two different kinds of future contracts on the Taiwanese futures exchange. Cheng et al. (2013) observe that future traders exhibit the strongest disposition effect during harsh market conditions when prices are falling rapidly. Thus, both studies give evidence in the literature that external market factors such as bull and bear markets affect investors' behavior although with conflicting outcomes. Our study extends the analysis by examining the capability of investors to learn during different market environments.

To avoid a certain behavior, investors have to recognize its harmful character. The literature gives rich evidence that the disposition effect is a behavior that harms investors' wealth by impairing the portfolio performance. Odean (1998a) finds that a widespread disposition effect may affect market prices, but its largest impact is on the biased investors themselves. His study demonstrates that investors renounce more than four percent of their returns by selling winning stocks too fast and keeping losing stocks too long. Locke & Mann (2005) demonstrate that the disposition effect is directly linked to the trading success of professionals, as the least successful traders are most prone to disposition behavior and the most successful traders are the least biased. With a similar approach, Seru et al. (2010) verify that the effect is costly for investors. They assign investors into five groups that reflect the investors' propensity for the bias from very low to very high. The authors show that investors in the low disposition group generate substantially higher returns than those in the other groups. The worst performance is shown by the investors classified into the group with the highest disposition effect.

As the literature suggests that the disposition effect is harmful to investors' portfolio performance, learning to avoid this bias is essential for investors' long-term trading success. Feng & Seasholes (2005) observe a decreasing tendency to the disposition effect for Chinese traders who have gained experience. By placing more trades, investors learn to attenuate the disposition effect but fail to avoid the bias completely. However, combined with sophistication, trading experience helps traders at least to eliminate their reluctance to realize losses. Exploiting data from an US discount brokerage firm, Dhar & Zhu (2006) observe that investors' trading frequency is negatively related to the disposition effect. Investors that exhibit no tendency for the disposition effect execute more trades than other market participants. One reason mentioned by Dhar & Zhu (2006) for this outcome might be that a higher frequency of trading could help investors to get accustomed to sell losers and to hold winners as repeated exposure reduces mental barriers. Similar results are found for the Korean futures market by Choe & Eom (2009) who demonstrate that trading activity is positively linked with a diminishing disposition effect.

In contrast, Koestner et al. (2012) show that investment habits like overconfidence decline as investors gain experience, but the disposition effect does not. Koestner et al. (2012) suggest that the reason for the differing learning progress is the disparate potential for detecting these behavioral patterns. While the excessive trading caused by overconfidence can be easily identified by investors, it is difficult to uncover the nature and resulting costs of the disposition effect. Seru et al. (2010) distinguish between two kinds of learning in the stock market. On one side, investors are able to improve their ability by experience; on the other side, they are able to learn about their inherent ability. Thus, if their natural trading skills are above average, trading is continued. If their trading skills are not sufficient to perform well in the financial markets, investors decide to cease trading. According to Seru et al. (2010), this self-selection is an essential part of investors' learning behavior.

Our paper builds on this work and uses the learning progress of investors over the entire period as a starting point. However, as the learning results for the whole time are only the sum of the different bull and bear market phases, we would probably miss some relevant information if we would not consider the different market conditions. For this reason, we go one step further and analyze learning during the single bull and bear markets. Furthermore, to examine the importance of learning about ability, we follow Seru et al. (2010) and measure the proportion of investors' self-selection during each period.

4.3. Data set and methodology

4.3.1. Data set

Using data from the Nasdaq OMX Baltic, this study employs a comprehensive data source that comprises all the stock transactions on the Nasdaq OMX Tallinn stock exchange (OMXT) for the time period from January 1st, 2004 to October 30th, 2010. Talpsepp (2011) uses a subset of the data which covers the first four and a half years of our data. As the Nasdaq OMX Tallinn is the only Estonian stock exchange, it covers all the stock transactions of companies listed in Estonia and hence allows us to analyze each trade dealt on the stock exchange for both domestic and foreign investors.

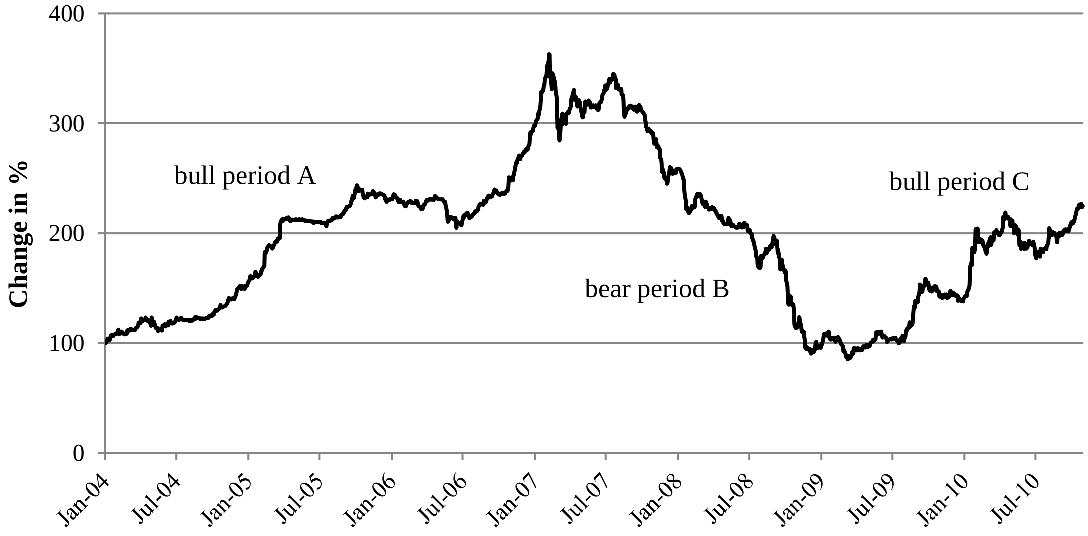

Figure 4.1: Development of the Nasdaq OMX Tallinn index

The graph shows the development (in percent of January 1st, 2004) of the Nasdaq OMX Tallinn index in the time period from January 2004 to October 2010. The different bull and bear market periods are indicated.

Between January 2004 and October 2010, the OMXT realized an average annual return of 12.6 percent. Despite the relatively moderate annual rate of return, the index was subject to large price changes during this period of almost seven years, with a low of 244.99 points and a peak of 1043.29 points. Investors were confronted with the global financial crisis in the years 2007 to 2009 and with the economic recovery in subsequent years. This volatile market environment allows us to divide the whole period into three sub-periods, two appreciation periods and one depreciation period (for a better understanding of the development of the Estonian stock market please see Figure 4.1). To describe the appreciation and depreciation periods, we apply the terms bull market (strong appreciation) and bear market (strong depreciation), as used by Pagan & Sossounov (2003) for extended price changes in the stock market of more than 20 percent. The first bull period starts in January 2004 and ends in February 2007 with a growth in value of more than 250 percent. The second bull period starts in March 2009 and ends in October 2010 with an increase of more than 150 percent. Embedded between these two bull periods is a bear market period from July 2007 to March 2009 with a decline of 75 percent in the OMXT.

