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Cut your losses and let your profits run? An analysis of the disposition effect among professional investors.

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Abstract

EN In this thesis, the relationship between trader characteristics and the disposition effect is analyzed. This effect describes a behavioral bias and captures the tendency to sell stocks that performed well faster than stocks that performed badly. In contrast to previous research that investigated the disposition effect on an aggregated level, this thesis contributes by analyzing it on the trader and member level, focusing on professional investors. By using OLS regressions, data from a large European stock exchange in 2007 are analyzed. The results show a significant disposition effect. Using trade frequency, trade value, portfolio size and member size as proxies, evidence was found that investor sophistication reduces the disposition effect. The same applies to algorithmic trading. Finally, a high disposition effect was found to harm profitability, making it a costly bias for investors.

DE In dieser Arbeit wird die Beziehung zwischen den Eigenschaften von Händlern und dem Dispositionseffekt analysiert. Dieser Effekt beschreibt einen Verhaltensbias und erfasst die Tendenz, Aktien, die sich gut entwickelt haben, schneller zu verkaufen als Aktien, die sich schlecht entwickeln. Im Gegensatz zu früheren Studien, die den Dispositionseffekt auf einer aggregierten Ebene untersuchten, leistet diese Arbeit einen Beitrag, indem sie den Effekt auf Händler- und Mitgliedsebene analysiert und sich dabei auf professionelle Händler konzentriert. Mithilfe von OLS-Regressionen werden Daten einer großen europäischen Börse aus dem Jahr 2007 analysiert. Die Ergebnisse zeigen einen signifikanten Dispositionseffekt. Unter Verwendung von Handelsfrequenz, Handelswert, Portfoliogröße und Mitgliedergröße als unabhängige Variablen wurde gezeigt, dass die Erfahrung der Anleger den Dispositionseffekt verringert. Das Gleiche gilt für den algorithmisch unterstützten Handel. Schließlich wurde festgestellt, dass ein hoher Dispositionseffekt die Rentabilität negativ beeinträchtigt, was ihn zu einer kostspieligen Verhaltensverzerrung für die Anleger macht.

Contents

1. Introduction

“Cut your losses and let your profits run” is one of the most frequently given advice regarding investment trading. The history of this quote goes back a long way, as it is part of David Ricardo’s three golden rules regarding the stock market. Nevertheless, the reality looks different since many investors don’t follow this rule (Kaustia, 2010). Due to the rational expectation paradigm, traders should act optimally and make fully informed decisions. However there exist a lot of studies showing that there are systematic deviations from rationality (Dhar & Zhu, 2006). These deviations, so-called behavioral biases, in financial markets influence investment decision-making and lead to irrational decisions (Kumar & Goyal, 2015).

It is crucial to understand not only that these biases exist but also how traders choose their trades and what behavioral regularities they underlie to understand market behavior better (Kaustia, 2010). In general, all behavioral biases lead to non-rational decision-making, again showing evidence against the efficiency market hypothesis. This hypothesis, called EMH, is based on the assumption that investors behave rationally in financial markets whereby all available information is considered in the prices of financial assets (Kumar & Goyal, 2015).

In this paper, one of the most documented biases in investment behavior is investigated: the disposition effect. This is the tendency of investors to sell stocks that developed positively (“winners”) in the sense that they can be sold with a gain fast. Opposed to that, stocks that developed negatively (“losers”) and could only be sold with a loss are held for a longer time – hoping these stocks will recover (Dhar & Zhu, 2006). This effect was first discovered by Shefrin and Statman (1985) who were the first ones that applied the concept of loss aversion discovered by Kahneman and Tversky (1979) to a market situation and called it disposition effect. In their paper Shefrin and Statman (1985) challenged the findings of Schlarbaum et al. (1978) by questioning whether individual investors really have stock selection skills or whether the return comes from the disposition of only realizing gains of stocks held in the portfolio (Kaustia, 2010). Nowadays, there is a lot of research that confirms that thesis by using different databases (Odean, 1998; Shapira & Venezia, 2001; Weber & Camerer, 1998). In general, underlying behavioral biases is leading to inferior returns (Kumar & Goyal, 2015). This also applies to the disposition effect: Knowing that there is not only a disposition effect, but it is disadvantageous for investors, making it even more interesting to investigate (Odean, 1998).

When investigating the existence of the disposition effect, it is important to understand its drivers and what investor characteristics impact the bias. If a certain type of investor is more prone to the disposition effect, this might have welfare and regulatory implications (Dhar & Zhu, 2006). In addition to that, it is important to analyze the impact of the disposition effect, and therefore, the question of how the disposition effect affects returns is posed and answered as well.

To test the disposition effect in this paper, 2,811 traders of a large European stock exchange are analyzed for the time period between January and April of 2007. This paper focuses on the analysis of the disposition effect at the level of each trader and investigates differences in the disposition effect across investors, following the logic of (Dhar & Zhu, 2006). The disposition effect is thereby measured as the gap between the proportions of gains realized (PGR) and the proportion of losses realized (PLR) – following the most common logic from Odean (1998). Additionally, the level of the member a trader belongs to is incorporated in the analysis by adding the member size to the regression models and using clustered standard errors. This makes it different from most of the other studies since usually, due to a lack of data access, aggregated data is used. This aggregated procedure could be problematic since evidence showed that traders are heterogeneous in terms of beliefs and trading styles, which makes it insufficient to use the mean across traders (Goetzmann & Massa, 2003).

The paper is organized as follows: Chapter 2 gives a review of current literature regarding the disposition effect, factors that might have an influence on the disposition effect, and impacts on return and profitability. Based on the current literature, the hypotheses are defined. Chapter 3 is about data and methodology. Chapter 4 is descriptively analyzing the disposition effect among traders and the data set. Additionally, it presents the empirical results answering the four hypotheses: (1) whether there exists a disposition effect, (2) how investor sophistication and trader characteristics influence, (3) what effect algorithmic order trading has, and (4) what impact the disposition effect has on the profitability of the traders. Chapter 5 discusses the findings and chapter 6 concludes and proposes some policy implications.

2 Literature review and hypothesis development

2.1 Day trading

Day traders execute many intraday trades and use the smallest price movements to gain profits. Due to the high frequency of trading, this can be profitable. The industry of day trading contains retail traders and professional traders. Retail traders risk their own capital and get all profits caused by trading, but they also must handle the losses. Additionally, they have to pay commission fees and they are not educated or get any training for trading. By contrast, professional traders are hired at a trading company. They don't trade with their own but with company capital and get a percentage of their profits and losses (Garvey & Murphy, 2004). In the following these trader types are called principals. Additionally, they get trainings about trading strategies and techniques (Garvey & Murphy, 2004). As a result, the principal traders in the data set are not only professional by the fact that they obtain a trading-job. Additionally, the 2,000 traders did more than 44 million transactions in 4 months. By comparing the dataset to Odean (1998), they obtained 10,000 traders doing around 100 thousand transactions over a six-year period. The number of trades itself increases the investor sophistication captured in the dataset. Agents, as the other account type in the dataset, capture all kinds of investors for whom the trader executed the trades. They contain individual and retail traders, but institutional traders as well, resulting in a quite heterogenous group.

