Disposition Effect and Time

Are investors increasingly reluctant to realize losses the longer they hold on to a stock?

Mathias Lien

The disposition effect is defined as the notion that investors hold on to losses for *too long*. In this paper I study how the disposition effect is influenced by the *longer* the investor holds on to a stock. Using a unique database of detailed Swedish trading records, I examine the dispersion in disposition effect across individual investors and confirm the existence of this bias in line with previous findings. My main results show that holding period exhibits a strong positive relationship with the magnitude of the disposition effect. I show that the difference in disposition effect between men and women dissipates after controlling for investor characteristics. Older investors generally display lower bias. Disposition effect is found to be attenuated by investor sophistication and experience, confirming previous findings. The results highlight the need of educating younger and less sophisticated investors of their susceptibility to this bias.

Keywords: Disposition effect, holding period, gender, age
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"I hate to lose more than I like to win"

- Larry Bird

Since the days of Adam Smith, economic research has largely been built on the assumption of rational agents attempting to maximize utility. In financial literature, this is often concretized by the individual attempting to maximize wealth while minimizing risk. By carefully studying risk and return of all possible investment opportunities, agents are assumed to decide on a portfolio that suits their level of risk aversion while also optimizing the risk-adjusted return. But as George Box famously noted: "all models are wrong, but some are useful". Useful in that sense that the assumption of rationality allows us to reduce complex ideas into simplified representations of how the financial markets work. Wrong in that sense that numerous studies finds that investors display systematic departures from what the rational expectations paradigm predicts.

Such deviations have been found in e.g., Grinblatt & Keloharju (2001), who presents evidence that Finnish investors disproportionally invests more money into stocks that are located closer to their city of residence even though this strategy does not increase returns. Goetzmann & Kumar (2008) finds that investors generally holds far less diversified portfolios than portfolio theory would predict. Barber & Odean (2000) show that US investors trade too frequently, and by doing so negatively impact returns.

In this paper, I focus on one of the most well-documented biases among investors in the financial literature, namely the disposition effect. The disposition effect posits that individuals are prone to realize gains to a higher degree than they are willing to realize losses, generally proven by the finding that investors tend to sell disproportionally more stocks for a gain, compared to a loss. Theorized by Shefrin & Statman (1985), and initially proven by Odean (1998), the disposition effect has thereafter been found to be one of the most robust findings within behavioral finance (see e.g., Barber et al. (2007), Shapira & Venezia (2001), Weber & Camerer (1998)). Considering the vast amount of literature confirming the evidence presented in Odean (1998), there is little to no need for a discussion regarding the existence of the disposition effect. Instead, it allows for greater focus on exploring the factors that impacts the prevalence of the disposition effect among investors. This is important for a number of reasons.

Firstly, understanding susceptibility to biases allow researchers to accommodate for heterogeneity among individuals when modelling investor behavior. Secondly, this could have implications in designing welfare policies as government retirement schemes are generally built on the assumption that participating investors act rational throughout life. Thirdly, relating to both the academic and regulatory field, asset prices during the course of bubbles and crashes are affected by differential trading heuristics among investors (Ofek & Richardson, 2003).

For policymakers it is difficult to identify investors who are prone for the disposition effect a-priori. Thus, it raises the interest of understanding the relationship that disposition effect has with more apparent investor characteristics. This has been the focus for many previous papers, identifying the role that these factors play. However, the results are far from conclusive. Especially age and gender seem to display different effects depending on demography where the disposition effect is studied.

I show that Swedish investors display the disposition effect, conclusive with the voluminous body of literature covering this phenomenon. I find modest evidence of the claim that Swedish investors realize a higher proportion of capital losses at the end of each tax-year, as a way to improve after-tax portfolio performance. The results presented suggest that the disposition effect does not seem to have a linear relationship with age, but rather that of a second order function. Initially the disposition effect seems to increase with age, up until about middle age and then start to decrease. Though not fully unambiguous, previous literature mainly suggests that age has a negative linear relationship with the disposition effect (Dhar & Zhu (2006), Kurniotis & Kumar (2011)). Throughout this analysis, the estimates of both proportion of gains realized (PGR) and proportion of losses realized (PLR) seem to decrease with age which is coherent with the findings in Frino et a. (2015). I also show that at first glance the average female investor exhibits a higher degree of disposition effect, which is in line with the findings in Barber et al. (2007). However, when controlling for portfolio differences, such as men trading more, the results show that men and women seem to be equally susceptible for the disposition effect, similar to the findings presented in Feng & Seasholes (2005).

Further, I find evidence that the disposition effect is significantly affected by the time the investor holds on to each stock. As stated in Odean (1998) the disposition effect is the result of investors holding on to their losers for *too long*. Here, I investigate how the disposition effect changes the *longer* the investor holds on to a stock. The results show that the disposition effect increases the longer investors hold on to their positions.

The most actively used framework for studying the disposition effect is the one introduced in Odean (1998), which estimates the disposition effect on an aggregate-level for all investors. Referring to the significant evidence of heterogeneity among investor trading styles and beliefs (Goetzmann & Massa, 2002), Dhar & Zhu (2006) argues that simply studying the disposition effect for the aggregate investor likely would mask substantial variance among individual investors. As a remedy, they introduce a method to study the cross-sectional investor-level disposition effect. Using a similar argument of necessity, Feng & Seasholes (2005) introduced a more computationally burdensome framework, studying the disposition effect on trade-level using a survival analysis approach. In this paper, I present a framework similar to the one introduced by Dhar & Zhu (2006) but here disaggregated to study trade-level effects.

Nudging investors susceptible to the disposition effect to make better financial decisions can improve portfolio efficiency among individuals. As most investors are reluctant to realize losses, improving investor understanding of the disposition effect and associated potential tax-benefits, can improve after-tax performance. Brokerage firms assisting investors in taking better portfolio decisions would be considered a value-added service. In this regard, governmental institutions can also play an important role in educating investors and making them aware of inherent trading biases, and by doing so improving financial savings.

The rest of this paper is organized as follows: in section 2 I summarize theoretical background on the disposition effect and how it interacts with investor behavior and characteristics. In section 3 I present the data used, how it is collected and the descriptive statistics for the sample of individuals in this analysis. In section 4 I motivate the methods used in this paper, and in section 5 I present the results found in this analysis and discuss them in the light of previous findings. In section 6 I conclude what has been found in this paper.

2. Theoretical Background

Behavioral finance is a study focusing on the effects of psychology on the financial decisions made by investors. Within this field, the focus is often to analyze the reasons behind why individuals depart from the predictions of the rational expectations paradigm. As briefly addressed above, there are numerous findings within this field displaying different forms of bias that seem to be general among investors. Much focus within this field of research focuses on identifying what differences between individuals help drive these inherent biases. Two of the most apparent differences between individuals is their age and gender, thus research have often been focused on studying disparities between these characteristics.

Related to age, the life-cycle model assumes that rational investors will alter their behavior throughout life as they aim to stabilize consumption. A younger individual generally has lower income, and thus borrows to increase consumption. As the individual ages, her income tends to increase which enables her to pay off the loans and increase savings to be used after retirement. Together with the general fact that individuals evolve over time, changes in life-situation alters financial decisions made throughout life. This tend to be visible in empirical findings. Attanasio & Weber (2010) presents a detailed analysis of how the individual changes her savings throughout life, and Cocco et al. (2005) show that theoretically optimal equity investments roughly are decreasing throughout life. Korniotis & Kumar (2011) find that aging has a positive effect on investor skill as older investors reflect greater investment knowledge by following rules of thumb. However, they find that aging has a negative effect as a result of cognitive decline. Generally, this adverse effect outweighs the positive effect that comes with experience. Further, Vissing-Jorgensen (2003) show that investor expectations of future returns change with age.

Related to gender, Barber & Odean (1999) finds that men display higher degree of overconfidence in investment decisions, by demonstrating that men trade more excessively than women. The authors find that men trade 45 percent more than women, reducing their net returns by 2.65 percentage points per year compared to the value of 1.72 percentage points for women. This analysis is made using the same dataset as in Odean (1998) that analyses the disposition effect. The same effect of overconfidence among men in financial matters are also found in the psychological literature. Prince (1993) finds evidence to support the claim that men tend to feel, and thus rate themselves as, more competent in financial matters compared to women. In an analysis of 15 different experiments of financial risk-taking, Charness & Gneezy (2012) finds strong evidence that women are more financially risk averse as compared to men. The authors also find that women tend to invest less money.

2.1. Financial behavior among Swedish investors

Empirical studies in behavioral economics rely on the need of disaggregated data, which often can be difficult to obtain. Scarcity incentivizes researchers to search the globe for good data, which often results in geographically diverse empirical results. Odean (1998) studies investors trading at a large US discount brokerage firm. Grinblatt & Keloharju (2001) analyze the trading of the entire Finnish population, and Barber et al. (2007) analyze the entire Taiwanese population. Chen et al. (2007) studies behavior among a subsample of the Chinese population, and Sapienza & Venezia (2001) takes a similar approach but studying Israeli investors. Generally, the findings in these papers present similar results, although there are some notable differences in trading behavior between different geographies. For example, Barber et al. (2007) finds that women in Taiwan tend to be more active in the stock market compared to men. This goes against the general norm that men tend to be more active in stock trading (se e.g., Barber & Odean, 1999). Thus, this emphasize a greater need of replication studies across different demographics in order for researchers to draw concrete conclusions if analyzed effects are generalizable across investors or local anomalies.

Considering the fact that Sweden is a relatively small country, it has a financial market that is rather substantial compared to other countries in the world. Formally, the International Organization of Securities Commissions (IOSCO) considers Sweden as one of the 16 largest financial economies in the world[1]. This is reflected in the high research interest in the Swedish financial market, also within the literature related to behavioral finance.

Massa & Simonov (2006) finds that investors earn substantial returns by investing in stocks that are either geographically or professionally close to them. Calvet, Campbell, and Sodini (2007) uses a unique dataset containing disaggregated wealth and income information for the entire Swedish population. They find that Swedish households are sufficiently internationally diversified to outperform the domestic equity market. Anderson (2013) studies the link between trading and diversification among Swedish online traders and documents that under-diversified investors tend to overtrade and thus negatively affect returns. Further, he finds that these individuals tend to be younger and have lower income and wealth, as well as lower formal education.

Using the same database as in their study from 2007, Calvet, Campbell, & Sodini (2009) finds that investors are increasingly likely to sell off all their stocks after experiencing portfolio gains. This effect is especially strong among less sophisticated households. The authors find similar tendency in behavior for mutual fund investors, they are more likely to completely exit the market after realizing gains in their mutual fund portfolios. Both of these findings are congruent with the disposition effect.

[1] See IOSCO Resolution of the Presidents Committee 4/2019.

2.2. Disposition effect

The disposition effect is the name of the phenomenon that individual investors tend to realize gains too quickly, while holding on to loosing stocks for too long. In the first section below, I will first present a brief overview of the background that led to the disposition effect. Barberis & Xiong (2009) crown this as one of the most steadfast findings related to individual investors, pointing to the fact of its remarkable robustness throughout the empirical literature. A voluminous body of articles have documented this finding in numerous countries. Additional to Calvet, Campbell, & Sodini (2009) documenting the disposition effect among Swedish investors, the results have also been documented among investors in the US, Finland, Estonia, Israel, China and Taiwan to name a few. In the second section below, I present the modern literature on the disposition, and present the different geographical findings.

2.2.1. Historical background

The initial spark for what later would become the disposition effect emanates from Schlarbaum et al. (1978), in which the authors analyzed the realized returns from round-trip trades by studying the purchasing and subsequently selling of stocks among 2 500 individuals at a brokerage firm during the period 1964-1970. They found that investors outperformed the market by approximately 5 percent each year. Further, the authors also found that 60 percent of trades resulted in a profit. The outperformance among the sampled investors did not seem to be the result of neither greater risk-taking nor market-timing. The results presented by the authors seemed to go against the existing literature at the time, e.g. Sharpe (1966) who finds that most professional fund managers underperform compared to the market. Similar findings have proved robust by other noteworthy papers such as Gruber (1996) and Fama & French (2010) which finds that the few professional investors who do outperform the market very rarely display a success rate of 60 percent. Schlarbaum et al. (1978) only analyzed round-trip trades, and hence disregarded the stocks that were purchased but not subsequently sold during the period when calculating the realized returns. Interestingly, the authors themselves raised the notion that the positive results displayed by the investors could be the result of a "*disposition to sell the winners and ride the losers*". However, they quickly dismissed this self-raised doubt by instead concluding that individual investors display notable skill in selecting stocks.

This conclusion was questioned by Shefrin & Statman (1985). They instead hypothesized that the observed superior skill among the investors predominantly was a result of them disproportionally realizing more gains while holding on to unsuccessful stock-picks. Arguing that individual investors tend to have a preference for holding on to stocks that have decreased in value (losers) while selling stocks that have increased in value (winners). In 1985 Shefrin & Statman labelled this the "disposition effect".

The initial discussion regarding the disposition effect in Shefrin & Statman (1985) was to some extent founded on the idea that rational and tax-conscious investors would be inclined to avoid realizing gains until they received a long-term tax status. Instead, investors would in theory be better off to realize more losses. As mentioned, this assumption was not in line with the findings in Schlarbaum et al. (1978) which illustrated that investors tended to realize more gains than losses across all durations of round-trip trades studied.

Initially, the empirical support for the disposition effect was limited to anecdotal findings that in one way or another supported the assumption that investors sell winners more readily than losers. Starr-McCluster (1995) states that circa 15 percent of households with stockownership have paper losses that account for more than a fifth of their portfolio. Poterba (1987) finds that capital gains offsetting was more common by investors realizing gains instead of losses. Heisler (1994) finds evidence of loss aversion in a limited sample of Treasury futures speculators, since the observed investors hold on to gains significantly longer than losses. But it was not until 1998 that Terrence Odean published what is widely considered the first hard evidence of the prevalence of the disposition effect among individual investors.

2.2.2. Modern findings related to the disposition effect

Studying the trading records of 10 000 accounts at a large US discount brokerage between 1987 and 1993, Odean (1998) finds that investors in general are prone to realize a higher proportion of gains as compared to losses. The author studies this by calculating the proportion of both realized gains and losses, and denotes the difference between these estimates as the disposition effect. The method introduced in Odean (1998) is widely used in subsequent studies examining the disposition effect among investors. Shapira & Venezia (2001) uses a similar approach and widely confirms the prevalence of the disposition effect for Israeli investors as well.