The data set comprises more than 410,000 trades, executed by 27,853 different accounts. The data consist of trading information such as transaction date, stock price and security number together with anonymous demographic details for each account.

Our Estonian data set offers a number of advantages that are unique in comparison to the data used by similar research. In contrast to data from a single brokerage firm, we have access to all the transactions on the Estonian stock exchange. This means, we avoid selection bias, which is the risk of focusing on a certain group of investors that might be overrepresented in the customer portfolio of a brokerage firm. Additionally, the long time period and the large number of transactions provide a further foundation for reliable results.

These benefits of the dataset offset potential problems like the focus on stocks only. As the accounts being observed do not consider positions of derivatives, we are not able to take account of hedging or arbitrage strategies that might be additional determinants for investors' behavior. Another limitation is the lack of foreign equities. For foreign investors the engagement in the Estonian stock market is probably only a part of a bigger portfolio strategy and potentially constitutes only a small fraction of the total amount invested in stocks. It is therefore difficult to conclude from their decisions in the Estonian stock market about their behavior in other markets. A third point to note is the small size of the stock market. With a market capitalization of around 3 billion Euro and with 22 companies listed, the OMXT is only a small stock exchange. As a direct consequence, investors are subject to diversification constraints. Any transfer of the results to bigger stock markets has to consider these limitations.

4.3.2. Methodology

To measure the extent of the disposition effect, we apply survival analysis. This method was first introduced for the bias by Feng & Seasholes (2005) who also present a comprehensive overview of the approach. Survival analysis offers an easy way of predicting the average time a stock will be held. It also provides information on how a change in trading related covariates affects the propensity of investors to sell a stock. In contrast to the PGR-PLR approach used by Leal et al. (2010) and Koestner et al. (2012), survival analysis controls for investors' differences at an individual level and includes the complete time until an event occurs. It therefore exploits all the available information.

We use the Cox proportional hazard regression model for survival analysis, as it allows flexible handling without any obligation for a specific probability distribution in advance. The Cox proportional hazard regression model also allows for censored observations, which is an important advantage over other models as positions have not to be closed by the end of the considered periods. Additionally, we are able to incorporate both fixed and time-varying covariates into the model. This facilitates the observation of the impact of changes in covariates, such as the number of trades, on changes in the probability of the investor selling a stock. The model's parameters are estimated through maximum likelihood estimation. The model is expressed as:

$$h(t, p, X, Z_t) = p\lambda t^{p-1}\exp(X\beta + Z_t\gamma + \epsilon_t)$$

Where the hazard rate h of a stock is a measure of the conditional probability that this stock is sold during the following time interval. Thus, the hazard rate of selling a stock at time t is the product of two factors, the baseline hazard $p\lambda t^{p-1}$ and the independent variables that reflect the changing conditions that might be correlated with the inclination to sell a stock. The baseline hazard depends on time t^{p-1} as well as on parameter p and the constant of integration λ. The model also considers fixed (β) and time-varying (γ) covariates. In this analysis, we are particularly interested in the covariates that change over time, like the number of completed trades or the time spent observing the stock market. Instead of reporting regression coefficients, we quote the hazard ratios of the coefficients of covariates. These hazard ratios of the coefficients of β and γ are equal to $\exp(\beta)$ and $\exp(\gamma)$. The hazard ratios can be understood as an indication of change in the hazard rate when a fixed or a time-varying binary covariate changes from zero to one. Using these hazard ratios allows us a straightforward way to interpret the change in the probability to sell a stock due to changes in continuous covariates. It also enables an easy comparison with results from former studies.

To calculate the extent of the disposition effect, we have to edit our data first. Following Shapira & Venezia (2001) and Feng & Seasholes (2005), we set a starting position for each investor, when he purchases his first stock after January 1st, 2004. We define a position as closed, when all of the position's stocks are sold. Subsequent purchases and sales are counted as single buy and sell transactions. We determine the starting position for the entire period and for each of the three sub-periods. This requires us to discard the trading information that is recorded before the start of that period. We use the volume-weighted average purchase price as the reference point for all positions. We calculate gains and losses for every day and every trading position of a period. For days when a position is not entirely sold, we compute paper gains and paper losses. If the daily low of a position held is above the reference point, the day is counted as a day with a paper gain, because an investor could have sold the position with a gain all day. If the daily high is below the reference point, the day is counted as a day with a paper loss. If a position is actually closed, we calculate the return by comparing the selling price with the reference point.

Like Feng & Seasholes (2005), we incorporate two self-defined key covariates in our model, the "Trading Gain Indicator" (TGI) and the "Trading Loss Indicator" (TLI). Both covariates indicate whether a stock is trading for a gain or a loss. The covariate TGI takes the value of one if the stock is sold for a gain or if the stock is trading with a paper gain. Otherwise, it takes the value of zero. The covariate TLI takes the value of one if the stock is sold for a loss or if the stock is trading with a paper loss and takes the value of zero otherwise. As the Cox proportional hazard regression model considers all position data until an event occurs, we calculate TGI and TLI for every position of all investors and for each trading day, making a total of almost 35 million observations.

4.4. Results

4.4.1. Disposition effect and learning over the entire period

In this subsection, we present the behavior of investors in terms of the disposition effect over the entire period without making any distinction between different market environments. We show that investors are prone to the disposition effect over the entire period and examine their ability to reduce the bias through experience, measured either by the number of trades or by the periods actively monitored the stock market.

4.4.1.1. Disposition effect over the entire period

In the following, we show that the average investor in the Estonian market is subject to the disposition effect. In Regressions 1 and 2 in Table 4.1, we report the strength of the disposition effect for all investors over the whole period from January 2004 to October 2010. A hazard ratio of less than one indicates a reduced probability of selling stocks, while a hazard ratio above one suggests a higher propensity to sell stocks. Presenting TLI or TGI as the only covariates, we can examine the disposition effect on average across all investors.