2.2 The disposition effect

When an investor chooses to sell a stock, it can choose either a positively developed or a negatively developed stock. In general, there is a tendency of individuals to avoid situations that trigger regret and seek situations that trigger pride (Chen et al., 2007). Selling a negatively developed stock causes regret in people, whereas positively developed stocks cause pride (Nofsinger, 2017). Shefrin and Statman (1985) found out that the tendency of individuals to avoid regret and seek pride is the reason for them to sell "winners" (the stock that increased in price) fast (or even too early) and hold "losers" (the stock that decreased in the price) longer. Thereby, the concept of loss aversion is applied. Loss aversion is one of the most important concepts of Kahneman and Tverskys (1979) prospect theory. According to the prospect theory, individuals judge gains and losses relative to a reference point. Thereby, the value function is concave-shaped in the gain section and convex-shaped in the loss section – meaning individuals behaving risk averse when it comes to gains and risk-seeking when it comes to losses. This is one behavioral pattern that leads to the disposition effect (Kahneman & Tversky, 1979). Other psychological elements leading to the disposition effect are mental accounting (Thaler, 1985), self-control bias (Shefrin & Statman, 1985) and regret aversion (Bell, 1982).

The disposition effect applies the tendency of loss aversion to financial markets and predicts that individuals are indeed more willing to sell their winners compared to their losers (Chen et al., 2007). Odean (1998) developed a methodology for measuring the disposition effect that is still widely used. There, every time an investor sells a stock, the number of stocks is counted that are sold for a gain or for a loss and the number of stocks that are held in the portfolio but could have been sold for a gain or for a loss. To determine whether a stock is a winner or a loser the current price of the stock is compared to the original purchase price. Afterward, the proportion of losses realized (PLR), the proportion of gains realized (PGR) is calculated, and the result of the difference between these two proportions gives the magnitude of the disposition effect. An investor shows a disposition effect when PGR is larger than PLR, and the higher the difference, the more severe the bias is (Odean, 1998). A lot of research has been done regarding the disposition effect and evidence was found: Frazzini (2006) showed the existence of the disposition effect for mutual fund managers. Weber and Camerer (1998) demonstrated the existence of the disposition effect in an experimental setting. Shapira & Venezia (2001) found the bias for professional investors in Israel. In general, much research shows the disposition effect for different countries, time periods and trader groups (Kumar & Goyal, 2015). It seems that the behavioral biases are lower in more sophisticated investors (Dorn & Strobl, 2023). Regarding the magnitude of the disposition effect, Frazzini (2006) analyzed mutual fund managers and found a significant disposition effect of 3.1% whereas Odean (1998) found a size of 5% for retail investors. Choe and Eom (2009) found a disposition effect of 8.5% among individual and 4% at institutional investors in the Korean stock index future market.

Dhar and Zhu (2006) found a disposition effect for individual traders, but also for 20% of the traders, a behavior opposite to the disposition effect, namely selling losers early and holding winners longer.

2.3 The disposition effect among countries and cultures

In general, the disposition effect is mostly analyzed for Western cultures, such as the US (Odean, 1998), Finland (Grinblatt & Keloharju, 2001), and Israel (Shapira & Venezia, 2001). A systematic review of the disposition effect is done by Kumar and Goyal (2015). They analyzed 31 papers that dealt with the disposition effect, whereby only eight papers contained data from Europe. Some evidence exists that biases might vary between cultures – for example Asian cultures underlie more behavioral biases than people from the US (Yates et al., 1997). Li et al. (2021) found a significant positive effect of air pollution on the disposition effect in China what emphasizes the relevance of the environment traders live and trade in. This effect was found due to an impact of pollution on cognition, leading to a different behavior in financial markets. In general, these study's results show the relevance of investigating behavioral biases like the disposition effect for different countries.

Bernard et al. (2022) analyzed the disposition effect for the German stock market for individual investors between 2001 and 2015 and found out that they suffer from a disposition effect of 6.19%. This poses the question of whether other European professional investors show that effect as well. Dorn and Strobl (2023) investigated the effect of the German stock market between 1995 and 2000 on individual investors and found evidence for the disposition effect as well, whereby the PGR of 0.54% exceeds the PLR of 0.41%, leading to a disposition effect of 0.13%.

This paper is different from the listed other papers regarding the timespan and region, using data from a large European stock exchange in the months of January until April 2007. In general, different markets show different results regarding the disposition effect (Zahera & Bansal, 2019). Hence, this makes it interesting to investigate the European stock market in 2007.

2.4 The disposition effect at different trader types

This study analyzes the disposition effect by investor characteristics capturing investor sophistication. Therefore, it is relevant to have a closer look at different trader characteristics, especially since financial theory supposes that the decisions made by professional investors are driving the market prices (Shapira & Venezia, 2001). Kumar and Goyal (2015) proposed to analyze different trader types for further research to gain more insights into their decision-making. A systematic review showed that there are a lot of variables, for example, demographic variables, that influence the disposition effect for individual investors, but there is no consensus on whether institutional investors are affected by the disposition bias (Zahera & Bansal, 2019).

By analyzing the Chinese as an emerging market, Chen et al. (2007) could find out that more experienced investors are not always less concerned about the disposition effect: When assigning a dummy for every trader where the disposition effect is positive, only 35% of the individual investors and 43% among the institutional investors showed a disposition effect in general (Chen et al., 2007). O'Connell and Teo (2009) investigated the disposition effect among institutional traders, and they could not find evidence for the disposition effect as found for individual investors. They argued that institutional investors trade for other people's money, and their past performance records are publicly available. Additionally, they seem sophisticated enough to simply avoid the disposition effect. In contrast to their findings, Grinblatt and Keloharju (2001) showed that Finnish institutional investors underlie that bias that might come from a lower level of sophistication compared to the institutional traders of O'Connell and Teo (2009). Additionally, they could find the disposition effect for both trader types but weaker for the institutional investors (Grinblatt & Keloharju, 2001). Dhar and Zhu, (2006) showed that individuals working in professional occupations show a significantly smaller disposition effect.

Hermann et al. (2019) investigated the disposition effect in an experimental setting. Focusing the experiment on how investors behave when they trade on behalf of somebody else, they compared experienced and non-experienced traders. In conclusion, they found out that there is a difference between trading for others or the self among experienced traders, but not significant. This experiment measured experience as self-reported trading experience whereby the participants were students, so no professional traders (Hermann et al., 2019). These results make it interesting to investigate whether trading on behalf of somebody else vs. trading for oneself makes a difference regarding the disposition effect.

Nevertheless, the results are consistent with Shapira and Venezia (2001) showing that professional investors are less biased than individual investors and thus less concerned by the disposition effect. Reasons for that might be higher experience and more trainings that reduce the bias but cannot eliminate it completely (Shapira & Venezia, 2001). Dhar & Zhu (2006) for example found out as well that non-professionals suffer from a higher disposition effect. In general, a higher education correlates with a lower disposition effect (Calvet et al., 2009).

This paper is different from the other mentioned papers since it investigates trader desks at banks and professional traders that trade their member's capital. Since there is no consensus on whether professional traders show the disposition effect, this paper contributes by adding insights of this trader type.

Accordingly, the prediction is that there is a disposition effect among European professional investors in 2007, similar to the large literature and evidence.

Hypothesis 1: *European professional investors (principals) show a disposition effect.*

2.5 The disposition effect and important trader experience characteristics

Another reason to expect differences in the disposition effect is due to different trader sophistication. It is assumed – and widely confirmed by other research papers – that trading frequency and investor sophistication reduce the disposition effect (Choe & Eom, 2009; Dhar & Zhu, 2006). The reason behind that is an incomplete adaptation to the prospect theory's reference point (Dhar & Zhu, 2006). The findings of List and Price (2011) show that higher market experience goes hand in hand with more rational behavior.