By assuming that all individual accounts and trades are independent, Odean (1998) employs this framework to calculate the disposition effect across all investors in the data, effectively aggregating all realized gains and losses together with all paper positions. In a later paper, the same author reflects that there is likely considerable variance between investors that is masked when calculating the aggregate disposition effect (Odean, 2000). Multiple findings support this concern, since there is substantial evidence that not all investors display the same degree of disposition effect. One example of this can be found in Odean's original 1998-paper, where he finds evidence to support the claim that frequent traders display a lesser degree of disposition effect.

Another example for the heterogeneity of the disposition effect is presented in Grinblatt & Keloharju (2001), where they use a regression to study the prevalence of the disposition effect among the whole Finnish population. By using a regression model, the authors are able to control for both overall market conditions and investor characteristics. Through this approach, they find strong evidence for the disposition effect. They found significant evidence of the disposition effect across all categories of investors studied: financial institutions, non-profit institutions, government institutions, non-financial corporations and households. The difference between financial institutions, which is arguably the most sophisticated type of investor, and the remaining categories are surprisingly modest.

Further, Dhar & Zhu (2006) argue that the Proportion of Gains Realized (PGR) does not necessarily correspond to the Proportion of Losses Realized (PLR) of the same individual when calculating the disposition effect at aggregate level, but rather that aggregating the calculation implicitly implies that all investors are treated as one representative agent. In order to investigate the potential cross-sectional variance among investors Dhar & Zhu presents an alternative take on studying the disposition effect by calculating PGR and PLR for each investor. The authors find that disposition effect among individual investors is higher for those with assumed lower financial literacy, when controlling for trading frequency and age. Related to the finding of age, the authors show that age has a linear negative relationship with observed disposition effect.

Feng & Seasholes (2005) introduced a novel approach in analyzing the disposition effect using survival analysis to calculate the conditional probability that the investor would realize either a gain or a loss after holding the stock for *t* number of days. Introducing a time-dimension into the analysis of the disposition effect allow the authors to focus on both timing and occurrence, instead of solely occurrence as in the previous literature. Studying the likelihood of a Chinese investor selling each stock, Feng & Seasholes were also able to capture the effect of different characteristics among investors. They state that women display a behavior that is more in line with the disposition effect. Feng & Seasholes (2005) also show that the youngest investors are less inclined to hold on to losses, which seems to contradict the findings presented in Dhar & Zhu (2006).

Barber et al. (2007) study all trades made on the Taiwan Stock Exchange between 1994 – 1999 and find that Taiwanese investors in aggregate are almost twice as likely to realize a gain compared to a loss. The authors also present a time-series approach to studying the disposition effect, indicating that the disposition effect is not necessarily stationary. Age is the only demographical variable Barber et al. (2007) have access to and display results that would indicate that men exhibit stronger disposition effect compared to women.

Talpsepp (2010) uses a similar approach as introduced by Feng & Seasholes (2005). He studies the disposition effect using survival analysis among Estonian investors and finds that the disposition effect is very similar for male and female investors, when controlling for investor characteristics.

The disposition effect has also been found to exist among investors in an experimental setting. By allowing investors to trade with each other throughout a series of rounds, Weber and Camerer (1998) find that even trading with fictive stocks gives arise for the disposition effect. Using a similar experiment to the one introduced in Weber & Camerer (1998), Rau (2014) finds support for the claim that women have higher disposition effect compared to men. The author argues that the difference for the disposition effect between men and women primarily stem from the difference in attitude towards realizing losses. He finds that women are significantly less inclined to realize a loss as compared to men. However, the difference in attitude for realizing gains was not significant when comparing men and women. Using a similar experiment design, DaCosta (2006) find that women sell a higher degree of losses which contrasts the findings presented in Rau (2014). The aggregate results in Rau (2014) suggests that there is no overall disposition effect, which would go against the results found in previous studies (e.g., all other papers referred to in this section). The reason as to why Rau (2014) does not find a significant result of the disposition effect on the aggregate level could be that the experiment only involves 55 students, which arguably is a quite small sample size compared to the aforementioned papers.[2]

Shefrin & Statman (1985) argue that tax-conscious investors would be prone to realize more losses than gains, especially for trades held for a shorter period. However, Constantinides (1984) finds that investors should gradually increase their tax-based selling throughout the

[2] Odean (1998) has a sample size of 6380 brokerage accounts, while Dhar & Zhu has a sample size of 7965 using the same database as Odean (1998). Grinblatt & Keloharju (2001) and Barber et al. (2007) base their calculations on the entire Finnish respectively Taiwanese population. Weber and Camerer however has a somewhat smaller sample size of 103 students.

calendar year. Odean (1998) studies how the disposition effect is affected by tax-based decisions by analyzing investor behavior at the end of each tax-year. Theoretically, he argues, investors are likely to be more prone realizing losses in December. In the paper he finds significant evidence to conclude that this is the case. Grinblatt & Keloharju (2004) also finds that Finnish investors tend to realize more losses than gains at the end of December, in order to realize capital losses for tax-related reasons.

2.3. Theoretical explanations for the disposition effect

Shefrin & Statman (1985) proposes a theoretical framework for the drivers of the disposition effect. They argue that the disposition effect rests on four pillars: prospect theory, mental accounting, regret aversion and self-control. Even to this day, the discussion of the underlying explanation for the disposition effect tend to revolve around these arguments. Below I present them in greater detail.

2.3.1. Prospect Theory

Typically, studies on the disposition effect tend to reference Kahneman & Tversky's (1979) seminal paper on prospect theory as the most influential cause of the reluctance to realize losses. The framework developed in 1979, and later refined in Khaneman & Tversky (1992), posits that individuals evaluate risky financial decisions (or gambles) by thinking in terms of individual gains and losses. This went against the standard hypothesis at the time, which stated that individuals evaluated risky financial decisions based on final wealth outcome.

Further, prospect theory argues that individuals do not process gains and losses using a linear value-function. Instead, arguing that individuals process this using a value-function that is convex for losses and concave for gains, i.e. they are loss-averse. The design of the value-function helps explain why people tend to be risk-seeking over moderate-probability losses but risk-averse over moderate-probability gains. The functional form of the utility function implies that people need to be disproportionately compensated when engaging in a financial gamble as they generally hate losing more than they like to win the same amount. To illustrate with an example, people tend to be risk-averse when it comes to gains – they would prefer to win 10 with certainty over a 50/50-bet to win either 20 or 0. However, when it comes to losses people tend to be risk-seeking as they would rather take a 50/50-bet to either loose 20 or 0, instead of unavoidably loosing 10.

Barberis & Xiong (2009) investigates more thoroughly the role prospect theory plays in the disposition effect and finds that the theory exhibits great difficulty in explaining the bias. Using a multi-period model, they find that prospect theory widely fails in predicting ratios of realized losses and gains found in empirical studies of the disposition effect. Instead, they propose a refined framework in which individuals ignore paper gains and losses but display prospect theory utility when it comes to realized gains and losses. The authors find that this modified version of prospect theory better predicts the disposition effect.

Kaustia (2010a) also critically examines the interaction between prospect theory and the disposition effect and finds that there are some inconsistencies between the theoretical framework and what can be seen in empirical data. Using the same dataset as in Grinblatt & Keloharju (2001) he finds that prospect theory can explain why investors hold on to losses, but it fails to accurately predict investors holding on to gains. He also finds that investors propensity to realize gains is constant or increased as the magnitude of the gain amplifies. However, when it comes to realizing losses the investor is insensitive to sell the stock as the value of the position continues to decrease. Kaustia (2010a) argues that these findings are not predictable using prospect theory with reasonable parameterizations.

2.3.2. Self-Justification

Selling a stock at a loss implicitly means that the investor admits to making an error, which tends to be an unpleasant experience for most individuals. Festinger (1957) describes this as the cognitive dissonance between one's attitudes and actions which in turn causes discomfort. If the individual instead changes attitude towards the issue at hand, this incurs a psychological cost. Kaustia (2010b) describes this with reference to the disposition effect as investors holding on to a positive self-perception in their ability to make investments by fitting their actions in accordance with this attitude. Barber et al. (2007) describes this using similar terminology, implying that people evaluate their decisions ex-post. Knowing this, investors are reluctant to admit their mistake by realizing a loss.

This theoretical explanation is consistent with the experimental findings in Weber & Camerer (1998). In the experiment one group of subjects were forced to sell all stocks at the end of each round, while the other group were allowed to trade freely throughout. The first group forced to sell at the end of each round were allowed to repurchase all the shares they wanted at the start of the following round. As there was no transaction costs in the experiment, standard economic theory posits that there should be no difference in behavior between the groups. However, the subjects in the first group actively bought back far fewer shares than they were forced to sell.

Especially, this group was much more reluctant to actively repurchase stocks at a price below the one at which the subject initially decided to purchase the share.

2.3.3. Alternative Explanations

Developed by Thaler (1980, 1985) and Kahneman & Tversky (1981), the mental accounting framework posits that people tend to organize money in different psychological accounts according to its source and intended use. For instance, treating a received salary in one mental account and income from stock investments in another mental account. Often these accounts are considered quite independent of each other, although the money within is perfectly fungible. Shefrin & Statman (1985) even argue that people tend to open new mental accounts for each stock purchased, thus evaluating each stock separately. This is related to prospect theory in that regard that issues are seemingly evaluated separately. Under this theory the investor would not necessarily rationally consider the after-tax portfolio benefits to outweigh the psychological cost incurred by realizing a capital loss.

Another alternative explanation for the presence of the disposition effect among individuals is that they hold a belief that today's losers will outperform in the future. If today's losers actually would outperform today's winners, then the investors' belief would be both rational and justified. Andreassen (1998) finds in an experimental setting that individuals trade stocks as if they would expect a mean reversion in the short-term.

2.4. Research question

Demographic characteristics have often been of substantial interest within behavioral finance, and the literature on the disposition effect is no different. Barber et al. (2007) mention it would be interesting to explore the relationship between demographic characteristics and the disposition effect. However, only having information of gender in the data, they limit their exploration to the difference between men and women. Korniotis & Kumar (2011) focus on studying the effect that age plays on investor behavior, but do not report detailed results that illustrate the difference between men and women. Feng & Scholes (2005) and subsequently Talpsepp (2010) both study the interaction between age and gender, using approximately the same method, but regardless present different results.

Considering the relationship between gender and the disposition effect the results presented in previous literature is not unambiguous. Barber et al. (2007) estimates that men exhibit stronger disposition effect, while Frino et al. (2015) illustrate the opposite. Neither paper however test the statistical significance of their respective claim, thus making it difficult to draw any conclusions. Talpsepp (2010) finds that the disposition effect is very similar for male and female investors, when controlling for investor characteristics. Feng & Seasholes (2005) finds that male investors are 30 percent more likely to realize a loss, but the difference between the genders disappear when controlling for factors as age, experience, and portfolio behavior. Rau (2014) finds in a small experimental setting that women display higher disposition effect than men, while DaCosta (2006) find that women sell a higher degree of losses using the same experimental design. The ambiguous findings when studying different demographics could hint that there are regional differences.

Hence, it is interesting to study the effect of gender on the disposition effect among Swedish investors, often considered one of the most gender-equal countries in the world (Hausmann, 2012), Anderson (2013) presents evidence that Swedish men and women behave differently in financial decisions. Calvet, Campbell & Sodini (2009) finds evidence for the existence of disposition effect among Swedish investors, but does not study differences between men and women. In this paper, I aim to examine what role gender plays on the disposition effect among Swedish investors.

The theoretical literature in behavioral finance finds that women generally are more risk averse (Charness & Gneezy, 2012) and tend to display a higher degree of loss aversion compared to men (Brooks & Zank, 2005). In reference to the various results found in previous literature, but strong findings with regards to the theoretical driving factors of the disposition effect I formulate the following hypothesis for Swedish investors:

H1a: Women exhibit a higher degree of disposition effect.

Related to the question of age, and the relationship it plays with the disposition effect the literature is also somewhat ambiguous. Using the same dataset, both Korniotis & Kumar (2011) and Dhar & Zhu (2006) find that the disposition effect generally attenuates with age. This indicates that older investors generally are less prone to hold on to losses. Feng & Scholes (2005) finds that the youngest investors in their sample display less proclivity to hold on to losses. Oreng (2021) reports that age is seemingly not associated with the disposition effect. Considering the inconclusive results between different demographics, allows for speculation that age might have a non-linear effect on disposition effect. Talpsepp (2010) discuss that this might be the case but does not explicitly test for this. Thus, formulating the following hypothesis with regards to the existing literature:

H1b: Disposition effect has a non-linear relationship with age.

Apart from demographic characteristics, the third analyzed inquiry into the disposition effect relates to the nature of the phenomenon itself: that investors hold on to losses for *too* long. Here, I aim to study the effect that hides within the term: *too*. What would be considered as too long, and is that static throughout. To study this, I analyze the holding period of each investment and how that interacts with the observed disposition effect when the stock is sold.

Discussing these factors raises the question of time, which is not necessarily applicable under neither the static approach of studying the aggregate-level disposition effect, nor the cross-sectional investor-level approach introduced in Dhar & Zhu (2006). Instead, I need to go deeper and study the disposition effect on trade-level. Feng & Seasholes (2005) introduce a method to study the likelihood of an investor selling a stock for each day, thus studying both investor characteristics and time-effects. By implicitly including holding period in the survival analysis modelling, Feng & Seasholes (2005) and Talpsepp (2010) examine the occurrence of disposition effect, but not the extent to which it changes over time.

The existing literature on how the disposition effect is related to holding period is limited. Brown et al. (2002) explicitly mentions the effect that holding period has on the disposition effect and reports that the bias ameliorates over time. They find that investors with a holding period of more than 200 days display no observable disposition effect. Based on the findings presented in that paper, I formulate the third hypothesis as:

H2: Disposition effect decreases the longer investors hold on to stocks.

3. Data

The data used in this paper are the transactions of Swedish individuals reported to the Swedish Financial Supervisory Authority (S-FSA, or *Finansinspektionen*) under MiFIR II. The database is denoted as Transaction Reporting System (TRS) and contains all trades made by Swedish individuals through an institution within the EU. The TRS contains data from 2018-01-01, and I set the posterior limit of this study to 2022-06-30. At time of writing, I am working at the S-FSA with this database. All data processing was made within the S-FSA IT-environment, and no information that could be used to identify an individual ever left this restricted environment. By a decision of disclosure with reservation, I was allowed to use the aggregated data for this study.[3] The issue of personal integrity has been handled with utmost care throughout the study and correspond to the rigid data-protection framework in place at the S-FSA.