Table 4.1: Hazard ratios for the average investor

	entire period		period A		period B		period C	
	Reg 1	Reg 2	Reg 3	Reg 4	Reg 5	Reg 6	Reg 7	Reg 8
TLI	0.46 (-138.8) ***		0.54 (-56.53) ***		0.45 (-56.95) ***		0.63 (-36.08) ***	
TGI		2.15 (136.1) ***		1.82 (55.3) ***		2.17 (55.05) ***		1.5 (32.47) ***

The table presents the hazard ratios for the average investor during the different periods. We regress an indicator variable for the sell or hold decision. On the right side of the regression, the Trading Loss Indicator (TLI) takes a value of one if the stock trades below the reference price and zero if the stock trades above the reference price. The Trading Gain Indicator (TGI) takes a value of one if the stock trades above the reference price and zero if the stock trades below the reference price. Row 1 reports hazard ratios for TLI and row 2 reports hazard ratios for TGI. A hazard ratio of less than one indicates that an investor has a lower propensity to sell a stock, while a hazard ratio above one suggests a higher propensity. Data for the entire period are from January 2004 to October 2010. Data for the sub-periods cover the bear (period B) and bull market phases (periods A and C). Z statistics are shown in parentheses and *** denotes significance at 0.1 percent.

Regression 1 presents the likelihood of investors of selling stocks, when these stocks are below the reference price. The measured hazard ratio of 0.46 is considerably lower than one and therefore indicates that the average investor is inclined to sell his stocks less than half as often than stocks that range at the purchase price. We can observe the opposite behavior for stocks with a gain with a hazard ratio of 2.15. Thus, investors are more than twice as inclined to sell a stock with a gain than they are at the reference price. Consequently, investors in the Estonian stock market are prone to the disposition effect on a large scale.

4.4.1.2. Learning by trading

To prevent a certain behavioral pattern, investors have to recognize it as a bias that causes inferior investment performance. Otherwise, there is no reason to learn to avoid this behavior. To find evidence for the disadvantageous character of the disposition effect within our data set, we group investors by their risk-adjusted performance. To calculate investors' performance, we use the approach of Modigliani & Modigliani (1997) and generate ten groups, ranging from low to high performance. Our results confirm that investors with the lowest performance show the highest inclination to the disposition effect. The better investors perform, the less likely they are prone to the bias. Investors with the highest performance in the Estonian stock market show no propensity to the bias at all. We thus can conclude that poor performance is related to a high disposition effect.

One possible way of learning to avoid the disposition effect could be through the accumulation of trading related experience. Following Seru et al. (2010) and Koestner et al. (2012), we use the number of trades as a proxy for experience. To measure whether investors are able to overcome the disposition effect by placing orders, we construct time-varying covariates. By definition, every investor has zero experience at the beginning of a period. For every day and for every investor, we count the trades that are placed. We classify the number of trades into seven groups, with each group representing a different experience level. If an investor has a certain number of trades, the dummy variable of the corresponding grouped number of trades takes the value of one, otherwise it is zero. Our baseline scenario covers all investors with one or two trades. The next category up is the group of three to five trades, followed by grouped covariables of 6 to 10, 11 to 20, 21 to 50, 51 to 100 and more than 100 trades[7]. Unlike Feng & Seasholes (2005), who use a linear classification, we apply a logarithmic classification to emphasize the diminishing marginal benefit of an additional trade.

Table 4.2: Experience as number of trades over the whole period

	TLI		TGI	
variable	exp(coef)	z-stat	exp(coef)	z-stat
TLI/TGI	0.47	-41.18***	2.07	40.10***
experience ϵ [3-5 trades] x TLI/TGI	0.94	-2.47*	1.06	2.39*
experience ϵ [6-10 trades] x TLI/TGI	0.98	-0.72	1.02	0.7
experience ϵ [11-20 trades] x TLI/TGI	0.99	-0.59	1.01	0.57
experience ϵ [21-50 trades] x TLI/TGI	1.02	1.12	0.98	-0.83
experience ϵ [51-100 trades] x TLI/TGI	1.17	7.01***	0.86	-6.61***
experience ϵ [> 100 trades] x TLI/TGI	1.58	23.81***	0.64	-23.25***
experience ϵ [3-5 trades]	1.10	6.56***	1.04	2.19*
experience ϵ [6-10 trades]	1.48	27.73***	1.46	21.16***
experience ϵ [11-20 trades]	2.27	59.75***	2.24	47.41***
experience ϵ [21-50 trades]	3.75	100.04***	3.84	83.11***
experience ϵ [51-100 trades]	6.50	126.88***	7.61	113.69***
experience ϵ [> 100 trades]	20.29	236.94***	32.02	233.89***
+ demographic controls				

The table presents the hazard ratios for investors during the entire period. We regress an indicator variable for the sell or hold decision. On the right side of the regression, the Trading Loss Indicator (TLI) takes a value of one if the stock trades below the reference price and zero if the stock trades above the reference price. The Trading Gain Indicator (TGI) takes a value of one if the stock trades above the reference price and zero if the stock trades below the reference price. The experience covariates are grouped by the number of trades investors have executed. We interact the grouped experience covariates with TLI or TGI to identify changes in the propensity to sell stocks due to a change in the covariates. Covariates without an interaction term are added as control variables. Z statistics are shown in parentheses and ***, **, * and . denote significance at 0.1%, 1%, 5% and 10%, respectively.

[7] To control whether this way of splitting the number of trades affects the learning results, we calculate hazard ratios for different splits. Modifying the categories does not change the results substantially.

To identify changes in the propensity to sell stocks due to a change in the covariates, we primarily focus on the interaction terms of these grouped trade covariates with the Trading Gain/Loss Indicator. Grouped trade covariates without interaction and demographic covariates are used as controls. To illustrate the extent of the disposition effect in regard to the experience level, we use total hazard ratios. These indicators are calculated as the product of the baseline hazard and the interaction term of the respective experience category . The different total hazard ratios (please see Figure 4.2, 4.3 and 4.4) help us to compare trading patterns for investors with different levels of experience and thus enable an easy overview over investors' trading response to experience.

Table 4.2 presents the hazard ratios for the grouped trade dummies. For stocks that trade with a loss, the baseline scenario with one to two trades has a hazard ratio of 0.47. This indicates that investors with no experience have a high reluctance to sell their stocks. For the subsequent grouped trade dummies that represent three to 50 trades, the hazard ratios are mostly insignificant. This means that with up to 50 trades, the experience covariate does not have any notable impact on investors over the whole period. Only the covariables that represent more than 50 trades reach a degree of the disposition effect that is significantly below the level of the baseline. For more than 100 trades, the hazard ratio reaches 1.58, which equals a total hazard ratio of 0.74. This higher total hazard ratio (0.74 > 0.47) signifies that highly experienced investors are far less prone to the disposition effect than are investors without experience. Figure 4.2 illustrates the increasing total hazard ratios for stocks with a loss with regard to the number of trades executed. We can notice a similar pattern for equities that are trading with a gain. The hazard ratio for one to two trades indicates a high propensity to sell stocks. We observe once more the lowest bias for the dummy that represents investors with experience of more than 100 trades.