Dhar & Zhu (2006) found evidence for several trader characteristics correlating with the disposition effect. Trader characteristics are, for example, trader activity measured as trading frequency (number of trades) and portfolio size (average portfolio value per trader). They found out that professionality, measured by working in a professional occupancy lowers the disposition effect. Additionally, they found a significant negative impact of the portfolio size and the (logarithmic) number of trades (trading frequency): The bigger the portfolio and the higher the trading frequency, the lower the disposition effect. Experience was assumed when the frequency of trading in a stock market was high (Dhar & Zhu, 2006).

Feng and Seasholes (2005) found out that experience in general as a trader characteristic reduces the disposition effect, yet, experience is hard to measure. They used different measures to capture experience, for example, age and gender, but also the number of stocks held (Feng & Seasholes, 2005). List & Price (2011) measured experience as the number of trades in a typical month. Choe and Eom (2009) found a significant negative effect of the (logarithmic) number of trades and the (logarithmic) value of trades that were used as a proxy for investor sophistication. Since it is widely accepted that professional investors have a higher trading volume and trading value than individual investors, these two variables serve as a proxy for investor professionality and sophistication (Choe & Eom, 2009).

As a result, in this paper, sophistication will be, on the one hand, captured by trading frequency, portfolio size (average of portfolio value per trader), and trading volume. On the other hand – what is not seen in literature so far – the member size is added. It is assumed that the member size might have a negative impact on the disposition effect since traders that belong to a larger member might be more sophisticated and educated.

This makes it interesting to investigate whether traders show a different magnitude of the disposition effect depending on the sophistication characteristics.

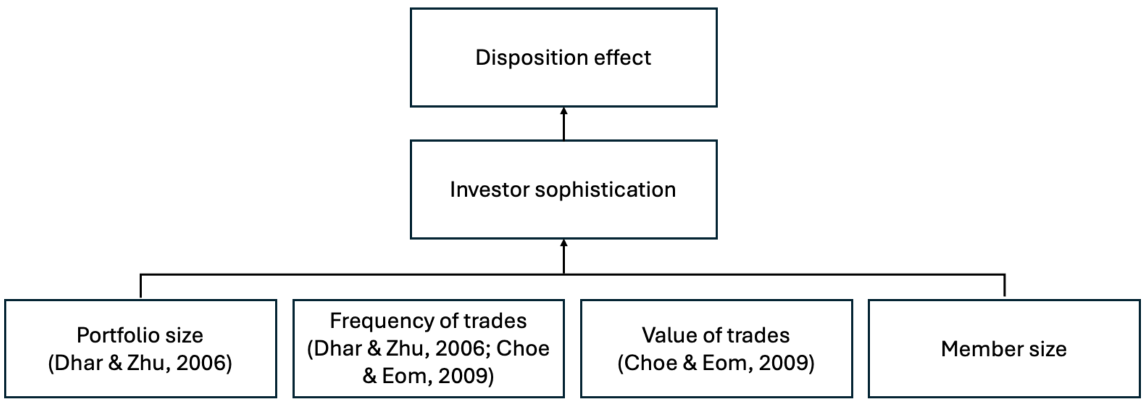

Figure 1: Trader-characteristic factors that influence investor sophistication (own figure)

Hypothesis 2: *Investor sophistication, captured by different trader characteristics, drives the disposition effect.*

Additionally, a further analysis regarding the algorithmic trading indicator is executed. Nowadays, decision-making is becoming more automated and can reduce behavioral biases such as the disposition effect in financial markets (Liaudinskas, 2024). One example that is using trading algorithms are so-called Robo-advisors, that provide high-quality advice and low-cost products to investors. They can help investors in making better informed and less biased decisions (Lisauskiene & Darskuviene, 2021). Robo-advising is proposing and executing financial advice through automated algorithms to support investors (D'Acunto et al., 2019).

For the years 2016 and 2017, Liaudinskas (2024) found out, that algorithms are not prone to the disposition effect and, in general, less affected by human biases. They found a significant difference in the disposition effect between humans and algorithms. By adding the dummy "human" in an OLS regression on the disposition effect, a significant positive coefficient of 0.032 was found (Liaudinskas, 2024). Opposed to that, humans are prone to the disposition effect. Li et al. (2024) analyzed whether ChatGPT can be a potential financial advisor for performance forecasts. They showed that the large language model can correct the optimistic biases of human analysts. Moreover, ChatGPT showed significantly fewer optimistic biases in the measures ROA, ROE, revenue growth and profit growth. Li et al. (2024) did not investigate the disposition effect as such but nevertheless showed that machines, in general, can reduce human biases. For investors who used a portfolio optimizer, the disposition effect was significantly lower than for those who did not use algorithmic support. Nevertheless, the bias diminished, but it did not fully disappear (D'Acunto et al., 2019).

Since automation of decision-making is very common, it's crucial to understand how algorithmic trading impacts the disposition effect. Even if there are many trades that are executed by an algorithm, there is rarely research done that investigates the disposition effect in the context of algorithmic trading. This paper contributes by adding algorithmic trading to the analysis and investigating its role in reducing human biases in financial decision-making.

Hypothesis 3: *Algorithmic trading has a negative effect on the disposition effect.*

2.6 Implication of the disposition effect on returns

Whereby the classical finance view thinks that behavioral biases are harmless and don't have price implications (Locke & Mann, 2005), different papers challenge that sight. Biased behavior and irrationality may lead to poor financial returns and, as a result, lower welfare levels (Lisauskiene & Darskuviene, 2021).

Goetzmann & Massa (2003) analyzed the disposition effect in the context of returns, risk and volatility at individual investors. They showed a negative correlation between the range of the disposition effect and the stock returns. Afi (2017) found similar results: the higher the disposition effect, the lower the returns of the stocks. Regarding mutual fund managers, Frazzini (2006) showed as well that the extent of the disposition effect adversely affects returns. Grinblatt and Han (2005) showed that the more investors show the disposition effect, the less their returns will turn out.

Chen et al. (2007) found out that institutional investors – as opposed to individual investors – in China make good trading decisions: the stocks they buy outperform the stocks they sell. Additionally, they set up a regression model and found a significant impact of trading frequency on returns, meaning accounts that trade a lot perform better (Chen et al., 2007). Odean (1999) found out as well that high trading frequency correlates with higher returns. The regression results from Chen et al. (2007) suggest that accounts that trade often show a significantly smaller disposition effect. But in contrast to the results of Chen et al. (2007) and Odean (1999), Barber & Odean (2000) found out that traders with a high frequency of trading underperform – due to different cognitive abilities.

Based on the study of Frazzini (2006) and Goetzmann & Massa (2003), the hypothesis is tested whether the disposition effect has a negative impact on returns.

Hypothesis 4: *The disposition effect affects returns in a negative way.*

3 Data and methodology

3.1 Data description

The millisecond-stamped transaction-level data used in this study contains 44,135,067 transactions from day-traders at a large European stock exchange. The period between January and April 2007 is analyzed. The descriptive statistic of the data is presented in Table 1.