From this vast database, 86 894 individuals were quasi-randomly sampled using an algorithm that selected persons based on the four last digits of their personal identification number as defined by the Swedish Tax Office. The four last digits contain information of the gender of the individual and place of birth for people born before 1990-01-01. Furthermore, the last digit is calculated through the Luhn-algorithm and depend on the previous digits of the full personal identification number. The developed sampling-algorithm was designed to account for information containing both birthplace and gender. The sampling-algorithm drew a series of numbers from a uniform distribution with minimum 0010 and maximum 9999. Among these four digits, the third number denotes if the individual is female (even number) or male (uneven number). To explicitly account for this, the sampling-algorithm included an additional number of each original number drawn by adjusting the third digit with either +1 or -1. However, the sampled data contains 24 547 female individuals and 62 347 male individuals.

To account for birthplace among people born before 1990-01-01, the sampling-algorithm was weighted to account for this to the extent it was expected to influence the underlying data. Since 38 percent of the Swedish population as of 2022 were born after this date, the sampling-algorithm adjusted for 62 percent of the first two digits of the random number drawn to be based upon place of birth. E.g., the most populated region in Sweden is Stockholm, thus the algorithm weighted 62 % of the random numbers to more often draw the first two digits as to represent someone who was born in Stockholm. For the remaining 38 percent of the sampling, no consideration was taken to account for the first two digits of the four-digits random number.

Table 3.1. Sample description

	Total Sample	Included in the analysis
Number of Individuals	86 894	50 260
Number of women	24 547	12 654
Number of men	62 347	37 606
Mean Age	44.8	44.1
Median Age	42	41

Table 3.1. Descriptive demographic statistics for the sample. The total sample is the trading data that was sampled from the TRS, but was later filtered out. E.g., due to individuals only trading other instruments than stocks, traded less than 3 transactions or that I was unable to find adequate prices for the stocks traded.

[3] Decision of disclosure with reservation from the S-FSA can be found in FI dnr: 22-11491

I do not include individuals younger than 18 in the sample. The rationale for this is two-folded. First, generally I was reluctant to analyze these individuals as personal integrity of those who are below 18 is often considered as even more important. Secondly, few individuals younger than 18 manage their own portfolio. Instead, these are commonly managed by the individual's guardians. In these cases, it is not defined within the TRS which individual that ultimately took the decision to trade. In order to treat individuals homogenously throughout the analysis, age is defined as the age of the individual as of 2022-06-30. The effect of the Luhn-algorithm was not explicitly adjusted for in the sampling, but implicitly handled through the law of large numbers.

Figure 3.1. Age distribution of sample

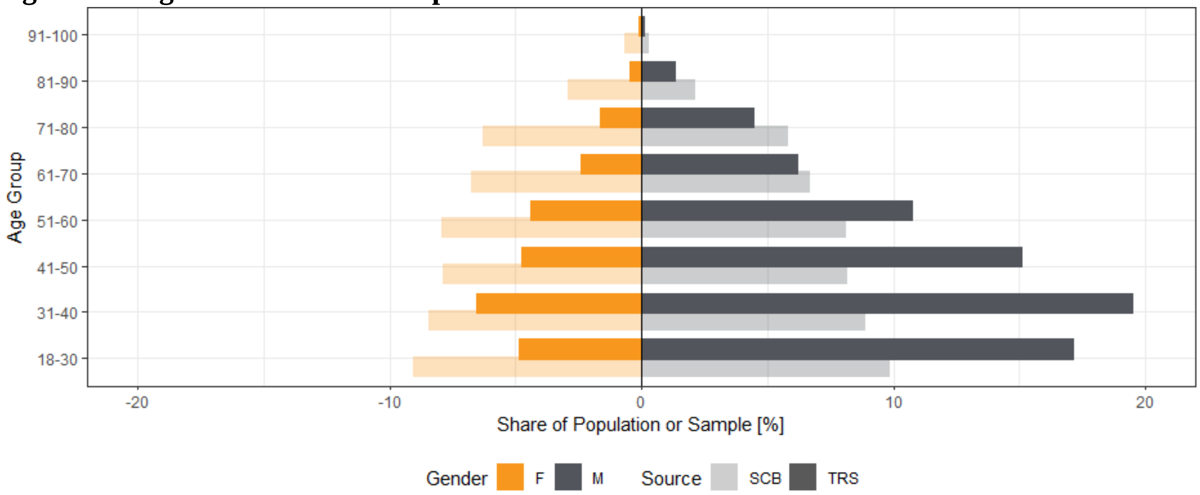

Figure 3.1. Illustrates the age distribution in the sample data (TRS) compared to the distribution among men and women in the Swedish population (SCB, 2022). The opaque bars represent the data for the Swedish population found in the Statistics Sweden (SCB) database. The solid-colored bars represent the data found in this sample drawn from the TRS-database.

Figure 3.1 illustrates that men are overrepresented while women are underrepresented in the sample data, when compared to the actual population demographic of Sweden. It is a widespread phenomenon that women participate in the stock market to a lesser extent than men. This is also empirically confirmed in Anderson (2013) for Swedish investors. The imbalance between men and women included in the sample is unfortunate. However, the results presented are still representable for the population.

Notably in Figure 3.1 is also that the distribution of age within the sampled individuals in the data roughly corresponds to the age distribution of the population of Sweden. The main difference between sampled data (TRS) and population (SCB) is that younger individuals and those being middle-aged are more active in the stock market, which is in line with findings in previous literature (see e.g. Barber & Odean, 1999).

Stock prices were primarily retrieved from within the TRS itself. The database contains all transactions made by both Swedish entities and individuals, hence there is substantial information regarding prices within the database. I calculate closing prices by taking the average price for each stock during the last hour of trading for each day for all reported transactions that took place on a public venue. To validate the price-information I compared the calculated prices with the closing prices for all stocks retrieved from Yahoo Finance. For any large deviation between calculated price in the TRS and the closing price found on Yahoo Finance, I used the price found on Yahoo Finance. The rationale being that the most common difference was found in mid- and small-cap stocks trading outside Sweden, as these issues are more seldomly traded by Swedish entities and thus less frequently found in the TRS. Likewise, if no price information was found in the TRS I used the value from Yahoo Finance. The stocks that did not contain at least 75 percent of price data during the relevant period were excluded.

Using this approach, I collected daily price-data for all stocks traded in Sweden and those included in the main indices for the remaining Nordic countries (Finland, Norway, Denmark, Iceland) and the Baltics (Latvia, Lithuania, Estonia). I also collect price data for stocks trading in the S&P500, FTSE100, DAX, MDAX, SDAX and TecDAX. The price data covers the same period as the transactions, that is from 2018-01-01 to 2022-06-30. Out of the 2 105 stocks in the aforementioned universe, 1 734 stocks were included after removing those issues without enough price information.

3.1. Descriptive Statistics

Below I present the descriptive statistics for the sample of individuals included in the analysis. I present the for the entire sample, as well as grouped for the demographic variables age and gender. Gender is straightforwardly defined as the gender encoded in the individuals personal ID-number. Age is divided into six mutually exclusive groups, using a similar range as in Talpsepp (2010).

Table 3.2. Descriptive statistics

	Total	Gender		Age					
		M	F	18-30	31-40	41-50	51-60	61-70	70+
Observations	50260	37606	12654	11072	12927	9 846	7 525	4 292	4 065
Avr. Portfolio Size	11.6	11.1	13.3	8.6	10.5	12.2	12.5	13.1	11.5
Median No. Trades	10	12	6	10	12	11	9	9	9
Avr. No. Trades	42.8	49.6	26.2	28.0	42.9	49.1	48.3	49.9	58.5
Median HomeBias	0.268	0.249	0.342	0.261	0.244	0.263	0.289	0.304	0.316
Avr. HomeBias	0.373	0.349	0.443	0.365	0.345	0.366	0.394	0.407	0.424
Median Portfolio HHI	0.105	0.113	0.102	0.116	0.103	0.104	0.105	0.100	0.089
Avr Portfolio HHI	0.145	0.142	0.155	0.155	0.141	0.147	0.146	0.142	0.128
Median Holding Period	100	90	132	71	93	102	117	141	178
Avr. Holding Period	178	167	207	118	175	161	178	209	363

Table 3.2 Displays the descriptive statistics for the individuals included in this analysis. Portfolio HHI is calculated as the concentration of stocks traded in each individual's portfolio with reference to the cross-sectional currency adjusted turnover. Similarly, Home Bias is calculated as the share of individual's turnover in Swedish stocks as compared to foreign equities. Holding Period is defined as the time between the last purchase of a stock and the subsequent selling of the same instrument. As notable 533 individuals are lacking when dividing the investors with regards to age, this is because of a non-standardized reported birthdate in the data. These observations are excluded in the calculations that uses age as a variable.

Anderson (2013) finds that under-diversification is more prevalent among younger investors in Sweden, which is in line with the results presented in Goetzmann & Kumar (2008). Similarly, Korniotis & Kumar (2011) finds that older investors generally hold more diversified portfolios. This seems to be coherent with the data presented in Table 3.2 where it is visible that portfolio diversification seems to increase with age, i.e. portfolio concentration which is measured as HHI decreases. Younger investors notably have more concentrated portfolios but tend to trade a higher degree of stocks that are listed outside of Sweden. Indicating that home bias and diversification seem to have divergent relationships with regards to age, as these variables seem to move in opposite directions for older investors.

Korniotis & Kumar (2011) also find that older investors display a lower degree of home bias, which does not correspond to what we can see in the table above. However, when discussing home bias among Swedish investors it is worth noting the findings presented in Simonov & Massa (2006), illustrating how Swedish individuals earn superior returns by investing in familiar stocks. Indicating that the finding presented in Korniotis & Kumar (2011) is perhaps not representable for Swedish investors.

Turing to the question of gender, it is notable that men tend to trade more than women in Table 3.2. above. This is a well-documented phenomenon in the empirical literature (see e.g. Barber & Odean, 2001). Karlsson & Nordén (2007) finds that Swedish men usually display a higher degree of home bias compared to women. The descriptive finding presented in Table 3.2

however seems to counteract this claim. Talpsepp (2010) presents that women generally have longer holding periods compared to men. This could be attributed to the fact that men trade almost twice as much as women. This is similar to what we can see for the Swedish population in Table 3.2.

4. Method

Studying the Disposition effect, I want to examine whether investors hold on to their losers too long while selling their winners too early. To determine if this is the case it would not be sufficient to study the sheer number of securities sold for a gain compared to those sold for a loss. Keeping in mind that the market between 2018-01-01 and 2022-06-30 has experienced some significant returns, we would find that an indifferent investor would in general sell more winners than losers.[4] This is simply due to the fact that the general investor is expected to hold more winners as compared to losers in her portfolio.[5] To study the individuals preference for holding losers and selling winners we must study the relative disposition to sell winners and losers compared to the individual's opportunity to do so.

The method employed to calculate the disposition effect is similar to the one introduced in Odean (1998). By studying each account's trading in a chronological order, a portfolio is constructed for each date that the individual trades a stock. Notably this will only represent a part of the total portfolio of each investor, as I do not have data describing each individual's portfolio paired with purchase prices before 2018-01-01. Odean (1998) and Barber et al. (2007) has a similar issue but argues that this selection process would not likely bias the portfolios. It is unlikely that the stocks found in the portfolios constructed would only be those that investors would possess any unusual preference with regards to realizing losses or gains. Each time that the individual sells a stock while holding a portfolio of at least two stocks, the selling price for each stock is compared to the average purchase price in order to categorize the transaction into one of the following alternatives:

1. Realized Gain: where a stock is sold for a gain
2. Realized Loss: where a stock is sold for a loss
3. Paper Gain: where the stock is not sold, but the value is above the purchase price[6]
4. Paper Loss: where the stock is not sold, but the value is below the purchase price

[4] OMXS30 has gained about 17.6 percent, S&P500 has gained about 43 percent throughout the whole period.
[5] Badrinath & Lewellen (1991) finds that 49 percent of round-trip trades are sold for a loss, while Odean (1998) reports this number to be 43 percent in his database. In my database the share of roundtrips that are sold for a loss, aggregated on a weekly basis, is 45 percent.
[6] Value of the stock is defined as the closing price for the relevant day and calculated after adjusting for splits.

In the rare event that a stock is sold, but to the same price as it was purchased for it is recorded as Neither Gain or Loss. These instances are disregarded in the calculation of the disposition effect. On days where the individual makes no trade, no paper gains or losses are tallied. As in the original paper, I exclude dividends when calculating whether the sales are made at a profit or loss. Similarly to Odean (1998) it is reasonable to assume that investors may not consider commissions paid when remembering what they paid for a stock. Further, in the TRSII there is no information regarding the commission paid for each transaction. Thus, including commissions would require assumptions that could affect the results presented in an unjustifiable direction. Hence, I do not include commissions in the analysis below.

To study the relative disposition for an individual to realize losses versus realizing gains, Odean (1998) introduces two ratios:

$$\frac{Realized\ Gains}{Realized\ Gains + Paper\ Gains} = Proportion\ of\ Gains\ Realized\ (PGR) \qquad [1]$$

$$\frac{Realized\ Losses}{Realized\ Losses + Paper\ Losses} = Proportion\ of\ Losses\ Realized\ (PLR) \qquad [2]$$

A sizeable difference between the Proportions of Gains Realized (PGR) and the Proportions of Losses Realized (PLR) would indicate that the investor is more prone to realize either gains or losses. Similarly to Odean (1998), Dhar & Zhu (2006) and Barber et al. (2007), the disposition effect (DE) is defined as:

$$DE = PGR - PLR \qquad [3]$$

When estimating the disposition effect in the data I filter out individuals having made less than 2 purchases before selling a stock during the period 2018-01-01 to 2022-06-30, similarly to what Odean (1998) does. Naturally, an investor with a portfolio consisting of only stocks trading above their purchase price will not realize a loss if she decides to sell one position. The opposite holds true for an investor with a portfolio consisting of only losses. The decision to realize gains or losses in these situations are arguably not driven by the investor’s behavioral proclivity for the disposition effect. Thus, I exclude these instances in the calculation.