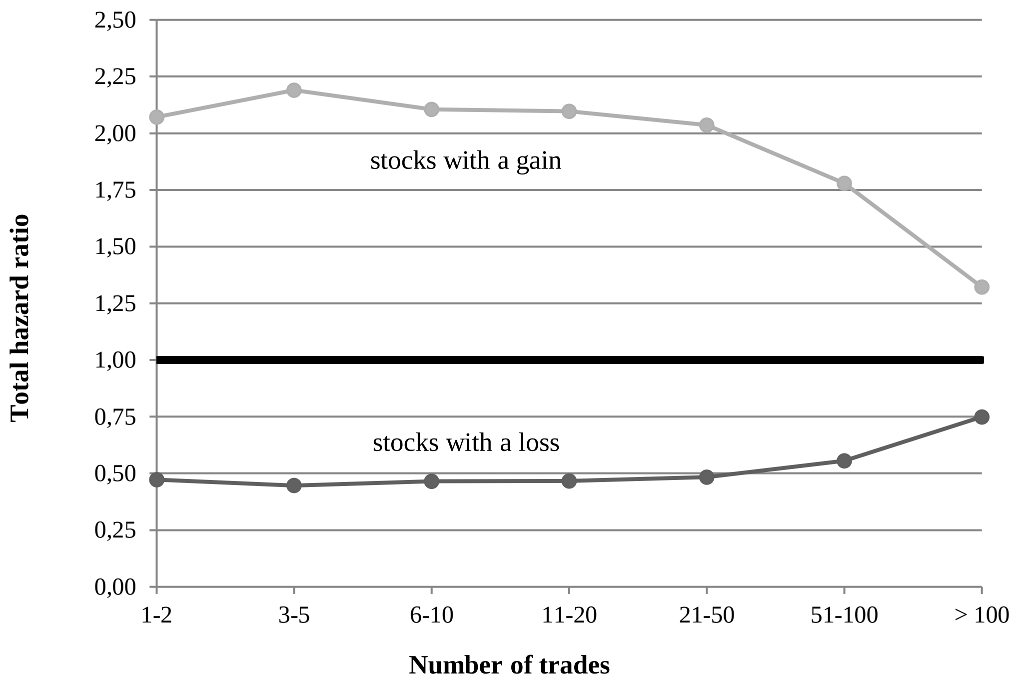

Figure 4.2: The disposition effect with regard to the number of trades over the entire period

The graph shows the total hazard ratios of the clustered number of trades for the entire period. The light grey line reflects the sell decisions for stocks with a gain; the dark grey line reflects the trading decisions for stocks with a loss. A total hazard ratio of one can be interpreted as the absence of the disposition effect. Table 4.2 allows a closer look at the data.

In conclusion, we observe a substantially reduced level of the disposition effect for the most experienced investors. An investor trading his 101st trade has a propensity to sell stocks with a loss that is 58 percent higher than that of an investor with low experience. For stocks trading with a gain, we see a reduction of 36 percent in the probability to sell stocks. Both results imply evidence of learning through trading with regard to the disposition effect. Investors are able to attenuate the disposition effect and its costly consequences if they place enough trades. Our learning related findings are in line with the results of Feng & Seasholes (2005) and Seru et al. (2010) who examined the bias for Chinese and Finnish investors. However, they contrast with the study of Koestner et al. (2012) who find a positive relationship between the cumulative number of trades and the disposition effect.

4.4.1.3. Learning by time

Not only the number of trades, but also the time an investor is actively monitoring the equity market can be used as proxies for experience (Nicolosi et al., 2009). Even if an investor does not trade continuously, he might monitor his existing portfolio and evaluate the decisions he has made. Because we cannot directly measure the time an investor has spent observing the stock market, we have to use the number of time intervals an investor was active in the stock market as a proxy. We assume that at each time interval an investor is trading, he is also spending time analyzing the market and gaining experience. Consequently, we use the number of time intervals an investor was active as our second proxy for experience.

Our data cover almost seven years. We thus divide our sample into 14 half-years. Every half-year starts on January 1st or July 1st and ends on June 30th or December 31th of the same year[8]. If an investor executes an order at least once in a half-year, we count this as an active half-year. For every trade in another half-year, we increase the count by one. We use this time-varying count as a dummy variable. All investors that trade for the first time within our sample form the baseline scenario. The other half-years are clustered into groups of 2 to 3, 4 to 5, 6 to 7, 8 to 9 and 10 and more active periods. Again, demographic variables are used as control variables.

[8] As our sample ends at October 31th, 2010, we also count the last period from July 1st, 2010 to October 31th, 2010 as a single half-year.

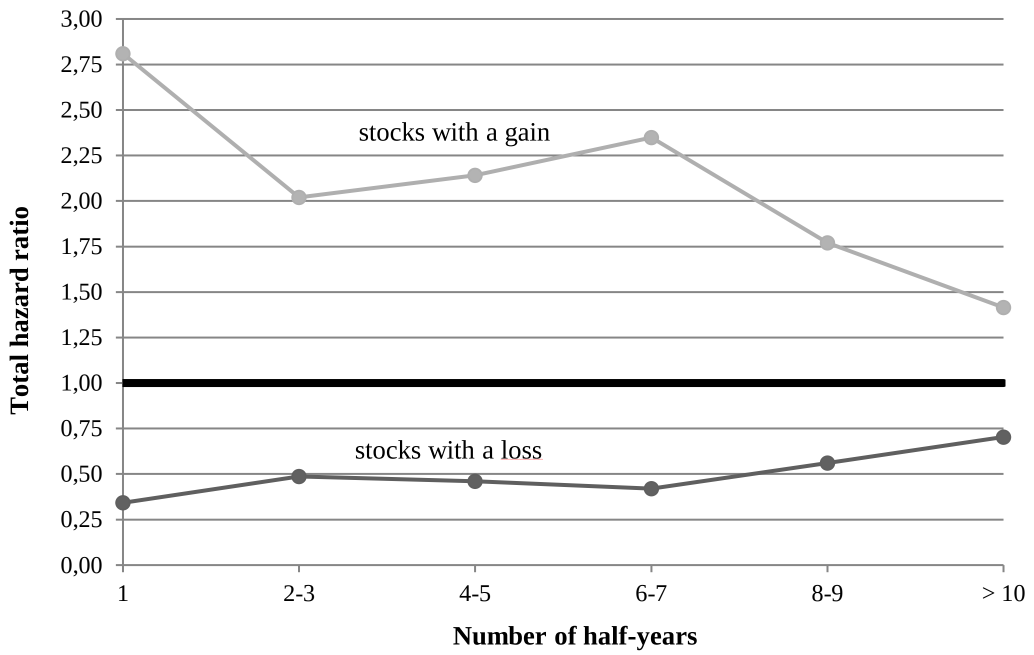

Figure 4.3: The disposition effect with regard to the time spent observing the stock market over the entire period

The graph shows the total hazard ratios of the clustered number of half-years an investor is active in the stock market. The light grey line reflects the sell decisions for stocks with a gain; the dark grey line reflects the trading decisions for stocks with a loss. A total hazard ratio of one can be interpreted as the absence of the disposition effect. Table 4.3 provides a closer look at the data.