The trade database contains one trade for every row, where the following details for every trade are observed: (1) information about the stocks that are traded (ISIN), (2) information about the trades (trade time, match price, trade size) and (3) there is the trader ID and the member ID (4) the trader belongs to. The member ID is the identifier of the exchange member, meaning the company registered to trade on the exchange. This is very rarely seen since so far, analyses on the disposition effect are mostly either done on individual data (i.e. Odean, 1998) or on aggregated data for professional traders (i.e. O'Connell & Teo, 2009). Liaudinskas (2024) used a very similar dataset with different professional traders and their members. The member ID and trader ID combined give the traders unique ID. Additionally, there is a (5) buy-sell-link indicator, making it possible to calculate the paper gains and paper losses. The account type (6), the order type (7) and the order routing indicator (8) make it possible to derive additional insights. The order routing indicator shows whether the order was sent via an algorithm and, as a result, whether the decision was made by a human or an algorithm (Liaudinskas, 2024). The account type is either principal, agent or market maker. Some investors traded in more than one role, which is why their transaction data are split based on the account type of the transactions. As a result, it might be that an investor is within the principal data set as well as within the agents' data set.

In the analysis, the transactions from principals as well as agents will be relevant in the analysis, but it is done for both account types separately. The focus in the main analysis lies on professional traders and their decisions, the regression results from the agents are found in the appendix. Since agent transactions are only executed but not chosen by the professional trader, they are analyzed separately. Another reason for the separated analysis is the heterogeneity of the agents group.

3.2 Measuring the disposition effect

When it comes to measuring the disposition effect, different approaches have been dominant so far. One of them is Odean (1998) that measure the effect ratio-based: First, every time a trader sells any stocks, the number of stocks that are sold for a loss (realized losses) and the number of stocks that are sold for a gain (realized winners) are counted for this trader. To determine whether it is a gain or a loss, the average purchase price is used. Afterward – at the same time point of the sale – the current paper gains and paper losses for that trader are calculated. Therefore, all positions in the portfolio of the trader are counted and the original purchasing price is compared with the daily high and low. If the purchasing price lies above the daily high, the stock is counted as a paper loss and if the purchasing price lies below the daily low, it is counted as a paper gain. As far as the purchase price lies beneath the daily high and low, it is not counted (Odean, 1998). After that, the four positions realized gains (RG), realized losses (RL), paper gains (PG) and paper losses (PL) are summed up for every trader. With this information, the proportion of gains realized (PGR) and the proportion of losses realized (PLR) can be calculated, firstly for every trader on its own and then aggregated among all traders. Calculating the disposition effect for every trader on its own makes it possible to examine the cross-sectional variation in the disposition effect, especially when investigating individuals with different trader characteristics (Dhar & Zhu, 2006).

$$PGR = \frac{RG}{RG + PG} = \frac{Realized\ Gain}{Realized\ Gain + Paper\ Gain} \tag{1}$$

$$PLR = \frac{RL}{RL + PL} = \frac{Realized\ Loss}{Realized\ Loss + Paper\ Loss} \tag{2}$$

Finally, the disposition effect can be calculated as the difference of each investor's PGR-PLR.

$$Disposition\ Effect\ (DE) = PGR - PLR \tag{3}$$

The larger the disposition effect, the higher the individual's probability of realizing winners than losers. This ratio-based approach experienced large popularity and many other studies followed this logic to calculate the disposition effect. The reasons for that are the easy implementation and interpretation (De Winne, 2020). This is why that approach is used in this paper as well.

Another widely used approach to investigate the disposition effect is using econometric techniques such as a regression analysis that allow understanding factors that influence the disposition effect (De Winne, 2020). Since in this analysis not only the existence of the disposition effect but also the influencing factors are relevant, the logic of Dhar and Zhu (2006) is applied to the second and third hypotheses. Hence, cross-sectional differences can be assessed.

3.3 Investigating the disposition effect: Models and methods

For the first hypothesis, a t-test is performed to learn about whether there exists a disposition effect in the dataset, among principal traders, among agent traders and all traders.

Afterward, a cross-sectional regression analysis to get insights about trader characteristics that capture trader sophistication is performed as follows:

$$DE = a + \beta 1 * Sophistication + \varepsilon \tag{4}$$

Sophistication describes the matrix of trader characteristics that, taken together, capture investor sophistication of the trader i: portfolio size (number of different ISINs traded), trading frequency, trading value and member size.

Regarding the third hypothesis, the impact of algorithmic trading will be measured. All traders in the dataset either use algorithmic trading or not, there are no traders that use the algorithms occasionally. A regression model is used to test whether the difference between the disposition effect of the groups (human vs. algorithm) is statistically significant. Thus, a dummy *Human* for non-algorithmic trading and decision-making is included in the regression model. Additionally, the trader *Sophistication* as presented in equation (4) is incorporated. As a result, the model looks as follows:

$$\begin{aligned} DE = {} & a + \beta 1 * Human + \beta 2 * Sophistication \\ & + \beta 3 * Human\ x\ Sophistication + \varepsilon \end{aligned} \tag{5}$$

After identifying the impact of algorithmic trading and sophistication characteristics, the impact of the disposition effect on investment performance is analyzed. Thereby, a cross-sectional regression analysis is performed to gain insights about the drivers of the profitability and, mainly, whether the disposition effect is mostly harmless or is indeed having a real impact on the profitability.

$$\begin{aligned} Profit = \; & a + \beta 1 * DE + \beta 2 * Sophistication + \beta 3 * Human + \\ & \beta 4 * DE \; x \; Sophistication + \beta 5 * Sophistication \; x \; Human \\ & + \beta 6 * DE \; x \; Human + \varepsilon \end{aligned} \tag{6}$$

Profit is the share in percentage of the profit achieved by trader i: the absolute profit divided by its total invest. *DE* is the disposition effect of the trader i. *Sophistication* and *Human* are the same variables as in equation (4) and (5). Again, the interaction terms between *Human* and *Sophistication, DE* and *Human* and *DE* and *Sophistication* are included in the model.

4 Results

4.1 Descriptive analysis

The 44 million transactions were executed by 2,811 traders and 243 members. As a result, the disposition effect is calculated either once or twice for every trader for the whole period. Once, if the trader traded exclusively as agent or principal (including market maker). Twice, if the trader traded in two roles: some trades as agent and some as principal (or market maker). 651 traders traded exclusively as principals or market makers and 1,959 traded exclusively as agents. The rest of the traders traded as agent as well as principal. In sum, 110 different stocks are traded. The following descriptive analysis is for all transactions executed by principal account types.

A principal trader has an average portfolio size of 503,206 euros. Around half of the traders show a negative cumulative portfolio size on average. The median of the portfolio size is 5210.46, indicating a skewed distribution. The average trading frequency is 13,683 transactions. On average, a trader belongs to a member that contains 42.94 different traders. Regarding the value of the trades, the average is around 449 million euros.

By having a closer look at the average number of trades and the trade value one can see that it is quite skewed with a few very active traders and a lot of traders that don't trade that much. The high Gini coefficient of 0.85 for trading frequency and 0.82 for trade value supports the result, showing that most of the trades are concentrated among a small number of traders.

Number of traders	2811
Number of members	243
Average (median) portfolio size	503,206,21 (5,210.46)
Average (median) number of trades	13,682.79 (1,941.5)
Average (median) value of trades	449,570,542 (77,711,543)
Average (median) member size	42.94 (35)

Table 1: Descriptive Statistics of the trader sample (own table)

In general, some of the 110 stocks are very often traded. The five most often traded stocks are Deutsche Telekom, SAP, Mercedes-Benz Group, Infineon and Siemens, with all of them more than 1.7 billion traded units within the four months of interest

Due to the skewness of the three variables portfolio size (*skew* = 12.97), number of trades (*skew* = 15.03) and trade value (*skew* = 11.43), all of them are logarithmically transformed and incorporated in the regression model. A logarithmic transformation results in a distribution that is closer to a normal distribution (Wooldridge, 2020).