4.1. Measuring the disposition effect on the Aggregate-level

Presented in Odean (1998) and largely described above, this approach is designed to capture the aggregate disposition effect among all investors in the observed sample. The calculation is computationally straightforward and executed by tallying the total sum of all realized gains and losses together with paper gains and losses across all investors. Then, PGR and PLR are calculated as in equation [1] and [2] using these total amounts. The difference between these estimates then yield the disposition effect for the observed aggregate investor, as defined in equation [3]. In this paper I aptly refer to this as the *aggregate-level* approach.

This approach is the most commonly used when studying the disposition effect. However, implicitly this assumes that all investors act homogenously, as all trades is tallied to represent a single aggregate investor. Assuming that all investors act similarly is not necessarily backed by empirical findings in the financial literature. One example is Goetzmann & Massa (2002) that finds significant evidence of heterogeneity among investor’s trading styles and beliefs. Further, tallying all trades into one representative agent implies that those individuals that trade more will have a higher overall impact compared to those that trade less. Considering these limitations, subsequent papers on the disposition effect have introduced alternative approaches.

4.2. Investor-level

Dhar & Zhu (2006) presents a different framework by introducing an approach for estimating the disposition effect on investor-level, arguing that only studying the aggregate disposition effect likely would hide cross-sectional variance among investors. The framework employed largely mimics the methodology presented in Odean (1998) but instead studying the effect for each individual. This means calculating PGR and PLR as described in equations [1] and [2], but tallying the total trades for each investor, and not across all investors. If either PLR or PGR is mathematically undefined the results are excluded. They then calculate the disposition effect in the same manner as described in equation [3] for each investor. When studying the disposition effect among a group of individuals, the mean is calculated within each group.

Table 4.1. Example of the difference in DE between the aggregate- and investor-level approach

	Investor 1	Investor 2	Investor 3	Mean Among Investors	The Aggregate Investor
Realized Gain	1	10	30		41
Paper Gain	10	50	50		110
PGR	0.09	0.17	0.38	0.21	0.27
Realized Loss	1	20	20		41
Paper Loss	5	100	100		205
PLR	0.17	0.17	0.17	0.17	0.16
Disposition Effect	-0.08	0	0.19	0.04	0.11

Table 4.1 The numerical example used in Dhar and Zhu (2006), illustrating the large variations in estimating the disposition effect depending on if calculated on an individual basis or as a market aggregate. The framework introduced presented in the aforementioned paper, which in this paper is denoted as the *investor-level* approach is exemplified in the column titled "Mean Among Investors".

Using the example presented in Table 4.1, Dhar & Zhu (2006)[7] illustrates that calculating the disposition effect on the aggregate level can lead to large differences in outcome compared to when calculating the average individual's disposition effect. Studying the table above, it can easily be shown that if we have three investors with the individual disposition effect of -0.08, 0 and 0.19 we can nonetheless calculate the aggregate-level disposition effect to be 0.18. Thus, finding a positive aggregate disposition effect even though only a third of the investors actually display the bias. By calculating the mean across investors, we instead obtain an estimate that closer resembles the disposition effect exhibited by the average investor, as exemplified in the column titled "Mean Among Investors". In this paper this approach is denoted as the *investor-level* approach, as I calculate the observed disposition effect for each investor.

Calculating the investor-level disposition effect implicitly assumes that the agent is indifferent as to when issues are realized, as the observed metric is based on the cross-sectional sum of all realized and paper positions throughout the period for each individual. This is a simplification that arguably does not correspond to findings in the empirical literature. Barber et al. (2007) finds that there are substantial differences in observed disposition effect for each year in the period 1995 – 1999 among Taiwanese investors. Boolell-Gunesh et al. (2009) presents similar findings, indicating that the observed yearly disposition effect between 1999 and 2006 among French investors is not necessarily static.

[7] This is found in a previous version of Dhar and Zhu (2006) circulated in 2002

4.3. Trade-level

Feng & Seasholes (2005) aimed to solve this problem of time-varying estimates by using survival analysis to study the disposition effect among investors. Analyzing the conditional probability that a given investor would sell a stock, allowed them to distinguish the probability of the investor either realizing a gain or a loss. If the difference in probability tilted towards the investor being more likely to realize a gain compared to a loss, then this would be an argument for the disposition effect. By doing this, Feng & Seasholes (2005) effectively studied the disposition effect on trade-level. Grinblatt & Keloharju (2001) took a similar approach by using a LOGIT regression to study the likelihood of an investor either selling a stock on a given day or holding on to it.

I make use of the method introduced in Dhar & Zhu (2006) in this paper, which for the sake of clarity is denoted as the investor-level approach. Beyond this, I also disaggregate the method by studying the observed disposition effect at the time of each trade. Similarly to what is described above, I calculate the PGR and PLR according to equation [1] and [2] using the portfolio and trading records for each individual, and then calculating disposition effect as defined in [3]. The implicit assumption under this approach is that all trades are made independently of one-another. In this paper this method is denoted as the *trade-level* approach, as I calculate the observed disposition effect at the time of each trade.

Considering that I only examine those trades where an investor had the possibility to realize either a gain or a loss, the outcome explicitly depicts the decision to realize one over the other. Fundamentally, it relies on a similar rationale as presented in Feng & Seasholes (2005), that investors faced with this decision tend to realize disproportionally more gains than losses. However, they mainly study this as a binary outcome, given the change in probability if the stock is held for a gain or loss. This closer reflects the findings presented in Barberis & Xiong (2009) that the investor display prospect theory utility when realizing gains and losses, but not necessarily considering paper positions. Using the trade-level approach, this is encoded for given the direction of the effect at the time of each trade.

Beyond direction of the effect, the size of the effect is estimated using the same fundamental assumptions as when PGR and PLR are calculated on both aggregate- and investor-level. Estimating how active of a decision it would be to realize a gain over a loss, or vice versa. This is affected by two aspects: the size of the portfolio and the composition of the portfolio. The downside is that it is not explicitly encoded which aspect that drives the results. However, one remedy for this could be to control for portfolio size.

If the investor has an equally balanced portfolio (i.e. paper gains = paper losses) the larger portfolio would reflect a smaller mental cost to decide whether to sell a gain or a loss. I.e., having 2 paper losses and 2 paper gains would arguably constitute a bigger decision for the individual when deciding to sell a stock, as compared to an investor with 20 paper losses and 20 paper gains. This builds on the theoretical framework presented in Festinger (1957) that reflects the psychological cost of aligning actions with beliefs. By realizing a loss the investor with the smaller portfolio would arguably have to incur a higher psychological cost as a share of total portfolio, congruent with the non-linear functional form of utility under prospect theory.

If the portfolio is unequally balanced (e.g., paper gains > paper losses) then the indifferent investor would be more likely to realize a gain over a loss. Instead, if the investor would realize a loss in this situation it would reflect a greater deviance from the expectation under the null (i.e., indifferent to realize a gain over a loss), which would be reflected in the calculation. Actual PLR would be higher than the potential PGR in this situation. (And vice versa if paper gains < paper losses.)

It would have been interesting to compare the trade-level approach taken in this paper to the one introduced by Feng & Seasholes (2005). However, this was not possible due to the heavy computational load such calculations would have required when dealing with a sample size of more than 50 000 individuals.[8]

4.4. Differences between methods

The different approaches mentioned to study the disposition effect all have their pros and cons, as discussed in the three previous sections. The main limitation with the aggregate-level approach is that it limits the possibility to study the relationship between disposition effect and investor characteristics. The investor-level and trade-level approach are in this regard both usable when studying investor characteristics. However, when studying trade characteristics, such as holding period, a trade-level model is needed. Although the three models differ in some regards, they are designed to estimate the same phenomenon and yield somewhat similar results.

[8] Given the sensitivity of the information contained, no micro-level data was allowed to be exported outside S-FSA IT-environment. Thus, restricting from the use of solutions with stronger computational capabilities.

Figure 4.1. Estimated Disposition effect over time, using different methods

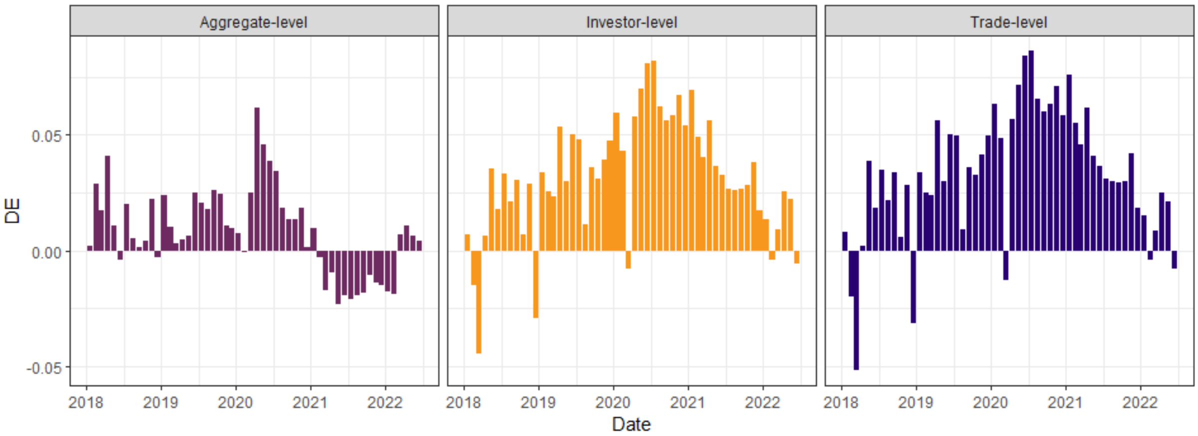

Figure 4.1. Illustrates the difference in measured disposition effect (measured as DE = PGR - PLR) over time when comparing the different approaches in measuring disposition effect. The purple bars display the aggregate investor's observed disposition effect using the same method as introduce in Odean (1998) aggregated for each month. The orange bars display the individual disposition effect among investors estimated using the investor-level approach, taking the average for each month across investors. The blue bars also display the individual investors disposition effect, calculated here using the trade-level approach then taking the average across investors for each month. The investor-level and trade-level approach will approximately reflect the same thing as period of time decreases.

Feng & Scholes (2005) find that the disposition effect has a time-varying component, which is also indicated in Barber et al. (2007) and Boolell-Gunesh et al. (2009). Leal et al. (2008) finds that disposition effect is correlated with overall market returns among Portuguese investors. Studying Figure 4.1. it is notable that the 12 months following March 2020 displays a comparatively high level of observed disposition effect, during which time stock indexes experienced significant returns (e.g., the OMXS30 climbed more than 60 percent under these 12 months).

Similarly to the vast majority of papers on the disposition effect, I only calculate PGR and PLR using transaction data. Thus, the studied individuals must first have purchased the stock before PGR and PLR can be calculated. Hence, the number of investors included in the analysis generally increase over time. Since the investors display different levels of disposition effect, increasing the number of observed people improves the estimate of DE. The downside of this can be seen at the beginning of the sample period in all three examples, that the estimates for 2018 are more volatile as a result of fewer people included in the analysis at that point.

By the same rationale as mentioned above, the observed portfolios among the investors included in this analysis generally increase over time. It can be easily shown mathematically that a larger portfolio leads to smaller estimates of PGR and PLR.[9] Hence, this would likely result in smaller

[9] Consider an investor realizing 1 gain while holding 3 paper gains, PGR would in this case be 0.25. If the same investor instead would hold 9 paper gains then PGR would equal 0.1.

estimates of PGR, PLR and thus DE over time. From Figure 4.1 it is notable that measuring the disposition effect for the individual investor yields a higher estimate as compared to when estimating the aggregate effect. This is coherent with the results presented in Barber et al. (2007) who includes an estimate for both the aggregate and the individual effect. In Figure 4.1 we can also see that the differences between the estimated individual disposition effect when using either the investor-level approach or the trade-level approach. As notable, the discrepancy between these measurements is quite marginal when studying monthly intervals.

5. Results

In this chapter I present the results found from the analysis. The first section of this chapter covers the observed disposition effect across all investors in the sample. Analyzing the general disposition effect and associated tax effect among Swedish investors allows us to compare these findings with the data found across different demographics in the previous literature. The second part focuses on explaining the different characteristics that can help explain variability of the disposition effect among investors. The findings presented in this section are based on the investor-level approach. Then, in the last part of this chapter I present the interdependence of the characteristics described in section 5.2., together with previously established characteristics that help explain the variability in observed disposition effect. I take trade characteristics into consideration when studying the disposition effect in the last section, thus studying the bias using the trade-level approach in the last part of this chapter.

5.1. Disposition effect among Swedish investors

Table 5.1. Average individual disposition- and tax-effect

	Full	Only Jan-Nov	Only Dec
PGR	0.2241	0.2187	0.1919
PLR	0.1883	0.1825	0.1592
Disp. Effect (DE)	0.0358	0.0362	0.0327
t-stat	35.953	34.202	19.026
Degrees of Freedom	100 314	78 545	40 817
KS-test (D-statistic)	0.1536	0.1565	0.1259
p-value	<0.001	<0.001	<0.001

Table 5.1. Illustrates the comparison between Proportions of Losses Realized (PLR) and Proportions of Gains Realized (PGR) on a general level calculated using the investor-level approach. The t-statistic is calculated using the welch two-sample t-test and reflects the null that the difference in proportions is equal to zero, implying that investors would not be disposed to selling winners and holding on to losers. The two-sample Kolmogorov-Smirnoff (defined as KS-test above) test is performed with a monte-carlo to simulate p-values using 10 000 replications.

Table 5.1 presents the investor-level PGR and PLR realized throughout the whole sample period, as well as the effect found during the month of December compared to the remainder of the year. Here, I find strong evidence that Swedish individuals display the disposition effect as PGR is notably higher than PLR. The difference between these estimates, i.e. the DE, is significant on the 1%-level. Thus, we can conclude that Swedish investors are prone to realize a higher proportion of gains as compared to losses. The two-sample Kolmogorov-Smirnoff statistic further indicates that the observed estimates of PGR and PLR are not likely representing the same underlying distribution. These findings are in line with previous literature covering the disposition effect.