The results in Table 4.3 support the assumption that investors in the Estonian stock market are able to learn from their experience. When stocks trade with a gain and an investor is active for the first time, we observe a hazard ratio of 2.81. Being active more than one half-year reduces this strong reluctance to sell a stock significantly. Participating more than nine half-years, the most active investors are least biased with a total hazard ratio of 1.4. Again, the most experienced investors can significantly reduce their aversion to sell stocks with a loss. This outcome holds for stocks with a loss as well as for stocks with a gain. When we compare the baseline hazard ratio with the hazard ratio of the most active investors, we see a decrease of 50 percent for experienced investors in the probability of selling winning stocks.

Figure 4.3 illustrates the declining disposition effect with regard to increasing experience.

Table 4.3: Experience as observing time over the whole period

	TLI		TGI	
variable	exp(coef)	z-stat	exp(coef)	z-stat
TLI/TGI	0.34	-61.44***	2.81	59.42***
experience ϵ [2-3 half-years] x TLI/TGI	1.42	19.71***	0.72	-18.52***
experience ϵ [4-5 half-years] x TLI/TGI	1.35	15.31***	0.76	-13.98***
experience ϵ [6-7 half-years] x TLI/TGI	1.23	9.76***	0.84	-8.51***
experience ϵ [8-9 half-years] x TLI/TGI	1.64	21.24***	0.63	-19.89***
experience ϵ [> 9 half-years] x TLI/TGI	2.06	31.12***	0.5	-29.67***
experience ϵ [2-3 half-years]	1.51	36.83***	2.11	52.91***
experience ϵ [4-5 half-years]	1.73	45.01***	2.3	53.56***
experience ϵ [6-7 half-years]	2.64	73.10***	3.2	68.87***
experience ϵ [8-9 half-years]	4.03	84.28***	6.49	107.47***
experience ϵ [> 9 half-years]	6.54	107.66***	13.21	151.78***
+ demographic controls				

The table presents the hazard ratios for investors during the entire period. We regress an indicator variable for the sell or hold decision. On the right side of the regression, the Trading Loss Indicator (TLI) takes a value of one if the stock trades below the reference price and zero if the stock trades above the reference price. The Trading Gain Indicator (TGI) takes a value of one if the stock trades above the reference price and zero if the stock trades below the reference price. The experience covariates are grouped by the number of half-years investors have observed the stock market. We interact the grouped experience covariates with TLI or TGI to identify changes in the propensity to sell stocks due to a change in the covariates. Covariates without an interaction term are added as control variables. Z statistics are shown in parentheses and ***, **, * and . denote significance at 0.1%, 1%, 5% and 10%, respectively.

In summary, our results show clear evidence for learning through experience. Both time-varying covariates − the number of trades and the number of active half-years − indicate a clear attenuation of the disposition effect for investors that gained experience. This holds for the whole period without regard to the stock market environment. But as the entire period is only the sum of its sub-periods, we would miss an important determinant by not considering the different market conditions (Leal et al., 2010; Nofsinger, 2012).

4.4.2. Disposition effect and learning during different stock market environments

In this section, we examine learning in regard to the disposition effect during different stock market environments. We show that investors are affected by the disposition effect, no matter whether they are facing a bull or a bear market. However, the extent of the disposition effect during the different periods does depend on developments in the stock market, as does the learning pattern to avoid this bias.

4.4.2.1. Disposition effect during bull and bear markets

Previous studies suggest that investors behave differently in their responses to periods of appreciation and depreciation in the stock market (Cohn et al., 2015; Kim & Nofsinger, 2007; Kim & Wei, 2002). To examine whether and how much investors are able to handle the change in the market environment in terms of the disposition effect, we divide the data set into three sub-periods, each covering a strong market movement. We distinguish two bull markets and one bear market.

Regressions 3 to 8 in Table 4.1 examine the disposition effect of the average investor for each of the three periods. Although investors suffer from the disposition effect in all periods, the extent of the bias varies considerably between the three periods. The disposition effect in the depreciation period is noticeably stronger than in the two appreciation periods. This applies for equities with a loss and with a profit. While investors in the bear market sell their stocks 2.17 times more often when they achieve a gain, investors facing a bullish market, sell their stocks only 1.82 and 1.5 times more often at similar terms. For investors with losses, we observe the same behavior with a much stronger disposition effect during the bear market.

The stronger bias during the market slump is in line with the findings of Cheng et al. (2013) who examine a stronger disposition effect for Taiwanese future traders under harsh conditions in the future market, but it stands in contrast to Leal et al. (2010) who find a lower disposition effect for Portuguese traders during the depreciation period. Thus, the literature gives additional evidence that investors react with different levels of the bias to a change in the market environment, though the findings are not homogenous.

4.4.2.2. Learning during bull and bear markets

For the entire period of almost seven years, Estonian investors exhibit significant learning results with regard to the disposition effect. To address possible differences during bull and bear markets, we determine the learning progress for the sub-periods.

Table 4.4 and 4.5 show the learning related hazard ratios for the bull and the bear market periods. For both bull markets A and C, we observe similar learning patterns. Investors are prone to the disposition effect during the upswings but are able to attenuate the bias significantly with experience. Once more, we find a more pronounced disposition effect during bull market A, with a hazard ratio of 1.82 for the baseline scenario for stocks with a gain. For the ensuing trade dummies that represent 3 to 100 trades there is a small but steady decline of the disposition effect with a total hazard ratio of 1.33 for the most experienced investors. That means that although investors can attenuate the bias noticeably, they are still prone to it. A similar learning progress can be seen for bull market period C with a total hazard ratio of 1.16 for more than 100 trades. Such a low total hazard ratio indicates that experience is nearly able to eliminate the disposition effect during this period. In conclusion, investors during bull periods A and C are able to decrease their disposition effect for stocks with gains by 27 and 25 percent. For stocks with losses, we can observe similar learning results.