4.2 Individual disposition effect

One of the main goals of the paper is to show whether the investigated 2,811 traders at a large European stock exchange show the disposition effect. The descriptive statistics of the disposition effect are shown in Table 2. The average disposition effect over all agent traders is 0.0043, the mode and the median are both 0. When it comes to the principal traders, the average of the disposition effect is 0.021 and the mode is 0 as well. The median is 0.0049. For analyzing the first hypothesis, independent t-tests are performed, analogous to Odean (1998). First, it is tested whether the disposition effect is different from zero, then it is tested whether the disposition effect is negative. The result for the first two-sided t-test among principal traders is significant ($p < .001$). When it comes to testing the one-sided test on positivity, the p-value is <.001 as well, indicating that the disposition effect is significantly positive, consistent with previous research (Odean, 1998).

As a result, principal traders show a disposition effect, meaning that their proportion of gains realized is bigger than the proportion of the losses realized: they are more prone to realize winners than realize losers. When conducting the two-sided ($p = .13$) as well as the one-sided t-test ($p = .06$) for the agents, no effect was found. There was no significant disposition effect among agents in the data set. The reason for this might be the large heterogeneity among agents, since different kinds of traders are captured in agents.

	Principals	Agents
Disposition effect (average)	0.021	0.0043
Disposition effect (mode)	0	0
Disposition effect (median)	0.0049	0

Table 2: The disposition effect for investors (own table)

Furthermore, the distribution of the disposition effect among the principals is shown in Figure 2. Per definition, the disposition effect is distributed between the borders -1 and 1. These extrema are the case when either PLR or PGR is zero and the other value is one, showing that the trader either only realizes losses or only realizes gains, whereby the former is more common. In the graph one can see that not all traders show a disposition effect; the mode is zero, and 817 traders show even a negative disposition effect, 234 show zero effect, which are more than 43% of all principal traders. This is quite large compared to the results of Dhar & Zhu (2006), who found that 19.7% of their traders had a smaller or equal zero disposition effect. The histograms look very similar to Choe & Eom (2009) – they also show zero as a mode and little peaks at the extrema -1 and 1, apart from that a bell shape.

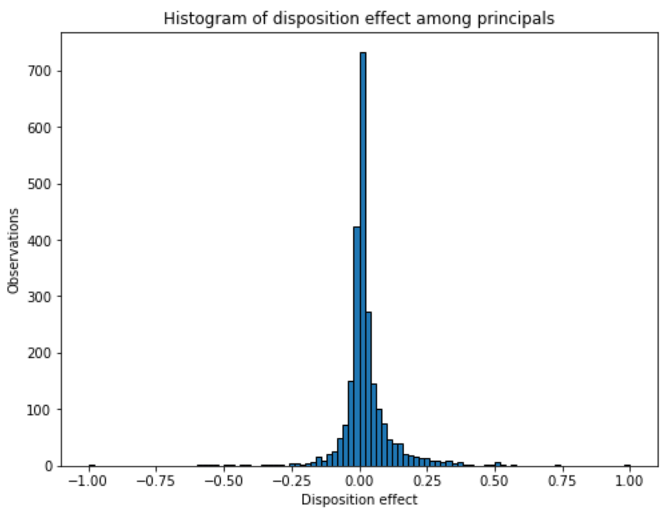

Figure 2: Distribution of the Disposition Effect (DE) of principal investors (own figure)

Now that we have found a significant positive disposition effect for principal traders, another descriptive analysis is done, where the dataset is split up into traders that show a positive vs. the traders that show a negative (including zero) disposition effect. This is a preliminary analysis to get insights into characteristics that may have an influence on the disposition effect. In Table 3, the traders with positive and negative disposition effects are compared according to different trader sophistication, algorithm, and profitability characteristics: trading frequency, portfolio size, member size, trading volume, algorithmic trading, and profitability.

	Disposition effect > 0	Disposition effect <= 0
Trading frequency	15,458.2	11,377
Member size	40.50	46.12
Trade value	503,590,417	379,411,523
Portfolio size	1,389,863	-648,352
Human	0.985	0.978
Profitability	0.55	0.066

Table 3: Characteristics of investors with and without the disposition effect (own table)

Traders with a positive disposition effect show more activity in the stock market, measured in trade frequency. They have a higher trade value and a larger and positive portfolio size. Yet, their member size is smaller, indicating that they belong to a smaller company than traders with a negative disposition effect. Plus, traders with a positive disposition effect traded less often with algorithmic support.

Regarding profitability, results show that traders with a disposition effect smaller or equal to zero had lower profitability than the ones with a positive disposition effect. The distribution of the profitability among the professional investors is shown in Figure 3.

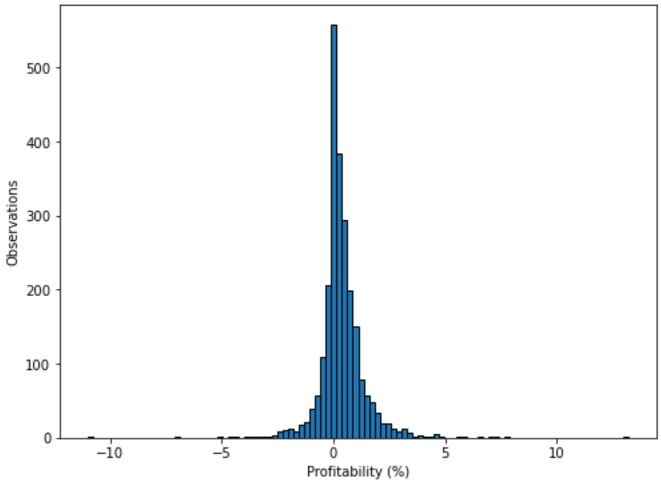

Figure 3: Distribution of the returns of investors (own figure)

These descriptive results show that the assumption about trader characteristics and algorithm usage that may drive the disposition effect might be supported. This indicates that some of the variables might show an effect in the following regression analysis.

Result 1: *European professional investors (principals) show a disposition effect. Agents show a smaller effect than the traders with principal account type. The effect within the principals is significantly positive.*

4.3 Regression Analysis: Drivers of the disposition effect

As already indicated, the disposition effect might have different forms among different trader characteristics. This suggests that there might be an effect of these characteristics that capture investor sophistication. To better understand these characteristics' impact, a regression analysis is performed and specified as DE = βX + ε as more detailed described in formula (4) in chapter 3. DE is the disposition effect. The X matrix contains the four variables, capturing investor sophistication, and ε is the i.i.d error term.

Since the variables trade value, trading frequency and portfolio size are positively skewed, the logarithm of these three variables is included in the second model. Both regressions are performed for agent traders and for principal traders. The focus of the interpretation of the analysis lies on principal traders.

Table 4 reports the results of the disposition effect regression analysis for the principal trader types.

In the base model in the first column, consistent with the hypothesis, the portfolio size, the trade value and the member size have a negative impact on the disposition effect. A bigger portfolio, a higher trade value and a larger member results in a lower disposition effect. Contrary to the hypothesis, the trading frequency has a positive coefficient, indicating a slightly positive impact. The impact of the three variables trading frequency, trade value and portfolio size is not significant. The member size has a significant negative coefficient in this model: the larger the member size, the smaller the disposition effect. When holding all other variables constant, increasing the member size of one unit (one trader) leads to a decrease in the disposition effect of 0.0004.