The estimated means for PGR and PLR presented in Table 5.1 are higher compared to e.g. Odean (1998) and Barber et al. (2007). This is a result of the difference in aggregation for how the estimates are measured. The former paper study the disposition effect on the aggregate level, and the latter observes the individual disposition effect using a survival analysis approach. In Table 5.2 below I present the disposition effect using the same method as employed in Odean (1998), allowing for a better comparison between the papers. In Table A.5.1 in the appendix I present a similar table as the one above, but calculated using the trade-level approach. These results are largely coherent, although there is a notable difference in the observed DE-related tax effect which is discussed below.

As initially discussed in Shefrin & Statman (1985) and later empirically proven in Odean (1998) investors tend to change their proclivity to sell losses at the end of each year in order to realize capital losses to improve after-tax returns. The results in Table 5.1 illustrates that there are some notable differences between the effects during the month of December compared to the observed effects during the remainder of the year. The difference between both PGR_{JanNov} - PGR_{Dec} and PLR_{JanNov} - PLR_{Dec} are both significant on the 1% level.[10] As Table 5.1 displays investors seem to realize both fewer gains and losses. This indicates that Swedish investors seemingly do change their behavior when it comes to realizing both gains and losses during the month of December. However, the difference between the disposition effect for December versus the rest of the year is insignificant on the 1%-level, as seen below.

[10] For PGR_{JanNov} - PGR_{Dec} the t-statistic is 19.233, and for PLR_{JanNov} - PLR_{Dec} the t-statistic is 15.989.

Table 5.2. Difference in disposition effect in December vs. rest of year

DE (Jan-Nov)	0.0362
DE (Dec)	0.0328
Difference	0.0034
t-stat	1.479
Degrees of Freedom	34 879

Table 5.2. Illustrates the comparison between Disposition Effect (DE) during the month of December compared to the remainder of the year, calculated using the investor-level approach. The t-statistic is calculated using the welch two-sample t-test and reflects the null that the difference in proportions is equal to zero. The Kolmogorov-Smirnoff test is performed with a monte-carlo approach to simulate p-values using 10 000 replicates.

In Table 5.2 we can see that the t-statistic for DE_{JanNov} - DE_{Dec} is 1.479, which is below the critical value of 2.576 corresponding to the 1%-level. Keeping in mind the significant changes in PGR and PLR, this indicates that Swedish investors seemingly do change their behavior when it comes to realizing both gains and losses during the month of December. But for the average individual we fail to identify a significant difference for the month of December compared to the rest of the year when studying the investor-level disposition effect.

However, the results of the difference between DE_{JanNov} and DE_{Dec} is significant when studying the tax effect using the trade-level approach. This can be seen by studying the results presented in Table A.5.2 in the appendix. The dissimilarity in the observed tax-effect highlights one of the differences between the investor-level approach and the trade-level approach. As discussed, the disposition effect is not necessarily static over time instead somewhat correlated with overall market performance (Leal et al., 2010). This time-varying component of the disposition effect could be one explanation for the different results obtained when calculating the average individual disposition effect on trade-level as compared to investor-level.

Another explanation could be that Sweden in 2012 introduced a new type of account where tax is not based on capital gains and losses, named *Investeringssparkonto* or ISK-account (translates to Investment Savings Account). The main difference between an ISK-account and a traditional brokerage account is how the assets within are subject for taxation. ISK-accounts are taxed using a template that is applied to the overall value of the assets within the account and calculated using an average of the value at the end of each quarter. For traditional brokerage accounts it is the net capital gains throughout the year that are subject for taxation. Selling a stock (either for a gain or loss) before the end of each quarter can be considered as tax-motivated selling as it reduces the value held within the ISK-account before the taxable assets are calculated. However, since losses cannot be netted against gains for tax-reasons there is no tax-related benefit for the individual to realize a loss instead of a gain within an ISK-account. Thus, intuitively there should not be tax motivated selling for the individuals trading through an ISK-account.

According to a report by the Swedish National Audit Office (Brink & Mattson, 2018) more than 2.2 million ISK-accounts had been created by Swedish investors. Considering that Sweden had about 10.2 million inhabitants 2018, it becomes clear that the share of ISK-accounts among Swedish investors is quite high. This might help explain why we cannot find support for the hypothesis that the investor-level disposition effect should be lower in December due to tax motivated selling among Swedish investors. However, as the TRS does not contain information regarding the type of account that an individual is using to trade, it is difficult to draw any concrete conclusions.

Studying the DE-related tax effect among French investors, Boolell-Gunesh et al. (2009) finds that investors using accounts exempt from capital gains tax still exhibit a proclivity to realize a comparatively higher degree of losses during the month of December. The author further finds that even for individuals switching account types, this effect is persistent over time although marginally decreasing.

Table 5.3. Aggregate disposition- and tax-effect

	Full	Jan-Nov	Dec
Realized Gain	1 167 687	1 084 693	82 994
Realized Loss	829 217	776 957	52 260
Paper Gain	7 714 306	7 116 711	597 595
Paper Loss	5 718 885	5 364 661	354 224
PGR	0.1315	0.1323	0.1219
PLR	0.1266	0.1265	0.1286
Difference (DE)	0.0049	0.0058	-0.0067
t-stat	28.411	32.429	-10.182

Table 5.3. Presents the aggregated numbers of realized gains and losses, as well as the paper gains and losses. Here DE is calculated using the aggregate-level approach. Based on these aggregated numbers PGR and PLR is calculated, along with the difference between these estimates. Using the same approach as in Odean (1998) a t-test is used to determine whether the difference is significant or not.[11]

Studying the disposition effect using the aggregate-level approach largely confirms the findings presented on investor-level. We can see that the general difference between PGR and PLR indicates that the aggregate Swedish investor exhibits the disposition effect. Further, we can see that this tends to be somewhat higher during the period between January and November

[11] The standard error for the difference in proportions PGR and PLR, as used to calculate the t-statistic, is defined as: $\sqrt{\frac{PGR(1-PGR)}{n_{rg}+n_{pg}}+\frac{PLR(1-PLR)}{n_{rl}+n_{pl}}}$. Where n_{rg}, n_{rl}, n_{pg}, n_{pl} are defined as the number of realized gains, realized losses, paper gains as well as the number of paper losses.

each year. During the month of December, the disposition effect disappears and investors realize proportionally more losses than gains. The reversal in DE during December is assumed to be the result of investors realizing capital losses in order to offset the tax-based income for each tax-year. These findings are in line with the results presented in previous literature studying the aggregate disposition effect among investors.

5.2. Investor characteristics and disposition effect

In this section I present the differences in observed disposition effect based on investor characteristics. Throughout the literature on behavioral finance gender and age has been recurring topics of interest, as discussed in section 2. The first part of this chapter aims to adress the question of gender, depicting the results found for the difference between the average male and female investor. In the second part I show the effect that age seems to have on DE for the investor. Lastly, I present the effect that holding period has on the disposition effect. The results presented in this section are calculated using the investor-level approach, and supplemental results on the trade-level disposition effect are presented in the appendix. The findings presented for the investor-level approach and the trade-level approach display similar results.

5.2.1. Disposition effect and gender

Table 5.4. PGR, PLR and DE for men and women

	Men	Women
PGR	0.2272	0.2148
PLR	0.1935	0.1729
Disp. Effect (DE)	0.0337	0.0419
t-stat	29.791	20.264
Degrees of Freedom	75 050	25 268
KS test (D)	0.1481	0.1784
p-value	<0.001	<0.001

Table 5.4. Illustrates the comparison between Proportions of Losses Realized (PLR) and Proportions of Gains Realized (PGR) for both men and women, calculated using the investor-level approach. The t-statistics reflect the null that the Disposition Effect (DE) is equal to zero. The Kolmogorov-Smirnoff test is performed with a monte-carlo to simulate p-values using 10 000 replicates and tests the null that the sampled distribution for PGR and PLR would come from the same actual distribution.

Studying the difference between men and women in Table 5.4. we can see that the average female investor generally tends to exhibit lower estimates of PGR and PLR, when compared to the average male investor. The result that men exhibit both higher PGR and PLR is consistent with the findings in both Barber et al. (2007) and Barber & Odean (2001). Frino et al. (2015) finds that PLR is notable lower, and PGR is marginally higher for men when studying Australian investors. As presented in table A.5.3. in the appendix, similar results can be seen when studying the difference between men and women using the trade-level approach. In both cases we can see that the estimates for PGR and PLR are higher for men as compared to women.

Table 5.5. Difference in disposition effect between men and women

DE (Men)	0.0337
DE (Women)	0.0419
Difference	-0.0082
t-stat	-3.0185
Degrees of Freedom	20 515

Table 5.5. Illustrates the comparison of observed Disposition Effect (DE) between the average male and female investor. The t-statistic is calculated using a welch two-sample t-test and reflects the null that the difference in proportions is equal to zero, implying that female investors would be disposed to selling winners and holding on to losers.

Testing for the difference in DE between men and women displays that the average effect is significantly higher among women than the effect among men. Indicating that women seem to realize proportionally more losses compared to gains when measuring the disparity between the genders. This is in line with the findings presented in Rau (2014) which finds that women display a higher degree of disposition effect when trading in an experimental setting. However, as seen in the descriptive statistics presented in Table 3.2. there are notable differences in how men and women trade. Men tend to trade more, hold more geographically diversified portfolios, and hold on to stocks for a shorter period of time. Chen et al. (2007) suggests that trading frequency has an attenuating effect on the displayed disposition effect among investors. Further, both Feng & Seasholes (2005) and Talpsepp (2010) reports that there is no discernable difference in DE between men and women when adjusting for portfolio characteristics. This leads to the question whether there could be underlying factors related to trading behavior that could help explain the difference in observed level of disposition effect between men and women. This inquiry is investigated more in depth in section 5.3. below.

5.2.2. Age

Figure 5.1. presents the average observed PGR and PLR with respect to age. Notably, both PGR and PLR seemingly decrease as age increases. The difference between these estimates (i.e. DE) seems to be the lowest among the youngest people and the increase with age.

Figure 5.1. Average PGR and PLR vs. age

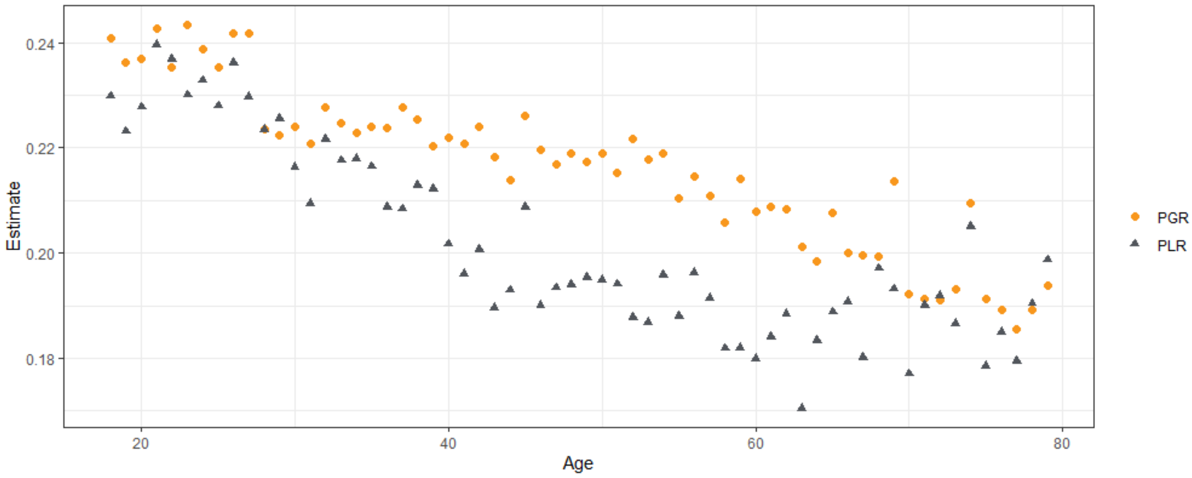

Figure 5.1. Displays the observed average investor-level estimate for PGR and PLR for respective age in the sample older than 18 and younger than 80. The orange circular dots depicts the average PGR among investors with the same age, similarly the grey rectangle illustrates the PLR.

From a theoretical standpoint, the standard life-cycle theory posits that younger individuals should save less, and rather borrow to increase consumption. But as the individual ages, an increasingly higher share of income will go towards saving for future consumption (i.e. retirement). When retiring the individual is assumed to start selling of savings in order to maintain consumption. In terms of portfolio size this assumes that the portfolios among young people will generally be smaller but will subsequently be growing as the individual ages up until the point of retirement when it is assumed to decrease. Studying the descriptive statistics presented in Table 3.2. we can see that this largely holds true as portfolio size generally increase up until retirement, and then start to decrease. As easily shown mathematically, a larger portfolio leads to smaller estimates of PGR and PLR.[12] This could be an explanation as to why the estimates of PGR and PLR seems to decrease with age. However, this effect does not explain why the disposition effect seems to increase up until the age of about 50-60 and then start to decrease. Grinblatt & Keloharju (2001) reflected on a similar issue and according to them there is modest evidence to suggest that life cycle trading would play a role in trading-patterns among individuals.

[12] Consider an investor realizing 1 gain while holding 3 paper gains, PGR would in this case be 0.25. If the same investor instead would hold 9 paper gains, then PGR would equal 0.1.

Table 5.6. PGR, PLR and DE across different age groups

Age group:	(1) 18 - 30	(2) 31 – 40	(3) 41 – 50	(4) 51 – 60	(5) 61 – 70	(6) 70+
PGR	0.2288	0.2270	0.2277	0.2237	0.2128	0.2070
PLR	0.2148	0.1968	0.1765	0.1706	0.1669	0.1695
Difference (DE)	0.0140	0.0302	0.0512	0.0531	0.0459	0.0375
t-stat	6.358	15.477	23.175	21.076	13.933	9.136
df	22 087	25 822	19 690	15 046	8 582	5 590
KS test (D)	0.0692	0.1103	0.1648	0.1685	0.1638	0.1502
p-value	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001

Table 5.6. Illustrates the comparison between Proportions of Losses Realized (PLR) and Proportions of Gains Realized (PGR) for each age group. The t-statistics reflect the null that the Disposition Effect (DE) is equal to zero. The Kolmogorov-Smirnoff test is performed with a monte-carlo to simulate p-values using 10 000 replicates and tests the null that the sampled distribution for PGR and PLR would come from the same actual distribution.