Table 4.4: Learning progress during bull and bear markets for loss trades

	bull market A		bear market B		bull market C	
variable	exp(coef)	z-stat	exp(coef)	z-stat	exp(coef)	z-stat
TLI	0.54	-22.11***	0.37	-19.1***	0.57	-10.71***
exp. ϵ [3-5 trades] x TLI	1.22	5.66***	0.86	-2.32*	1.14	2.01*
exp. ϵ [6-10 trades] x TLI	1.25	6.17***	0.98	-0.27	1.21	3.07**
exp. ϵ [11-20 trades] x TLI	1.32	7.84***	0.92	-1.39	1.25	3.86***
exp. ϵ [21-50 trades] x TLI	1.29	7.11***	1.17	2.67**	1.23	3.73***
exp. ϵ [51-100 trades] x TLI	1.41	7.08***	1.25	3.52***	1.16	2.55*
exp. ϵ [> 100 trades] x TLI	1.38	8.93***	2.16	13.85***	1.48	7.12***
exp. ϵ [3-5 trades]	1.17	7.89***	2.04	14.37***	1.48	13.55***
exp. ϵ [6-10 trades]	1.62	23.83***	3.2	23.66***	2.19	28.11***
exp. ϵ [11-20 trades]	2.52	45.72***	5.38	35.76***	3.25	43.67***
exp. ϵ [21-50 trades]	4.46	74.63***	9.59	49.42***	6.62	73.86***
exp. ϵ [51-100 trades]	7.41	80.23***	16.62	55.63***	12.76	93.22***
exp. ϵ [> 100 trades]	25.43	167.44***	30.05	75.13***	31.53	136.07***
+ demogr. controls						

The table presents the hazard ratios for investors holding stocks with losses for the bull market periods A and C and for the bear market period B. We regress an indicator variable for the sell or hold decision. On the right side of the regression, the Trading Loss Indicator (TLI) takes a value of one if the stock trades below the reference price and zero if the stock trades above the reference price. We interact the grouped experience covariates with TLI to identify changes in the propensity to sell stocks due to a change in the covariates. Covariates without an interaction term are added as control variables. Z statistics are shown in parentheses and ***, **, * and . denote significance at 0.1%, 1%, 5% and 10%, respectively.

Investors during bear market period B show a slightly different learning pattern. Starting from an already high disposition effect for the baseline scenario, the hazard ratio for three to five trades increases even further. With a total hazard ratio of 3.06, investors with low experience sell their winning stocks more than three times as often as their stocks at the purchase price. The subsequent trade dummies, that represent an experience higher than five trades, indicate a steady decline of the disposition effect. For investors with more than 100 trades, we record a total hazard ratio of 1.24 and thus a comparatively low bias level. Investors are able to reduce the disposition effect for stocks with a gain by 52 percent. Figure 4.4 enables a straight comparison between bull markets A and C and bear market B.

Table 4.5: Learning progress during bull and bear markets for profit trades

	bull market A		bear market B		bull market C	
variable	exp(coef)	z-stat	exp(coef)	z-stat	exp(coef)	z-stat
TGI	1.82	21.61***	2.57	18.14***	1.55	8.72***
exp. ϵ [3-5 trades] x TGI	0.82	-5.81***	1.19	2.77**	0.91	-1.52
exp. ϵ [6-10 trades] x TGI	0.8	-6.35***	1.04	0.6	0.86	-2.47*
exp. ϵ [11-20 trades] x TGI	0.75	-7.95***	1.1	1.58	0.83	-3.19**
exp. ϵ [21-50 trades] x TGI	0.78	-7.01***	0.88	-2.19*	0.88	-2.39*
exp. ϵ [51-100 trades] x TGI	0.71	-7.07***	0.82	-3.17**	0.95	-0.97
exp. ϵ [> 100 trades] x TGI	0.73	-8.82***	0.48	-13.09***	0.75	-5.39***
exp. ϵ [3-5 trades]	1.43	12.86***	1.74	14.29***	1.64	9.02***
exp. ϵ [6-10 trades]	2.03	24.37***	3.12	30.59***	2.55	17.87***
exp. ϵ [11-20 trades]	3.35	41.68***	4.93	44.15***	3.93	27.09***
exp. ϵ [21-50 trades]	5.76	58.77***	11.07	69.07***	7.67	42.04***
exp. ϵ [51-100 trades]	10.46	56.80***	20.54	81.49***	13.79	50.88***
exp. ϵ [> 100 trades]	34.99	118.64***	64.05	127.31***	42.96	79.58***
+ demographic controls						

The table presents the hazard ratios for investors holding stocks with gains for the bull market periods A and C and for the bear market period B. We regress an indicator variable for the sell or hold decision. On the right side of the regression, the Trading Gain Indicator (TGI) takes a value of one if the stock trades above the reference price and zero if the stock trades below the reference price. We interact the grouped experience covariates with TGI to identify changes in the propensity to sell stocks due to a change in the covariates. Covariates without an interaction term are added as control variables. Z statistics are shown in parentheses and ***, **, * and . denote significance at 0.1%, 1%, 5% and 10%, respectively.

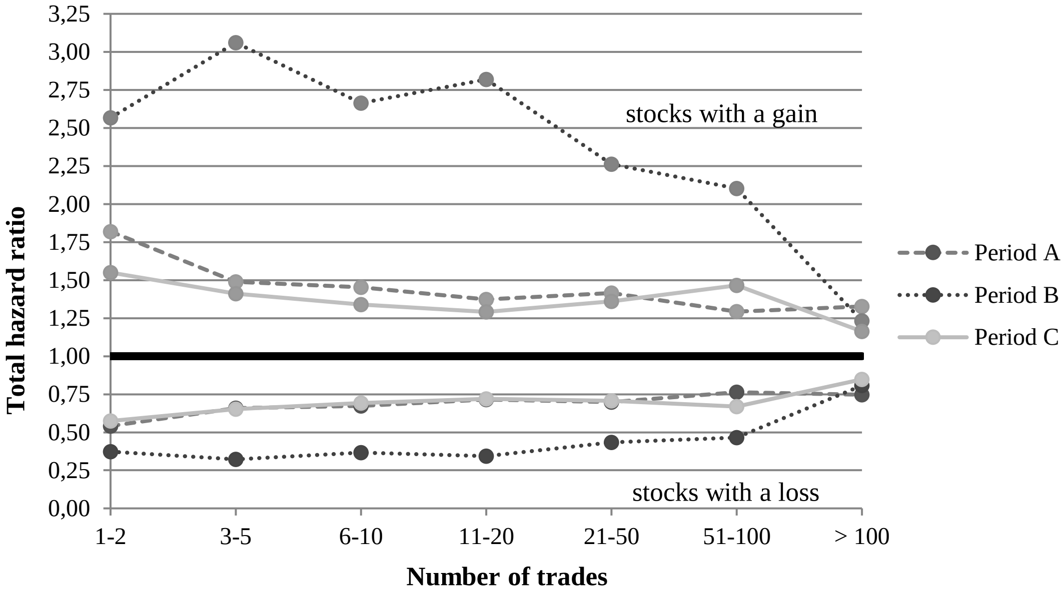

Figure 4.4: The disposition effect with regard to the number of trades for bull and bear periods

The graph shows the total hazard ratios of the clustered number of trades for the bull and bear market periods. The dashed lines reflect the hazard ratios for investors during bull period A, the dotted lines reflect the hazard ratios for investors during bear period B and the continuous lines reflect the hazard ratios for investors during bull period C. Table 4.4 and 4.5 provide a closer look at the data.