This supports the hypothesis that trader sophistication, measured as for example size of the member, might reduce the magnitude of the disposition effect of the traders.

In the logarithmic model in the second column the results are quite similar. The logarithmic portfolio size, the logarithmic trading frequency and the member size have a negative effect on the disposition effect. A bigger portfolio, a higher trading frequency and a larger member leads to a smaller disposition effect. The logarithmic trade value has a positive but not significant coefficient.

The coefficients of the logarithmic portfolio size as well as of the member size are significantly negative, indicating that traders with a larger portfolio and a larger member that they belong to, show a smaller disposition effect. In particular, when the member size increases by one trader, the disposition effect decreases by 0.0003 units holding the other variables constant. When the portfolio size rises by one percent, the disposition effect decreases by 0.0057%, ceteris paribus. To sum it up, regarding principal traders, the member size shows a quite stable, significantly negative effect in these regressions, while the other three variables vary within their direction.

Dependent variable	DE	
Model No.	(4)	(4) with ln
Intercept	0.0375 (8.337)***	0.0853 (1.092)
Trading frequency	1.7e-8 (0.446)	
Portfolio size	-1.6e-12 (-0.347)	
Trade value	-1.5e-12 (-0.938)	
Member size	-0.0004 (-4.841)***	-0.0003 (-4.355)***
Ln(trading frequency)		-0.0016 (-0.270)

Ln(portfolio size)		-0.0057 (-2.346)**
Ln(trade value)		0.0025 (0.368)
Adj. R^2	0.014	0.025
N	2416	2416

Note: * means significant at 10%-level; ** means significant at 5% level; *** means significant at 1% level.

Table 4: Impact of investor characteristics on the disposition effect (own table)

When conducting both regression analyses again for the agent account type only, the results show no significant results: none of the variables that capture investor sophistication have a significant coefficient. The same results are seen in both models, the baseline model and the model with logarithmic variables. The reason for seeing no effects here might be the large heterogeneity among the agent traders and, as a result, a loss of information that happened due to the aggregation. The regression outcome can be found in the appendix.

In summary, the findings regarding investor sophistication among principal traders are as follows. In the base model, there is a negative influence of the variables portfolio size, trade value and member size, whereby only the coefficient of member size is significant. When incorporating the logarithm of the skewed variables, member size, trading frequency and portfolio size show a negative impact on the disposition effect: member size and portfolio size have a significant negative coefficient. Taken together, investor sophistication in general might reduce the disposition effect. These results are partly in line with and pretty similar to Choe & Eom (2009); their coefficient for the logarithm of the number of trades was -0.011. The coefficient found by Dhar & Zhu (2006) was -0.046, in this analysis -0.0016.

Result 2: *Investor sophistication has a negative impact on the disposition effect among principal traders. Among agent traders, no effects could be found.*

4.4 Regression Analysis: Impact of non-algorithmic trading on the disposition effect

The differences in the disposition effect between humans and algorithms are analyzed by regressing the disposition effect variable on the dummy variable *Human*. Table 5

presents the results of the regression as specified in model (5). The coefficient of *Human* was 0.063 and is not statistically significant (p = 0.5). This means, since a trader is either trading with algorithmic support or not, that, changing from support to no support (and therefore deciding by themselves) increases their disposition effect by 0.063 units. This is in line with the hypothesis that algorithms can play a role in overcoming biases. The difference of 0.063 is close to the significant difference of the disposition effects of 0.032 found by Liaudinskas (2024) at the Copenhagen stock exchange.
Regarding the second model, the human factor alone does again not show significance, but its interaction with trading frequency is significantly positive (p <.001) and portfolio size (p =.038) is significantly negative. The effect that these two variables have on the disposition effect, depends on the human trading indicator. Overall, significant interaction effects reveal a more complex relationships between the predictors and the disposition effect.

When incorporating the logarithm of the trade value, trade frequency and portfolio size, no significant results of human trading were found anymore. Regarding the agent trader types, no significant effect of the human indicator was found, yet, the coefficient was positive. This indicates even at the agents data set, that a lower percentage of algorithm usage could increase the disposition effect. A reduction of the disposition effect could be achieved, independent from the trader type, whenever human decision-making is replaced with algorithmic trading that is used as decision-making support.

In conclusion, the traders who decided by themselves and did not use algorithms to make their decisions showed a higher disposition effect. This provides evidence for the hypothesis that the disposition effect is not caused by profit-maximizing motives but due to human-specific causes such as emotions and cognitive biases (Liaudinskas, 2024).

Dependent variable	DE		
Model No.	(5)	(5) with interaction	(5) with ln
Intercept	0.0152 (1.656)*	0.0235 (2.080)**	-0.0106 (-0.101)
Human	0.0063 (0.669)	0.0144 (1.163)	0.0967 (0.724)
Trading frequency		-2.9e-7 (-5.319)***	

Portfolio size		3.7e-11 (2.101)**	
Trade value		7.2e-12 (1.739)*	
Member size		-7.7e-5 (-0.228)	-0.0003 (-0.972)
Ln(trading frequency)			-0.0143 (-1.046)
Ln(portfolio size)			-0.0029 (-0.763)
Ln(trade value)			0.0109 (1.060)
Human x Trading frequency		3.1e-7 (4.557)***	
Human x Portfolio size		-3.9e-11 (-2.09)**	
Human x Trade value		-9.0e-12 (-1.952)*	
Human x Member size		-0.0003 (-0.823)	-3.1e-5 (-0.104)
Human x ln(Trading frequency)			0.0129 (0.885)
Human x ln(Portfolio size)			-0.0028 (-0.627)
Human x ln(Trade value)			-0.0085 (-0.657)
Adj. R^2	0	0.013	0.023
N	2416	2416	2416

Note: * means significant at 10%-level; ** means significant at 5% level; *** means significant at 1% level.

Table 5: Impact of human trading instead of algorithmic support on the disposition effect (own table)

Result 3: *Algorithmic trading has a negative effect on the disposition effect. Among principal traders, the effect was negative, yet not significant. For agent traders, the effect was negative significant.*

4.5 Regression Analysis: Impact of the disposition effect on the returns

After identifying the relationship between investor sophistication, algorithmic trading, and the disposition effect, it is now of interest to show whether this behavioral bias is problematic. Therefore, the impact of the disposition effect on the investment performance will be analyzed. Another OLS regression is conducted as specified in equation (6). Table 6 reports the coefficients from the regression of the profitability on the disposition effect, sophistication, algorithmic trading and all interaction terms.