To allow for better examination of how age corresponds to investor-level disposition effect I categorize individuals into six exclusive age-groups and study the differences between them, the results of this can be seen in Table 5.6 above. Here, I present statistical evidence that confirms what could be seen in Figure 5.1. i.e., that DE increases with age up to a certain point and then starts to decrease again. The difference of observed DE for age group (1) and (2), respectively (2) and (3) is statistically significantly increasing. The difference between (3) and (4) is not significantly different. Then, I find that the difference between (4) and (5) as well as (4) and (6) are both significantly decreasing. The associated t-values for the difference in DE among age groups can be found in Table A.5.6 in the appendix.

These results are not strictly in line with the findings in neither Dhar & Zhu (2006) nor Kurniotis & Kumar (2011), as both finds the disposition effect to generally decreases with age. One explanation for this could be that the sampled individuals in this study generally are younger. The two aforementioned papers use the same underlying database for their analysis, namely the same database presented in Barber & Odean (2001). In that database the average age is 50 (median = 48) while the average age for the sample for this paper is 43 (median = 41). Studying the observed disposition effect for each age group in Table 5.6. we can see that DE continuously increases for each age group from 18-30 until 51-60. Thereafter the disposition effect seems to decrease for the subsequent age groups. Considering that the underlying sample in Dhar & Zhu (2006) and Kurniotis & Kumar (2011) in general consisted of older individuals, it is not unreasonable that the decreasing DE among elderly people outweighed the increasing DE among younger people observed. Frino et al. (2015) finds that PGR and PLR seemingly decrease with respect to age, but they do not find that DE would increase with age. However, they do not test these differences explicitly, thus making it difficult to draw concrete conclusions with regards to their findings.

Another explanation could be that diversification seemingly does increase with age, as presented in Table 3.2. Anderson (2013) finds that younger Swedish investors generally are less diversified. This is coherent with the presented results in Kurniotis & Kumar (2011) that older investors are likely to display a higher degree of portfolio diversification. Portfolio diversification relates to the disposition effect in the same regard as discussed above, that holding a wider variety of stocks leads to a lower observed estimate of PGR and PLR.

5.2.3. Holding Period

Figure 5.2. PGR and PLR with respect to holding period

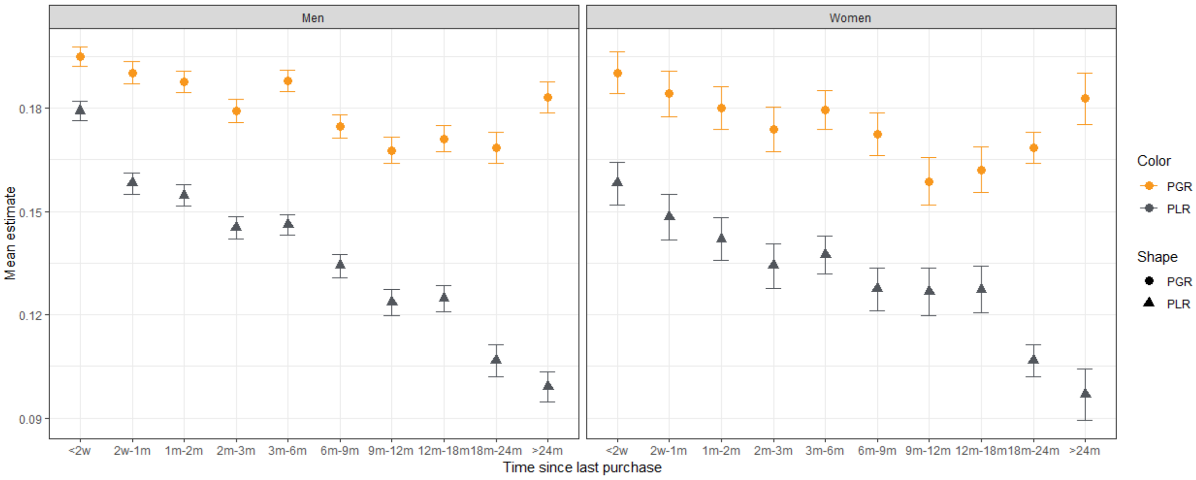

Figure 5.2. Displays the mean estimate for PGR and PLR, with respect to the time the realized stock has been held by the individual. Holding period is here defined as time since last purchase in each stock and is divided into 10 time-buckets. Results are presented based on gender. Estimates are presented with a 95 percent confidence interval.

By allocating the realized issues into different buckets depending on their holding period allows for closer examination of the relationship between DE and holding period. Holding period is here defined as the number of days between the last observed purchase of a stock and the subsequent selling in the same instrument. Investor's trades are categorized within each of these time buckets, and the cross-sectional sum of realized gains and losses in bucket *t* is used to calculate PGR and PLR according to equation [1] and [2], together with portfolio paper gains and losses, respectively.

In Figure 5.2 I graphically present the relationship that holding period has on the investor-level estimates of PGR and PLR, disaggregated by gender. Although there seems to be some variation between men and women, it is clear to see that the difference in most cases lies within the 95% confidence level. The notable exception is that the estimate of PLR for stocks held less than 2 weeks is significantly higher for men than women. Interestingly, when excluding stocks that has been held for a shorter period than 2 weeks and studying the same results presented in

Tables 5.4 and 5.5 the difference in disposition effect between the genders becomes non-significant. This would indicate that the difference between men and women could be explained by other factors than gender itself. This coincides with the discussion that men also trade more frequently than women. As trading frequency is measured as number of transactions made, this implies that people who have a higher turnover in trades generally have shorter roundtrip transactions.

In Table A.5.7., located in the appendix, I present a more detailed view of how DE is affected by holding period. The results presented therein is congruent with the picture painted by Figure 5.2., but also displays the statistical significance of the difference in DE between time-buckets. The estimates of DE with respect to holding period is increasing throughout, although not all of the differences are significant. E.g., the change in DE between a holding period of 3m-6m and 6m-9m is positive, albeit not significant.

The proportion of realized gains and losses in Figure 5.2 and Table A.5.7. is calculated as the realized issues within each time bucket, as a share of the complete portfolio of paper gains and losses. The drawback of this approach is that the proportion of gains and losses are implicitly decreasing as a result of fewer realized positions as holding period increases while the paper positions remain constant.[13] However, this effect does not seem to impact the estimate of PGR to the same extent, as we can see that investors do realize gains and losses in different regards as a result of holding period.

5.3. Regression results

Below I present the results from regressing the disposition effect calculated using the trade-level approach, on the variables discussed in the previous sections. I estimate the regressions using fixed effects (FE) models, where the year and month is treated as fixed effects. This can be likened to adding a dummy with 53 levels, i.e. one for every month. As seen above the disposition effect does not seem to be static throughout the observed period. This is further illustrated by the fact that 34 out of the 53 these aforementioned dummies are significant on the 1%-level when testing using a dummy-based OLS-model. These results suggests as previously hypothesized that disposition effect has a time varying component. Feng & Seasholes (2005)

[13] E.g. if an investor sells stock A and B for a loss at a certain time, where A has been held for less than 1 month and B for more than 1 month. If we assume that the individual holds 5 paper losses at this point, the observed aggregate PLR would equal 0.286. While the observed PLR for each time-bucket would equal 0.167. This effect explains why the estimates presented in Figure Fx all fall below the average PGR and PLR for all individuals presented in table tx(R1).

tests for a comparable approach using time dummies for each month throughout the sample period and find similar results.

Table 5.7. Regressing age and gender on DE

	(1)	(2)	(3)	(4)
Fixed Effect: Year and Month	Yes	Yes	Yes	Yes
(Dummy) Male	-0.0017 (-2.85)*	-0.0013 (-2.17)	-0.0021 (-3.47)*	-0.0018 (-3.01)*
Age	-0.0001 (-4.94)*			
(Ln) Age		0.0018 (2.69)*		
(Sqrd) Age			-0.0016 (-12.10)*	
(1st Orth. Poly) Age				-1.5762 (-5.03)*
(2nd Orth. Poly) Age				-13.2609 (-42.77)*
Adj. R-squared	-0.0000	-0.0000	0.0000	0.0009
Degrees of Freedom	1 945 806	1 945 806	1 945 806	1 945 805

Table 5.7. Represents the model estimates and associated t-values for the regression specified as $DE = \gamma D + \beta X + \varepsilon$, where D represents the dummy variable and X the numerical variables. The first row indicate which variable that has been used as index for the fixed effects. The dependent variable is DE, the disposition effect, measured using the trade-level approach. (*-significant on 1%-level).

In Table 5.7 I illustrate the effects that gender and different transformations of age has on explaining the variance of DE among investors. Here we find that age generally has a negative relationship with age, indicating that older investors display lower disposition effect. Explanatory power seems to increase as I include measurements of the squared effect of age. Especially, model (4) illustrates that using the 1st and 2nd orthogonal polynomial of age adds the most explanatory power. Running the same model with the ordinary first two polynomials of age yield similar results, however due to the high multicollinearity between age and age^2 the Variance Inflation Factor (VIF) is way over 10. Thus, using the orthogonal polynomials reduces multicollinearity among the independent variables. This allows for a better estimate of the standard errors related to this effect.

The effect estimated in model (4) is illustrated by Figure A.5.2 in the appendix, showing a similar non-linear effect as previously discussed. One difference however is that the linear trend is estimated as negative, while the non-linear curve displays that DE is initially increasing among investors up until middle age when it starts to decrease.

5.3.1. Holding Period and ensemble regression

Previous literature has found the concepts of sophistication and experience to help explain variance in DE among different investors. Dhar & Zhu (2006) finds that disposition effect is lower among investors assumed to be more sophisticated. I have no information of the individuals in this database beyond what can be extracted from the numbers in their personal ID. Hence, in order to control for investor sophistication, I extract information from the data that has found to have high correlation with this concept, namely portfolio diversification. Diversification is here measured as the portfolio concentration (i.e., the negative of diversification) and home bias. Portfolio concentration is determined by calculating the Herfindahl Hirschman Index as a function of the amount traded within each stock as a share of total turnover. Home bias is calculated as the share of turnover traded in Swedish stocks as a percentage of total turnover. High portfolio concentration has been found to be associated with less sophisticated investors, according to Goetzmann & Kumar (2008). Karlsson & Lindén (2007) finds a strong link between home bias and investor sophistication among Swedish individual investors. Feng & Seasholes (2005) argues for also including gender and age to code for investor sophistication among Chinese individuals. However, as I am explicitly studying differences in gender and age this would be counterintuitive. Further, there is limited evidence supporting that such claim would hold for Swedish investors, especially for gender.

Beyond controlling for sophistication, Feng & Seasholes (2005) introduces a variable coding for experience that is constructed by calculating the number of positions taken by the investor up until date *t*. Consistent with the remaining framework, I study fixed variables coding for investor characteristics. Thus, I approximate the variable coding for experience as the number of trades carried out by the investor. The distribution of this variable is positively skewed, and thus I transform this variable by taking the logarithm of number of trades. Dhar & Zhu (2006) takes a similar approach by controlling for number of trades in their models.

Table 5.8 displays the results of regressing DE on a set of variables coding for investor characteristics, when treating year and month as a fixed effect. In model (2) the individual investor is also treated as an effect, but as seen by the adjusted r-square for this model this approach is less favorable. The reason being that we implicitly add about 50 000 dummies to the regression, which negatively impacts the adjusted r-square that is sensitive to number of parameters. Further, using the Hausmann test confirms that the FE-model is preferred compared to the combined random effects model (2) in Table 5.8. Considering that the results below aligns with the results presented A.5.9, further indicates that pseudo-replication is not an issue.

Table 5.8. Regressing holding period on DE

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Fixed Effect: Year and Month	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effect: Individual Investor	No	Yes	No	No	No	No	No	No
(Ln) Holding Period	0.0081 (64.58)*	0.0041 (26.77)*	0.0081 (64.53)*	0.0083 (65.69)*	0.0060 (44.25)*	0.0072 (56.68)*	0.0080 (63.55)*	0.0068 (49.36)*
(Dummy) Male			0.0004 (0.66)					0.0035 (5.88)*
(1^{st} Orth. Poly) Age				-1.5639 (-5.02)*				0.7802 (2.39)
(2^{nd} Orth. Poly) Age				-13.7540 (-44.40)*				-14.6151 (-47.03)*
(Ln) No. of Trades					-0.0056 (-40.15)*			-0.0020 (-12.53)*
Home Bias						0.0761 (61.66)*		0.0522 (38.10)*
(HHI) Portfolio Concentration							0.1905 (67.35)*	0.1397 (45.41)*
Adj. R-squared	0.0021	-0.0249	0.0021	0.0031	0.0029	0.0041	0.0044	0.0065
Degrees of Freedom	1945807	1895547	1945806	1945805	1945806	1945806	1945806	1945777

Table 5.8. Represents the model estimates and associated t-values for the regression specified as $DE = \gamma D + \beta X + \varepsilon$, where D represents the dummy variable and X the numerical variables. The first two rows indicate which variable that has been used as index for the fixed effects. The dependent variable is DE, the disposition effect. Holding period is measured as the number of days since the last purchase in the same stock. Home Bias is measured as the share of turnover the investor has in domestic stocks, and Portfolio concentration is measured as the Herfindahl Hirschman Index as a share of turnover concentration. (* -significant on 1%-level).

The coefficient for holding period is significant and positive in all regressions above, indicating that the estimate for this variable is robust. Interpreting the effect of holding period shows that 1 percent increase in holding period leads to an assumed increase by about 0.0007 in DE. This confirms the findings presented in section 5.2.3., namely that the disposition effect increases with holding period.

The effect that gender has on the disposition effect notably disappears when controlling for investor characteristics in regression (7). Outwardly, men seem to display lower DE as seen in Table 5.7, but when controlling for other variables this difference dissipates. Studying the combined effect between holding period and gender on DE we find a strong link that establishes the difference between men and women, as seen in Table 5.9. There we can see that although holding period has a positive effect for both genders, men are affected to a significantly lesser extent as seen by the negative interaction term.

When controlling for investor characteristics it is evident that Age in model (4) has a similar effect as discussed in the previous section. Confirming that age has non-linear and mainly negative relationship with disposition effect. The linear trend related to age is not significant on the 1%-level when controlling for investor sophistication, indicating that the effect of age can to some extend be explained by sophistication and experience.