In summary, the more experienced investors are, the more they can obviate the disposition effect. This applies for all market environments. However, our main finding is the different speed of learning during bull and bear market periods, with investors in decreasing markets attenuating the disposition effect at the fastest pace.

A possible explanation for the rapid learning during bear markets might be the higher quitting rate of undisciplined investors from the stock market during falling markets, an effect we control for in the next section.

4.4.3. Learning by doing vs. learning about ability

In the previous section, we found evidence for significant learning during all periods. Apart from improvements through learning by experience, the withdrawal of investors with a high propensity to the disposition effect might be a further reason for the impressive learning results.

Seru et al. (2010) suggest that the overall learning consists of two separate learning processes − learning by doing and learning about ability. Learning by doing covers investors' improvement of their trading ability through trading itself. With growing experience, investors are able to improve their trading. In contrast, learning about ability describes investors' realization of their inherent trading abilities. After a certain number of trades, investors may recognize that they are not able to get valuable information or to evaluate valuable information in an appropriate way, even with a higher level of trading experience. These investors realize that their abilities are not sufficient for them to be successful in the stock market and that it is beneficial for them to stop trading. So far, we have only reported aggregated learning results, without distinguishing between the two different types of learning. In the following section, we examine the extent of learning by doing to determine the learning progress for investors who actually stay in the stock market.

We identify learning by doing with a new data sample, where we choose only investors that trade regularly. For this purpose, we select all investors that trade at least once in each of the three periods A, B and C. Thereby, we ensure that we consider only investors who are active all the time and have not left the stock market. Accordingly, investors with trading activity in fewer than three periods are not considered in the sample.

To test how fast regularly trading investors learn through experience (learning by doing), we use the same time-varying covariates as in Section 4.4.2.2 and also control for demographic differences. We compare the hazard ratios between the dummies for one to two trades with the dummies for more than 100 trades, to identify the learning progress for the period. For regularly trading investors who hold winning stocks in periods A, B and C, we determine reductions of 41, 45 and 40 percent, respectively. For our initial sample with all investors, we observe reductions of 27, 52 and 25 percent for these periods. The learning progress of both samples is compared in Figure 4.5. While regularly trading investors exhibit a higher reduction in the bias in periods A and C, the sample of all investors sees a higher reduction in period B. This inconsistent learning progress stands in contrast to the findings of Seru et al. (2010). If, as Seru et al. (2010) suggest, overall learning consists of two single learning processes, learning by doing and learning about ability, the sample with all investors should be expected to exhibit a constantly higher reduction of the disposition effect, as it includes both learning processes. In contrast, the subsample of regularly trading investors should have a lower speed of learning, because it does not include investors with bad performance leaving the stock market. Our results cannot confirm a generally higher proportion of learning about ability in the overall learning results. Only the results of bear market period B show a slightly higher learning progress for all investors. This might indicate that at least in sharply declining markets some investors with high inclination to the disposition effect leave the stock market. Because the differences between regularly trading investors and all investors are too small, investor attrition does not fully explain the different learning progress during bull and bear markets.

In summary, we are not able to determine a high level of learning about ability in our data. Only during the bear market, we are able to observe some investors with a high disposition effect leaving the market. Thus, a large portion of the overall learning outcome can be traced back to learning by doing.

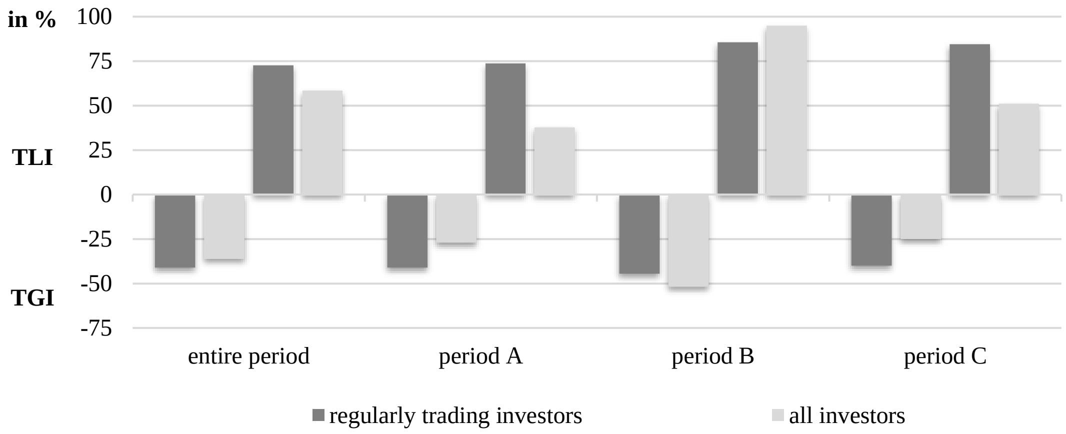

Figure 4.5: Reduction of the disposition effect of regularly trading investors and all investors

The graph shows the learning effects in relation to the disposition effect for different periods for investors that trade regularly (dark grey) and all investors (light grey). The bars represent the reduction in the disposition effect in percent. The learning progress is calculated for investors with an experience level of more than 100 trades in relation to investors with an experience level of one to two trades. The upper half of the graph represents the disposition effect for stocks with a loss (TLI), and the lower half represents the results for stocks with a gain (TGI).

4.4.4. Robustness of the learning differences between bull and bear markets

To control whether the differences between bull and bear markets arise only by chance, we perform a robustness check with three new sub-periods. Each of the new sub-periods covers exactly one-third of the entire period without consideration of falling or rising stock markets. This means for example that the second period includes transactions in the bull market in period A and the bear market in period B. Thus, our outcome for the second period should indicate two tendencies: we expect a higher disposition effect and a slower learning progress than during the bear period B, because bull market A contains transactions with a lower disposition effect and slower learning. The results underline our findings in Sections 4.4.2.1 and 4.4.2.2, as the bias for the new periods is in each case closer to the average of the three periods. For example, the disposition effect during the new second period is noticeably lower than that during the bear market period B. Similar results are obtained for the learning progress.