Dependent variable	Profitability	
Model No.	(6)	(6) with ln
Intercept	0.5581 (3.460)***	-2.0463 (-1.154)
Disposition effect	-2.2274 (-3.106)***	-3.2968 (-2.651)***
Trading frequency	2.8e-7 (0.133)	
Ln(Trading frequency)		-0.1655 (-1.062)
Portfolio size	9.9e-10 (1.500)	
Ln(Portfolio size)		-0.0688 (-0.998)
Trade value	6.1e-11(0.809)	
Ln(Trade value)		0.2732 (1.544)
Member size	-0.0034 (-1.635)	-0.0031 (-1.364)
Human	-0.2370 (-1.416)	0.5505 (0.278)
Disposition effect x Human	2.8544 (4.257)***	3.3585 (5.136)***
Disposition effect x Trading frequency	1.6e-5 (0.812)	
Disposition effect x Ln(Trading frequency)		0.6411 (2.679)***
Disposition effect x Portfolio size	1.1e-9 (0.444)	
Disposition effect x Ln(Portfolio size)		0.6016 (4.137)***
Disposition effect x Trade value	1.7e-12 (0.003)	
Disposition effect x Ln(Trade value)		-0.6102 (-3.133)***
Disposition effect x Member size	0.0404 (4.840)***	0.0287 (2.930)***
Human x Trading frequency	-5.6e-7 (-0.250)	

Human x Ln(Trading frequency)		0.0406 (0.233)
Human x Portfolio size	-8.6e-10 (-1.305)	
Human x Ln(Portfolio size)		0.0778 (1.111)
Human x Trade value	-5.8e-11 (-0.734)	
Human x Ln(Trade value)		-0.1279 (-0.664)
Human x Member size	0.0030 (1.391)	0.0023 (1.027)
Adj. N^2	0.049	0.079
N	2416	2416

Note: * means significant at 10%-level; ** means significant at 5% level; *** means significant at 1% level.

Table 6: Impact of the disposition effect on profitability (own table)

The coefficients suggest a negative significant relationship between the disposition effect and profitability. This result is in line with the findings of Choe & Eom (2009). An increase of 0.1 in the disposition effect would reduce the profitability by 22%, holding all other variables constant. Additionally, the interaction term of disposition and human decision-making, as well as the interaction term of disposition and member size, was significantly positive. This is a little counterintuitive since the results of hypothesis two would predict that higher member size would lead to fewer biases and yet higher profitability. However, the results could also show that a large member is professional enough and uses available information more efficiently to achieve a high profitability, even when the traders behave biasedly. The interaction between the disposition effect and humans was also significantly positive, showing that the impact on the disposition effect depends on whether the trader decided on his own or algorithmically supported. Regarding the model with the logarithmic variables, the disposition effect and all interactions were significant. This supports again the thesis that the disposition effect has a significant negative effect on the profitability of traders.

When looking at the results of the agent account types, no significant impact of the disposition effect was found. This might again be due to heterogeneity among the agent transactions.

To sum it up, the results show that underlying the disposition effect is disadvantageous and a costly behavioral bias. Overall, the results are in line with Choe & Eom (2009) and Odean (1998), yet inconsistent with Locke and Mann (2005).

Result 4: *The disposition effect has a negative impact on returns.*

5 Discussion

This research has some limitations that should serve as a warning regarding the results for the reader.

First, the analysis only covers a small period of only four months, and as a result, this might be insufficient to look at since the generalizability of the results could suffer and trends could be missed. To get more detailed insights into the evolvement of the disposition effect over time and especially across long cycles, analyzing a broader time horizon would be interesting.

Second, the data available is already quite old. This might be problematic since behavior and available technology changed drastically in the last 17 years. For example, recently, large language models (LLMs) such as ChatGPT were applied in various disciplines, such as finance (Li et al., 2024). As a result, the currently used algorithmic instruments may vary significantly from those used in 2007. This challenges the results in terms of applicability. Nevertheless, the technological instruments improved, and since the results for 2007 already suggested a significant reduction of the behavioral bias when using decision-support from algorithms, this should not cause concerns. One positive aspect of old data is that it represents a period prior to the global financial crisis. This allows an analysis of the traders under normal market conditions. For further research, it would be interesting to compare data collected in normal market conditions versus data from periods of high market volatility, such as during financial crises or economic recessions. This comparison could reveal how the disposition effect changes when the market conditions change.

Third, one can criticize that the very common measure of the disposition effect following the logic of Odean (1998) is used, where only the number of stocks are counted that could have been sold for a gain or for a loss and the value is completely disregarded. This could be problematic since the chosen method to analyze the disposition effect but also the implementation could lead to differences in results and implications (De Winne, 2020). Dhar & Zhu (2006) used two more different approaches to calculate the disposition effect when checking the robustness of their results: The approach from Weber & Camerer (1998) and another formula that avoids the scaling bias (RG/RL – PG/PL). Even when they used another formula to calculate the disposition effect, the results did not change. For further research, other formulas containing the trades' value should be considered.

Fourth, the regression approach of an OLS regression used for the second and fourth hypotheses might lead to biased results when analyzing the cross-sectional differences in the disposition effect. The issue is that the disposition effect may be linked to the behavioral variables that are incorporated in the regression design as potential influence factors, since they are measured simultaneously. This is describing an endogeneity problem (De Winne, 2020). Choe & Eom (2009) addressed the endogeneity problem by performing a regression where the current year's return was regressed on the disposition effect from the previous year. The results were in line with the results before. Another method to further investigate the disposition effect is to conduct a probit-model, whereby the dependent variable is 0 or 1, depending on whether the disposition effect is positive or negative, as performed by Dhar & Zhu (2006). This analysis could be replicated for further research, using a different approach to control for endogeneity.
Fifth, one should be cautious when interpreting the results of the agents' database. Since the agent account type captures only the role in which the trader was active when trading, many different decision-makers are captured and aggregated. This results in a large heterogeneity among these traders. For further research, it would be interesting to analyze different trader types that are not aggregated. Investigating the disposition effect of individual investors compared to professional and institutional investors would add valuable insights. Additionally, examining how these groups respond differently to behavioral biases, in combination with market fluctuations or stress events, could help understand their unique contributions to overall market dynamics.
Sixth, it is crucial to pay attention to the assumptions of the OLS regression when interpreting the results. One important assumption of OLS is normality, meaning that the error term is independent and normally distributed (Wooldridge, 2020). In Figure 1, it seems that the dependent variable, the disposition effect among traders, is not normally distributed. By definition, the disposition effect is bounded by -1 and 1. There are spikes towards the tails visible, but besides that, the histogram is bell-shaped. These spikes and extreme values could be reasonable for the results shown in the regression analysis, potentially biasing the results since the non-normality of the residuals could be present. Nevertheless, OLS is applicable even if the errors are not even approximately normally distributed, since, in line with the central limit theorem,

the estimators satisfy asymptotic normality. This is only the case in large sample sizes (Wooldridge, 2020). As a result, the distribution should not be too problematic.

6 Conclusion

It seems that professional traders are differently reluctant to realize their losses. The tendency for principal traders is clear: The less educated and sophisticated or simply the less professional, the larger the disposition effect. Within the sophistication, the member size played an important role: the larger the member the trader belongs to, the lower the disposition effect. Regarding algorithmic trading, no significant effect was found. Still, the tendency was clear: The more the trader decided on his own, the higher the disposition effect and the less rational their behavior was. By analyzing the gravity of the disposition effect, a significant negative effect of the disposition effect on profitability was found. Again, this shows that some behavioral biases, such as the disposition effect, might be costly and disadvantageous.

Therefore, it is especially crucial for organizations or members of the individual investors to help the most prone investors to get awareness of the bias they underlie. Additionally, it would be useful to help individual investors with their trading strategy to avoid the disposition effect and avoid lowering their profitability. This could be done by education and information. Being less prone to the disposition effect leads to selling losers earlier, positively affecting the after-tax portfolio performance. (Dhar & Zhu, 2006). Even though knowledge, professional training and experience can't eliminate the disposition effect completely, it can help reduce it (Choe & Eom, 2009; Zahera & Bansal, 2019). Evidence was found that investor sophistication might reduce the disposition effect, so as a result, all measures leading to a higher investor sophistication might be beneficial.