Less sophisticated investors display higher disposition effect. Studying models (6), (7) and (8) we see that home bias and portfolio concentration have a positive relationship with the disposition effect. Both of these variables are shown to have significant explanatory power in all regressions. Both Dhar & Zhu (2006) and Feng & Seasholes (2005) establish the same connection, finding that more sophisticated investors display a lower propensity to sell winners.

More experienced investors display lower disposition effect. This is evident as the estimate for number of trades is significantly negative, both in the reduced model (5) and in the ensemble model. However, when studying the combined effect of holding period and number of trades, we can see that the effect of number of trades dissipates, as presented in Table 5.9, below. This would suggest that the combined negative effect of holding period and number of trades better explains variation in DE caused by trading frequency, rather than the number of trades alone.

Table 5.9. Interaction terms when regressing holding period on disposition effect

	(1)	**(2)**	**(4)**
Fixed Effect: Year and Month	Yes	Yes	Yes
(Ln) Holding Period	0.0209 (39.85)*	0.0214 (64.24)*	0.099 (33.44)*
(Ln) No. of Trades	0.0000 (0.14)		
(Ln) Portfolio Size		-0.0040 (-8.51)*	
(Dummy) Male			0.0072 (6.08)*
Interaction Term	-0.0021 (-29.38)*	-0.0056 (-40.74)*	-0.0022 (-6.64)*
Adj. R-Square	0.0034	0.0065	0.0021
Degrees of Freedom	1 945 806	1 945 806	1 945 806

Table 5.9. Represents the estimates and associated t-values for regression (1) and (2) specified as $DE = \beta_1 X_1 + \beta_2 X_2 + \beta' X_1 X_2 + \varepsilon$, where X represent the numerical variable i, and β' represents the coefficient estimate for the interaction term. For regression (3) the model is specified as $DE = \gamma D + \beta X + \beta' XD + \varepsilon$, where D represents the dummy variable and X the numerical variable. In all models the interaction term is defined as the combined effect of Holding period and number of trades, portfolio size and Male, respectively for model (1), (2) and (3). The dependent variable the disposition effect, calculated using the trade-level approach. (* - significant on 1%-level).

In Table 5.9. we can also see that portfolio size helps explain a significant degree of the variance in DE, both by itself but also as an interaction term with holding period. Here portfolio size is calculated as the sum of paper gains and losses at the time of each trade. The explanation is likely that investors with smaller portfolios generally hold on to stocks for a longer period.

When measuring the disposition effect using the trade-level approach, we measure the individual's decision to sell either a gain or a loss compared to both the size and composition of the remaining portfolio. Thus, portfolio size intuitively has an impact to the estimated disposition effect using this approach.

5.3.2. Test of regression robustness

Considering that portfolio size has a potential implicit relationship with disposition effect, it is important to study the impact of this variable from a robustness perspective. Hence, explicitly controlling for portfolio size illustrates the potential impact this variable would have on overall results. As most investors hold relatively small portfolios, the variable portfolio size is skewed. To adjust for this in the regression I take the logarithm of portfolio size.

In Table A.5.8. I present the effect that controlling for portfolio size has on the regressions presented above in Table 5.8. Studying the results indicates that portfolio size helps explain a significant aspect of the variance, but beyond that the estimates for the remaining coefficients are robust for most variables. The notable exception is that number of trades becomes insignificant in the reduced model (8), while being significant in the ensemble model (9) when controlling for portfolio size. Also, the estimate of the 1st polynomial of age displays a linear positive trend with DE. This can likely be explained by the fact that older individuals are likely to hold larger portfolios, as seen in the descriptive statistics.

Further, the results presented with regards to sophistication and experience closely resembles the findings presented in Dhar & Zhu (2006), who estimates the effect these variables have on DE measured using the investor-level approach. To test for robustness across aggregation level for calculating DE, I run similar regressions as shown in Table 5.8, but instead on investor-level. As all variables, except for holding period, already is calculated for each investor I calculate the average holding period to be used in the investor-level regressions. This variable is positively skewed, thus I transform this average holding period by taking the logarithm.

Studying the results presented in table A.5.9, we can see that coefficients remain steadfast in regard to significance and direction. The variable coding for average holding period displays a significantly positive effect, showing that the effect of holding period is consistent across different ways of estimating DE. With regards to the first polynomial of age, we see that the estimate is positive, as compared to the main model in Table 5.8. Gender is still insignificant in the ensemble model (7) in the investor-level model, adding to the pile of evidence that gender has no significant effect when controlling for investor characteristics.

6. Conclusion

This paper studies the disposition effect using detailed trading records from Swedish individual investors. While my results confirm previous findings of the existence of the disposition effects, I also show that there is wide dispersion of this bias across investors. I examine the factors that help explain this variation in disposition effect, as reflected by the hypotheses formulated at the beginning of this paper. For both age and gender I show that results might present one thing at first glance, but when controlling for investor characteristics the results paint a picture that has often been overlooked in previous literature, especially with regards to age. The results found does not necessarily contradict previous findings, indicating that these characteristic effects are general across different demographics.

H1a: *Women exhibit a higher degree of disposition effect.* At first glance women display higher disposition effect, but when controlling for investor characteristics the difference between men and women dissipates.

H1b: *Disposition effect has a non-linear relationship with age.* Outwardly age seems to have a bell-shaped relationship with the disposition effect, initially increasing until middle-age and then starting to decrease. When adjusting for characteristics such as investor sophistication the initially positive relationship recedes, in favor of a more non-linear negative relationship.

Beyond demographic characteristics, I study the relationship between disposition effect and trade characteristics. Specifically focusing on the nature of the phenomenon itself, that investors hold on to losses for too long. By studying the effect of holding period I find that this help explain a significant part of the variation in disposition effect.

H2: *The disposition effect decreases the longer investors hold on to a stock.* The findings presented display strong evidence that the disposition effect increases the longer an individual has been holding on to a stock, displaying that investors are increasingly reluctant to realize losses the longer they have hold on to them.

Further, I find that investor sophistication and experience help explain variation in disposition effect among Swedish individuals. More sophisticated investors display lower disposition effect. Similarly, more experienced investors display lower disposition effect as well. Both of these findings are coherent with the results presented in Feng & Seasholes (2005) and Dhar & Zhu (2006). Sophistication is measured by variables coding for portfolio diversification, and experience is measured as the number of trades made by the individual. The construction of these variables resembles the approach taken in the aforementioned papers.

The results highlight the need of policymakers to intervene early and educate investors, allowing them to understand their own susceptibility to bias in order to reduce behavior that harm portfolio returns. A small improvement in savings when individuals are young can have substantial impact on overall retirement savings by the effect of compounding interest. Combining this with the finding that less sophisticated investors display higher disposition effect emphasizes the need of educating investors of this inherent bias.

The findings that disposition effect increases with holding period presents brokerage houses with an opportunity to help clients increase returns by nudging them to cut losses that have been held for a long period. This would constitute a value-added service both to the investors who could increase returns by reducing bias, but also for the brokerage house who would benefit from wealthier clients. With demographic and portfolio information, brokerage firms can target younger individuals with less diversified portfolios who are more likely to exhibit the disposition effect.

Future research into understanding the disposition effect is needed to better understand the underlying factors driving reluctance in investors to realize losses. Combining trading data with survey data would allow researchers to connect the findings of disposition effect to investor characteristics such as risk-taking, trading strategy and motivation. Furthermore, the disposition effect was first proven in 1998, despite this we continuously find strong evidence of its continuous existence among investors. Considering this, it would be interesting to study learning behavior among individuals, and better understand what efforts that could help investors limit biased actions in financial decisions.

References

Anderson, A. (2013). *Trading and under-diversification.* Review of Finance, 17(5), 1699-1741.

Andreassen, P. (1988). *Explaining the price-volume relationship: The difference between price changes and changing prices.* Organizational Behavior and Human Decision Processes 41:3, 371–389.

Attanasio, O. P., & Weber, G. (2010). *Consumption and saving: models of intertemporal allocation and their implications for public policy*. Journal of Economic literature, 48(3), 693-751.

Barber, B. M., Lee, Y. T., Liu, Y. J., & Odean, T. (2007). *Is the aggregate investor reluctant to realise losses? Evidence from Taiwan*. European Financial Management, 13(3), 423-447.

Barber, B. & Odean, T. (2000). *Trading is hazardous to your wealth: The common stock investment performance of individual investors*. Journal of Finance 55:2, 773–806.

Barber, B. & Odean, T. (2001). *Boys will be boys: Gender, overconfidence, and common stock investment*. Quarterly Journal of Economics 141:1, 261–292

Barberis, N. & Xiong, W. (2009). *What drives the disposition effect? An analysis of a long-standing preference-based explanation*. Journal of Finance 64:2, 751–784.

Boolell-Gunesh, S., Broihanne, M. & Merli, M. (2009). *Disposition effect, investor sophistication and taxes: Some French Specificities*. Finance, 30, 51-78.

Brooks, P., & Zank, H. (2005). *Loss averse behavior*. Journal of Risk and uncertainty, 31(3), 301-325.

Brown, N., Da Silva, R., & Walter, T. (2006). *The Reach of the Disposition Effect: Large Sample Evidence Across Investor Classes*. International Review of Finance, 6(1-2), 43–78.

Byrnes, J. P., Miller, D. C., & Schafer, W. D. (1999). *Gender differences in risk taking: A meta-analysis*. Psychological bulletin, 125(3), 367.

Calvet, L.E., Campbell, J., & Sodini P. (2007), *Down or Out: Assessing the Welfare Costs of Household Investment Mistakes*, Journal of Political Economy 115:707-747.

Calvet, L.E., Campbell, J., & Sodini P. (2009). *Fight or Flight? Portfolio Rebalancing by Individual Investors.* Quarterly Journal of Economics 124:301-348.

Charness, G., & Gneezy, U. (2012). *Strong evidence for gender differences in risk taking*. Journal of Economic Behavior & Organization, 83(1), 50-58.

Constantinides, G. (1984). *Optimal stock trading with personal taxes: Implications for prices and the abnormal January returns*, Journal of Financial Economics 13, 65– 69.

Cocco, J. F., Gomes, F. J., & Maenhout, P. J. (2005*). Consumption and portfolio choice over the life cycle*. The Review of Financial Studies, 18(2), 491-533.

Coval, J. D., & Moskowitz, T. J. (1999*). Home bias at home: Local equity preference in domestic portfolios*. The Journal of Finance, 54(6), 2045-2073.

Dahlquist, M., Pinkowitz, L., Stulz, R. M., & Williamson, R. (2003). *Corporate governance and the home bias*. Journal of financial and quantitative analysis, 38(1), 87-110.

Dhar, R., & Zhu, N. (2006). *Up close and personal: Investor sophistication and the disposition effect*. Management Science, 52(5), 726-740.

Fama, E., & French, K. (2010). *Luck versus skill in the cross section of mutual fund returns*. Journal of Finance, 65(5), 1915-1947.

Festinger, L. (1957). *A theory of cognitive dissonance*. Stanford, CA: Stanford University Press

French, K. R., & Poterba, J. M. (1991). *Investor diversification and international equity markets*.

Frino, G., & Wright, D. (2015). *Investor characteristics and the disposition effect*. Pacific-Basin Finance Journal, 31, 1–12.

Goetzmann, W. N., & Massa, M. (2002). *Daily momentum and contrarian behavior of index fund investors*. Journal of Financial and Quantitative Analysis, 37(3), 375-389.

Goetzmann, W. N., & Kumar, A. (2008). *Equity portfolio diversification*. Review of Finance, 12(3), 433-463.

Grinblatt, M., & Keloharju, M. (2004). *Tax-loss trading and wash sales*. Journal of Financial Economics, 71(1), 51-76.

Hausmann, R., Tyson, L. D. A., & Zahidi, S. (2012). *The global gender gap report 2012.* Geneva: World Economic Forum.

Kahneman, D., & Tversky, A. (1979). *On the interpretation of intuitive probability*: A reply to Jonathan Cohen.

Kahneman, D., & Tversky, A. (1981). *The simulation heuristic*. Stanford Univ CA Dept of Psychology.

Kahneman, D., & Tversky, A. (1992). *Advances in prospect theory: Cumulative representation of uncertainty*. Journal of Risk and uncertainty, 5(4), 297-323.

Karlsson, & Nordén, L. (2007). Home sweet home: Home bias and international diversification among individual investors. Journal of Banking & Finance, 31(2), 317–333.

Kaustia, M. (2010a). *Prospect theory and the disposition effect*. Journal of Financial and Quantitative Analysis, forthcoming (June issue).

Kaustia, M. (2010b). *Disposition effect*. Behavioral finance, 6, 169-189.

Korniotis, G. M., & Kumar, A. (2011). *Do older investors make better investment decisions?*. The Review of Economics and Statistics, 93(1), 244-265.

Leal, C., Rocha Armada, M. J., & Duque, J. C. (2010). *Are all individual investors equally prone to the disposition effect all the time? New evidence from a small market. New Evidence from a Small Market* (October 1, 2010). Frontiers in Finance and Economics, 7(2), 38-68.

Massa, M. & Simonov A. (2006). *Hedging, Familiarity, and Portfolio Choice,* Review of Financial Studies 19:633-685.

Mattson, I. & Brink, A. (2018). *Investeringssparkonto – en enkel sparform i ett komplext skattesystem*. Riksrevisionens granskningsrapport. Dnr: 3.1.1-2017-0864

Odean, T. (1998). *Are investors reluctant to realize their losses?*, Journal of Finance 53:5, 1775–1798.

Odean, T. (1998). *Do investors trade too much?,* American Economic Review 89:5, 1279–1298.

Ofek, E., & Richardson, M. (2003). *Dotcom mania: The rise and fall of internet stock prices*. The Journal of Finance, 58(3), 1113-1137.

Prince, M. (1993). *Women, men, and money styles*. Journal of Economic Psychology, 14(1), 175–182.

Rau, H. A. (2014). *The disposition effect and loss aversion: Do gender differences matter*?. Economics Letters, 123(1), 33-36.

Sapienza, P., Zingales, L., & Maestripieri, D. (2009). *Gender differences in financial risk aversion and career choices are affected by testosterone*. Proceedings of the National Academy of Sciences, 106(36), 15268-15273.

Statistics Sweden (SCB). (2022). Population Statistics: Statistical database. Stockholm: Statistiska centralbyrån. URL: https://www.statistikdatabasen.scb.se/pxweb/sv/ssd/START__BE__BE0101__BE0101A/BefolkningNy/ (retrieved: 2022-08-29)

Schlarbaum, G., Lewellen, W. & Lease, R. (1978). *Realized returns on common stock investments: The experience of individual investors*. Journal of Business 51:2, 299–325.