4.5. Analysis and discussion

Summarizing the findings in Section 4.4, we can conclude that investors in the Estonian stock market are able to attenuate the disposition effect when gaining experience. Highly experienced investors are hardly affected by the disposition effect. This outcome holds for the entire period and for the single sub-periods. However, although investors reduce the bias in bull and in bear market periods, they show the most pronounced learning progress during phases with declining stock prices, when the inclination for the disposition effect is also the highest. These results demonstrate the relevance of the market environment for analyses of investors' learning behavior.

An underlying reason for the different learning progress might be the distinct extent of the disposition effect in dependence on the varying market conditions. While the probability of selling stocks with gains rises by 117 percent during the bear market in comparison to the probability for stocks without gains, the likelihood of selling stocks during bull markets rises by only 82 and 50 percent. And the more prone investors are to the disposition effect, the more likely they might be to become aware of the bias and recognize its costly consequences.

This crucial impact of the market environment can be observed for the learning behavior as well. Although starting out highly biased, investors during bear period B manage the strongest learning achievements. While bear market investors with an experience of more than 100 trades have a total hazard ratio of only 1.24 for stocks in positive territory, investors during bull market A with the same experience show a total hazard ratio of 1.33. The impressive learning progress during market downturns could have various causes. One cause might be the possibility of faster feedback during bear markets. Periods of decline allow investors to make a faster evaluation of their investment decisions because market volatility is higher (Maheu & McCurdy, 2000). A volatile market generates losses and gains more quickly, and the prompter and therefore more direct feedback enables investors to assess the sources of information more immediately without a possibly biasing time delay. Investors can measure the outcome of their decisions directly. This helps them, to relate their success or failure immediately to a certain behavior and thus allows for a faster and more precise learning process.

Additionally, overreactions caused by the high affective state during declining markets (Lo & Repin, 2002; Steenbarger, 2004) entail harsher consequences. Whereas the results of wrong decisions during bull markets are more likely to be missed opportunities, wrong decisions during a bear market probably cause substantial losses. For these reasons, prompter feedback and the higher probability of harsh financial punishment contribute to the conditioning of investors and thus might provide the background for a faster learning process during bear markets.

A further reason for the faster learning during bear markets could be that investors with a high disposition effect are leaving the stock market during this period. However, the evidence for such behavior is weak, as we found only slight investor attrition during the bear market B and no such pattern during the bull markets A and C. This indicates that learning about ability, as found by Seru et al. (2010), affects our results only marginally.

Our findings in regard to the disposition effect for the entire period are in line with the results of Feng & Seasholes (2005) and Seru et al. (2010). For the average of years under review, both studies find evidence that investors are able to attenuate the bias when gaining experience. In contrast, Koestner et al. (2012) find no evidence for a positive correlation between experience and the avoidance of the bias. We believe that there are two main reasons for the diverging results. First, Koestner et al. (2012) apply the PGR-PLR approach to measure the disposition effect and do not exploit the survival analysis used in our study and in the works of Feng & Seasholes (2005) and Seru et al. (2010). As the PGR-PLR approach cannot take advantage of the time until an investor sells the stock, this method misses parts of the information used by survival analysis. Another, and we believe even more important reason for the different results is the non-consideration of the market environment by Koestner et al. (2012). As mentioned by the authors themselves, their data set, covering the years 2000 to 2007, shows considerable variation between the average disposition effect estimates in the various years. We suggest that the reason for this huge difference might be the varying market conditions during this time. The time period being observed was subject to two distinct market environments − a bear market with a decline of more than 70 percent and a bull market with an increase of almost 250 percent. Without considering the different market environments, it is hard to estimate whether learning took place in at least some sub-periods. Hence, it is possible that there is learning in regard to the disposition effect during the bear market, but that this progress is counterbalanced by a strong impairment in the bull market. These different results concerning learning underline the importance of taking the market conditions into account when analyzing investors' behavior.

4.6. Conclusion

The disposition effect is a costly habit for investors. Learning to avoid this bias can considerably improve their performance. However, investors are confronted with different market conditions, such as bull and bear markets, that could affect their learning behavior. This study examines how much the market environment affects learning in regard to the disposition effect.

We found evidence that investors are prone to the disposition effect to a large extent over the entire period. But gaining more experience, investors can attenuate their propensity for the bias by more than 50 percent. However, an aggregated examination of the whole period does not take into account the different market environments investors were confronted with. To analyze investors' trading habits in different environments, we divided the data into bull and bear markets. Our results show a clear distinction in investors' behavior between periods of declining and appreciating stock prices. Although we measured a pronounced disposition effect during all periods, we observed a significantly higher disposition effect during the bear market.

These differences in relation to the market conditions remained, when we examined the learning progress. Whereas inexperienced investors during bull markets showed the highest inclination to the disposition effect, they were also able to attenuate the bias most, when they continued trading. For very experienced investors, we measured a similar disposition effect during the bear market as during the bull markets. This means that investors who are facing a pronounced bear market still suffer from the bias but are able to reduce it to the same level as during bull markets. The reasons for the faster learning during bearish stock environments might be the prompter feedback and the higher probability of harsh financial punishment, both of which contribute to the conditioning of investors.

To control whether we really measured learning through experience, we created a new subsample with investors that trade regularly. By differentiating between learning by doing and learning about ability, we found strong evidence for learning by doing and only little evidence for learning about ability. Consequently, learning by placing trades is a substantial part of all the learning we measured in our sub-periods.

Finally, our results suggest that by ignoring the different market conditions, researchers will miss an important explanatory source of investors' behavior. Future studies about learning in financial markets should therefore consider this external factor. A second implication of our work is that it emphasizes the challenges for inexperienced investors. This group of investors does not only suffer from a more pronounced disposition effect and hence shows poor performance in comparison to the overall market, but it also has bigger problems to attenuate the bias when accumulating only limited experience, especially during downturns. To address these problems, investors should not only be informed about the existence of the disposition effect and its costly consequences, but they should also be prepared to cope with the emotional challenges during a bear market in a suitable way.

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Selbständigkeitserklärung

Ich bezeuge durch meine Unterschrift, dass meine Angaben über die bei der Abfassung benutzten Hilfsmittel, über die mir zuteil gewordene Hilfe sowie über frühere Begutachtungen meiner Dissertation in jeder Hinsicht der Wahrheit entsprechen.

Trier, 06.09.2018 Stefan Muhl