For further research, it would be interesting to analyze whether traders that trade as agents behave differently when trading with their own money. That way, one could answer the different trading behaviors in different roles by investigating the same person. Additionally, to gain additional insights about the disposition effect, the dataset could be divided into one-month sets and the regression analysis could be done again. The main advantage might be ensuring the consistency and stability of the results over time. To control for endogeneity, one could perform another regression where the disposition effect is regressed on trader characteristics from another point in time, such as Choe & Eom (2009) have done for a robustness check.

Furthermore, it would be especially interesting to analyze data containing December. This was irrelevant in this study, since only data from January until April 2007 was available. Nevertheless, it is expected that the disposition effect will disappear in December, since then, investors usually realize more losses and fewer gains, compared to the rest of the months. This happens due to tax-motivated selling (Odean, 1998). As a result, seeing the difference between December and the other months of the year when it comes to the different account types or algorithmic trading support would give valuable insights.

Another approach for further insights is including the overall market situation in the analysis. Bernard et al. (2022) stated that most of the analyses are done in boom periods and that the disposition effect is higher in bust periods. They indicated that the investigated period from January until April 2007 had been a boom period in the German stock market as well, and thus, the results may underestimate the disposition effect. As a result, it would be interesting to compare the behavior of the same traders in a bust market as well. This could be done by analyzing a larger period of the same traders and incorporating boom and bust months as dummy variables, following the logic of Bernard et al. (2022).

To sum it up, this thesis provides a comprehensive analysis of the disposition effect within professional traders by exposing different trader characteristics. When analyzing the data from a large European stock exchange in 2007, significant effects and insights about member size and other variables of investor sophistication, algorithmic trading and the relationship of the disposition effect with profitability were gained. Due to the high complexity, further research will be necessary to gain insights into the different trader types and the disposition effect. This thesis contributed to behavioral finance and offers a foundation for future studies that aim to understand investor behavior and behavioral biases in finance markets better.

The advice to "cut your losses and let your profits run" seems valid given the significant impact of the disposition effect on profitability observed in our study. Nevertheless, it should be handled carefully given the complexities and risks inherent in financial markets that may override simple strategies.

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Appendix

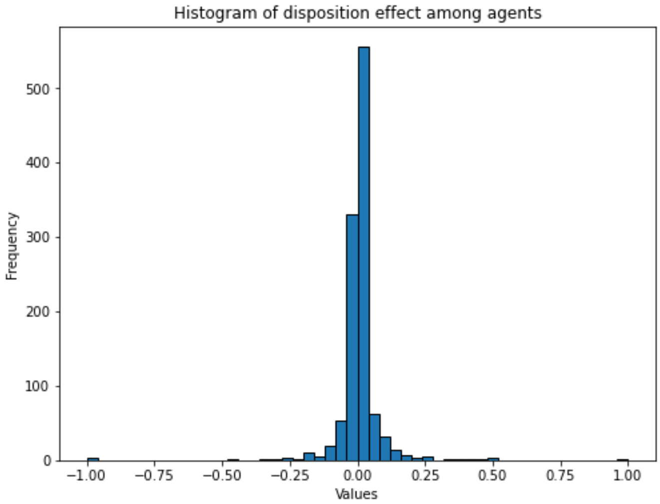

Figure A.1: Distribution of the Disposition Effect (DE) of agent investors (own figure)

Dependent variable	DE	
Model No.	(4)	(4) with ln
Intercept	0.0108 (2.362)**	-0.0901 (-0.494)
Trading frequency	1.4e-8 (0.376)	
Portfolio size	1.0e-11 (1.359)	
Trade value	-9.3e-13 (-0.541)	
Member size	-0.0002 (-1.839)*	-0.0002 (-1.755)*
Ln(trading frequency)		-0.0115 (-0.693)
Ln(portfolio size)		0.0004 (0.105)
Ln(trade value)		0.0102 (0.589)
Adj. R^2	0.001	0.008
N	1119	1119

Note: * means significant at 10%-level; ** means significant at 5% level; *** means significant at 1% level.

Table A.2: Impact of investor characteristics on the disposition effect (own figure)

Dependent variable	DE		
Model No.	(5)	(5) with interaction	(5) with ln
Intercept	-0.0169 (-1.395)	-0.0283 (-1.442)	-0.8647 (-3.837)***
Human	0.0243 (1.923)*	0.0455 (2.271)**	1.0768 (4.067)***
Trading frequency		8.3e-8 (0.972)	
Portfolio size		5.1e-11 (1.063)	
Trade value		-1.5e-13 (-0.139)	
Member size		0.0004 (0.783)	-0.0008 (-1.668)*
Ln(trading frequency)			-0.0814 (-3.837)***
Ln(portfolio size)			0.0216 (1.391)
Ln(trade value)			0.0676 (2.762)***
Human x Trading frequency		-2.4e-8 (-0.231)	
Human x Portfolio size		-4.3e-11 (-0.893)	
Human x Trade value		-3.2e-12 (-0.966)	
Human x Member size		-0.0006 (-1.205)	0.0006 (1.332)
Human x ln(Trading frequency)			0.0962 (3.955)***
Human x ln(Portfolio size)			-0.0244 (-1.555)
Human x ln(Trade value)			-0.0826 (-2.997)***
Adj. R^2	0.006	0.009	0.183
N	1119	1119	1119

Note: * means significant at 10%-level; ** means significant at 5% level; *** means significant at 1% level.

Table A.3: Impact of human trading instead of algorithmic support on the disposition effect (own table)

Dependent variable	Profitability	
Model No.	(6)	(6) with ln
Intercept	0.3215 (4.619)***	0.0153 (0.031)
Disposition effect	1.8977 (1.460)	1.6373 (1.158)
Trading frequency	8.3e-7 (1.282)	
Ln(Trading frequency)		0.0485 (0.808)
Portfolio size	3.4e-10 (1.092)	
Ln(Portfolio size)		-0.0475 (-1.463)
Trade value	-1.4e-11 (-0.571)	
Ln(Trade value)		0.0356 (0.560)
Member size	-0.0016 (-0.651)	-0.0025 (-1.085)
Human	-0.0372 (-0.479)	0.5881 (0.679)
Disposition effect x Human	-0.8246 (-0.578)	-3.2086 (-3.108)***
Disposition effect x Trading frequency	-2.4e-5 (-1.199)	
Disposition effect x Ln(Trading frequency)		-0.5183 (-0.973)
Disposition effect x Portfolio size	2.5e-8 (1.866)*	
Disposition effect x Ln(Portfolio size)		0.6142 (2.938)***
Disposition effect x Trade value	8.8e-10 (1.115)	
Disposition effect x Ln(Trade value)		-0.0803 (-0.399)
Disposition effect x Member size	0.0105 (0.853)	-0.0039 (-0.385)
Human x Trading frequency	-1.9e-6 (-1.532)	
Human x Ln(Trading frequency)		0.0183 (0.214)

Human x Portfolio size	-1.1e-10 (-0.315)	
Human x Ln(Portfolio size)		0.0207 (0.538)
Human x Trade value	6.3e-11 (1.281)	
Human x Ln(Trade value)		-0.0585 (-0.665)
Human x Member size	-0.0002 (-0.087)	0.0009 (0.409)
Adj. N^2	0.047	0.078
N	1119	1119

Note: * means significant at 10%-level; ** means significant at 5% level; *** means significant at 1% level.

Table A.4: Impact of the disposition effect on profitability (own table)