Shapira, Z. & Venezia, I. (2001). *Patterns of behavior of professionally managed and independent investors.* Journal of Banking and Finance 25:8, 1573–1587.

Sharpe, W.F. (1964). *Capital asset prices: a theory of market equilibrium under conditions of risk*, The Journal of Finance, 19: 425-442.

Sharpe, W. (1966). *Mutual fund performance*. Journal of Business 39:1(Part 2), 119–138

Shefrin, H. & Statman, M. (1985). *The disposition to sell winners too early and ride losers too long*. Journal of Finance 40:3, 777–790.

Starr-McCluer, M. (2002). *Stock market wealth and consumer spending*. Economic Inquiry, 40(1), 69-79.

Talpsepp, T. (2013). *Does gender and age affect investor performance and the disposition effect?*. Research in Economics and Business: Central and Eastern Europe, 2(1).

Thaler, R. (1980). *Toward a positive theory of consumer choice*. Journal of economic behavior & organization, 1(1), 39-60.

Thaler, R. (1985). *Mental accounting and consumer choice*. Marketing science, 4(3), 199-214.

Vissing-Jorgensen, A. (2003). *Perspectives on behavioral finance: Does" irrationality" disappear with wealth? Evidence from expectations and actions*. NBER macroeconomics annual, 18, 139-194

Weber, M., & Camerer, C. F. (1998). *The disposition effect in securities trading: An experimental analysis*. Journal of Economic Behavior & Organization, 33(2), 167-184.

Appendix

Table A.5.1. Average individual disposition- and tax-effect

	Full	Only Jan-Nov	Only Dec
PGR	0.2140	0.2091	0.1883
PLR	0.1707	0.1645	0.1506
Disp. Effect (DE)	0.0433	0.0446	0.0377
t-stat	45.542	44.557	22.379
Degrees of Freedom	100 445	78 639	40 865
KS test (D)	0.1623	0.1508	0.1978
p-value	<0.001	<0.001	<0.001

Table A.5.1. Illustrates the comparison between Proportions of Losses Realized (PLR) and Proportions of Gains Realized (PGR) on a general level calculated using the trade-level approach. The t-statistic is calculated using the welch two-sample t-test and reflects the null that the difference in proportions is equal to zero, implying that investors would not be disposed to selling winners and holding on to losers. The two-sample Kolmogorov-Smirnoff (defined as KS-test above) test is performed with a monte-carlo to simulate p-values using 10 000 replications.

Table A.5.2. Difference in disposition effect in December vs. rest of year

DE (Jan-Nov)	0.0445
DE (Dec)	0.0377
Difference	0.0068
t-stat	2.949
Degrees of Freedom	35 146

Table A.5.2. Illustrates the comparison between Disposition Effect (DE) during the month of December compared to the remainder of the year. The t-statistic reflects the null that the difference in proportions is equal to zero, implying that investors would not be disposed to selling winners and holding on to losers. The Kolmogorov-Smirnoff test is performed with a monte-carlo to simulate p-values using 10 000 replications. These results are calculated using the trade-level approach.

Table A.5.3. PGR, PLR and DE for men and women

	Men	Women
PGR	0.2159	0.2084
PLR	0.1745	0.1596
Disp. Effect (DE)	0.0414	0.0488
t-stat	38.481	24.407
Degrees of Freedom	75 155	25 291
KS test (D)	0.1446	0.1829
p-value	<0.001	<0.001

Table A.5.3. Illustrates the comparison between Proportions of Losses Realized (PLR) and Proportions of Gains Realized (PGR) for both men and women, calculated on trade-level. The t-statistics reflect the null that the Disposition Effect (DE) is equal to zero. The Kolmogorov-Smirnoff test is performed with a monte-carlo to simulate p-values using 10 000 replicates and tests the null that the sampled distribution for PGR and PLR would come from the same actual distribution. These results are calculated using the trade-level approach.

Table A.5.4. Difference in disposition effect between men and women

DE (Men)	0.0414
DE (Women)	0.0488
Difference	-0.0074
t-stat	-2.688
Degrees of Freedom	20 508

Table A.5.4. Illustrates the comparison of observed Disposition Effect (DE) between the average male and female investor. The t-statistic is calculated using a welch two-sample t-test and reflects the null that the difference in proportions is equal to zero, implying that female investors would be disposed to selling winners and holding on to losers. These results are calculated using the trade-level approach.

Table A.5.5. PGR, PLR and DE across different age groups

	18 - 30	**31 – 40**	**41 – 50**	**51 – 60**	**61 – 70**	**70+**
PGR	0.2152	0.2156	0.2184	0.2154	0.2064	0.2022
PLR	0.1949	0.1779	0.1598	0.1553	0.1511	0.1541
Difference (DE)	0.0203	0.0377	0.0586	0.0601	0.0553	0.0481
t-stat	9.623	20.298	27.819	24.980	17.556	12.212
df	22 087	25 822	19 690	15 046	8 582	5 590
KS test (D)	0.0884	0.1382	0.1998	0.2021	0.1925	0.1723
p-value	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001

Table A.5.5. Illustrates the comparison between Proportions of Losses Realized (PLR) and Proportions of Gains Realized (PGR) for each age group. The t-statistics reflect the null that the Disposition Effect (DE) is equal to zero. The Kolmogorov-Smirnoff test is performed with a monte-carlo to simulate p-values using 10 000 replicates and tests the null that the sampled distribution for PGR and PLR would come from the same actual distribution. These results are calculated using the trade-level approach.

Table A.5.6. Difference in DE between age-groups

Age	**18 - 30**	**31 – 40**	**41 – 50**	**51 – 60**	**61 – 70**	**70+**
18 - 30		-0.01627 (-4.749)*	-0.03724 (-10.306)*	-0.03924 (-10.120)*	-0.03196 (-7.016)*	-0.02359 (-4.422)*
31 – 40			-0.02097 (-6.271)*	-0.02297 (-6.332)*	-0.01569 (-3.611)*	-0.00732 (-1.419)
41 – 50				-0.00200 (-0.525)	0.00528 (1.176)	0.01366 (2.586)*
51 – 60					0.00728 (1.547)	0.01565 (2.864)*
61 – 70						0.00837 (1.404)
70+						

Table A.5.6. Illustrates the comparison of Disposition Effect (DE) between each age group as presented in Table 5.6 in the main text. As in Table 5.6, the values are calculated using the investor level approach. The difference of DE-estimates -between the different age groups are tested using a welch two-sample t-test to determine whether or not the dissimilarity is significantly different from 0. The value reported within the brackets is the t-statistic from said test. (* -significant on 1%-level).

Figure A.5.7. Difference in DE between time-buckets

	< 2w	2w-1m	1m-2m	2m-3m	3m-6m	6m-9m	9m-12m	12m-18m	18m-24m
< 2w		0.01318 (5.502)*	0.01417 (5.988)*	0.01610 (6.520)*	0.02109 (9.152)*	0.02180 (8.871)*	0.02237 (8.560)*	0.02414 (9.320)*	0.04253 (14.533)*
2w-1m			0.00010 (0.402)	0.00292 (1.138)	0.00791 (3.287)*	0.00862 (3.377)*	0.00920 (3.400)*	0.01096 (4.088)*	0.02936 (9.760)*
1m-2m				0.00192 (0.759)	0.00692 (2.909)*	0.00763 (3.019)*	0.00820 (3.062)*	0.00997 (3.753)*	0.02836 (9.501)*
2m-3m					0.00499 (2.014)	0.00571 (2.175)	0.00628 (2.267)	0.00804 (2.928)*	0.02644 (8.621)*
3m-6m						0.00071 (0.288)	0.00128 (0.489)	0.00305 (1.173)	0.02144 (7.303)*
6m-9m							0.00057 (0.207)	0.00234 (0.854)	0.02073 (6.780)*
9m-12m								0.00176 (0.614)	0.02016 (6.330)*
12m-18m									0.01839 (5.811)*
18m-24m									

Table A.5.7. Illustrates the comparison between Disposition effect (DE) for each time-bucket. The results reported in this table reflects the same findings as presented in Figure 5.2 in the main text, and is thus calculated using the investor-level approach. Each row displays the difference from the left-hand group to the group identified by each column. The t-statistics is presented within the brackets and reflect the null that the Disposition Effect (DE) is equal to zero. E.g., subtracting the disposition effect found within time-bucket "< 2w" from the effect found in bucket "2w-1m" equals 0.0132, and the difference is significantly different from 0 as the t-statistic is 5.502. (* - significant on 1%-level).

Figure A.5.1. Estimated effect of Age and Age^2 on the disposition effect.

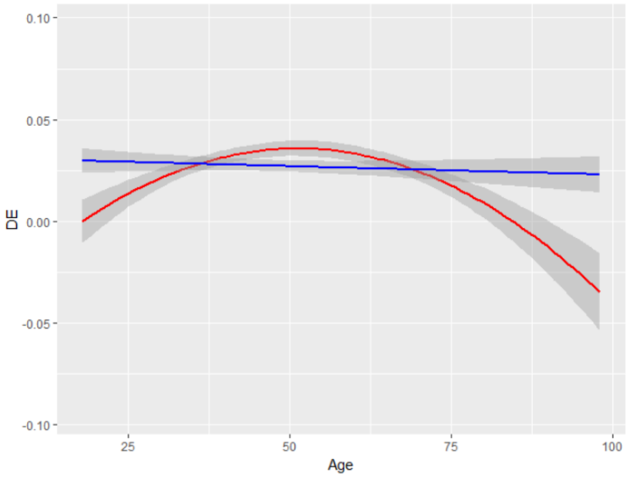

Table A.5.1. Illustrating the relationship between DE and the regression estimates of the first and second order polynomial of age. The blue straight line depicts the first order polynomial, and the second order is defined by the curved red line. These results are based on the regression estimates found in Table 5.7.

Table A.5.8. Regressing holding period and portfolio size on DE

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Fixed Effect: Year and Month	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effect: Individual Investor	No	Yes	No	No	No	No	No	No	No
(Ln) Portfolio Size	-0.0202 (-82.94)*	-0.0163 (-51.29)*	-0.0203 (-83.03)*	-0.0211 (-84.70)*	-0.0173 (-67.85)*	-0.0164 (-63.12)*	-0.0156 (-57.15)*	-0.0202 (-72.54)*	-0.0165 (-56.39)*
(Ln) Holding Period	0.0088 (70.20)*	0.0059 (39.22)*	0.0088 (69.95)*	0.0090 (71.54)*	0.0081 (63.71)*	0.0086 (68.40)*	0.0082 (64.77)*	0.0088 (62.59)*	0.0088 (61.79)*
(Dummy) Male			-0.0024 (-4.06)*				0.0006 (0.31)		0.0001 (0.03)
(1^{st} Orth. Poly) Age				4.3860 (13.76)*			3.5492 (11.08)*		2.9350 (8.93)*
(2^{nd} Orth. Poly) Age				-14.1833 (-45.86)*			-14.4185 (-46.63)*		-14.1644 (-45.60)*
Home Bias					0.0504 (39.12)*		0.0406 (30.30)*		0.0433 (31.43)*
(HHI) Portfolio Concentration						0.1226 (40.55)*	0.0988 (31.69)*		0.1023 (32.52)*
(Ln) No. of Trades								0.0001 (0.28)	0.0014 (8.42)*
Adj. R-squared	0.0056	-0.0218	0.0056	0.0068	0.0064	0.0065	0.0081	0.0056	0.0082
Degrees of Freedom	1945807	1895547	1945806	1945805	1945806	1945806	1945777	1945806	1945776

Table A.5.8. Represents the model estimates and associated t-values for the regression specified as $DE = \gamma D + \beta X + \varepsilon$, where D represents the dummy variable and X the numerical variables. The first two rows indicate which variable that has been used as index for the fixed effects. The dependent variable is DE, the disposition effect, is calculated for each investor using the investor-level approach. Portfolio size is the number of paper gains and losses at the time of each trade. Holing period is the number of days since the last purchase in the stock. Home bias is the share of turnover that each investor has in the domestic stock market. Portfolio concentration is the HHI of portfolio as a share of turnover in different stocks. Number of trades indicates the number of transactions the individual has made throughout the period. (*- significant on 1%-level).

Table A.5.9. Regressing holding period and investor-level DE

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Intercept	-0.0489 (-9.30)*	-0.0463 (-7.72)*	-0.0460 (-8.69)*	-0.0600 (-11.43)*	-0.0722 (-13.39)*	-0.0155 (-1.66)	-0.0865 (-7.50)*
(Ln) Avr. Holding Period	0.0186 (16.66)*	0.0185 (16.36)*	0.0180 (15.92)*	0.0175 (15.49)*	0.0193 (17.25)*	0.0167 (13.67)*	0.0185 (14.26)*
(Dummy) Male		-0.0026 (-0.95)*					0.0017 (0.62)
(1st Orth. Poly) Age			1.1938. (4.56)*				1.1405 (4.11)*
(2nd Orth. Poly) Age			-2.1189 (-8.03)*				-2.1913 (-8.31)*
Home Bias				0.0437 (9.99)*			0.0298 (6.19)*
(HHI) Portfolio Concentration					0.1408 (12.71)		0.1269 (10.39)*
(Ln) No. of Trades						-0.0051 (-5.21)*	0.0015 (1.31)
Adj. R-squared	0.0064	0.0064	0.0082	0.0090	0.0117	0,0070	0.0145
Degrees of Freedom	49 459	49 458	49 457	49 458	49 454	49 458	49 449

Table A.5.9. Represents the model estimates and associated t-values for the regression specified as $DE = \gamma D + \beta X + \varepsilon$, where D represents the dummy variable and X the numerical variables. The first two rows indicate which variable that has been used as index for the fixed effects. The dependent variable is DE, the disposition effect, is calculated for each investor using the investor-level approach. The t-statistics presented are calculated using the White heteroskedasticity-consistent approach. Holing period is the number of days since the last purchase in the stock. Home bias is the share of turnover that each investor has in the domestic stock market. Portfolio concentration is the HHI of portfolio as a share of turnover in different stocks. Number of trades indicates the number of transactions the individual has made throughout the period. (*- significant on 1%-level).