Does Gender and Age Affect Investor Performance and the Disposition Effect?

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Abstract

The focus of the paper is on individual investor trading characteristics, the disposition effect bias and its links to performance. The analysis is based on the individual investor subsample of the complete transaction data of the Estonian stock market. The Cox proportional hazard model, along with PGR-PLR analysis, is used to measure the disposition effect and trading intensity. I show that different gender and age groups have different trading intensity and security holding periods, which realise in differences in the disposition effect bias and performance. Portfolios of older age groups and female investors perform better. Lower portfolio returns are connected with a higher level of trading intensity, shorter holding periods and a higher level of the disposition effect bias.

JEL classification codes: **G11, G12**
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1. Introduction

Individual investors' trading have been found to be hazardous to their wealth (Barber and Odean, 2000), and (as hypothesised) of being less sophisticated, individual investors show inferior results compared to institutional investors (Grinblatt and Keloharju, 2000). In addition, it has been shown in many studies that individual investors tend to realise gains too early and at the same time fail to realise losing positions. Such a bias is known as the disposition effect.

As the literature lacks detailed analysis of gender and age groups, I concentrate on the individual investor subsample of the Estonian stock market dataset to study the behaviour of individual investors, gender and age differences in more detail. The focus of the study is on the disposition effect bias and its connection with trading performance. Estonian data is used as it enables to study the whole universe of trades for one country and the stock exchange, which would, even if such data would be provided, be computationally extremely difficult for any other bigger stock exchange. The used dataset includes details of all trades made on the Tallinn stock exchange from 2004 till July 2008. Such a comprehensive dataset has only been available for the Finnish stock market and most of the other previous studies have not been able to study all transactions of a stock exchange and used subsamples of discount brokers instead. The current paper analyses every single trade for every stock and provides a unique perspective to the results obtained; as such data is not available for most of the similar studies.

The paper provides detailed analysis of the account size, risk level and trading intensity of different age groups, concentrating on gender differences in an emerging market setup. There is currently no empirical work for a young emerging market in western cultural environment that can have clear implications on investor behaviour (see e.g. Hens and Wang, 2007). Previous disposition related works (see e.g. Grinblatt and Keloharju, 2000), have shown differences between local and foreign investors, but the current study focuses more on differences of age groups, where distinction of the disposition effect bias is less evident. The contribution of this paper is purely empirical, as I provide evidence that the disposition effect bias, trading intensity and performance results tend to differ across gender and age groups; whereas, a higher level of the disposition effect bias translates into lower portfolio return, which is also negatively affected by higher trading intensity.

The paper is organised as follows: Section 2 gives an overview of related literature; Section 3 presents the methodology; Section 4 describes the used account data, investor portfolios, performance and trading intensity results. Disposition effect related results are presented in Section 5 and conclusions in Section 6.

2. Related Literature

The most prominent disposition effect explanations include the prospect theory approach (Shefrin and Statman, 1985), the contrarian strategy and the belief that all stocks revert to the mean (Barber and Odean, 1999), rebalancing needs (Lakonishok and Smidt, 1986) and mental accounting combined with backward looking optimisation (Hens and Vlcek, 2006). The following subsections give an overview of disposition and trading motivation related empirical studies with a focus on a few gender related studies.

2.1. United States

Gender differences have been studied in the USA by Barber and Odean (2001), who show that men trade more excessively than women, which reduces their returns and can be caused by overconfidence. Additional US studies (Odean, 1998; Barber and Odean, 2000) show the existence of the disposition effect and excessive trading for the whole sample of individual investors.

With the same data, Kumar (2009) shows that behavioural biases are stronger when there is greater market-wide uncertainty, as reflected by higher mean stock-level volatility and higher unemployment rate. He found that investors are more overconfident and exhibit disposition effect when stocks are more difficult to value.

Dhar and Zhu (2006) find empirical evidence that wealthier individual investors in professional occupations exhibit less disposition effect. They also find that trading experience tends to reduce the disposition effect.

Garvey and Murphy (2004) study the trading of proprietary day traders of a large US brokerage company in 2000. They find that day traders who liquidate practically all positions before market close, realise their winning trades almost twice as fast as losing trades.

Kumar and Lee (2006) study retail investor sentiment and document that the trading activities of retail investors contain a common directional component, meaning that when retail investors buy (sell) one group of stocks, they tend to buy (sell) other groups.

2.2. Europe

Shapira and Venezia (2001) analyse the investment patterns of a large number of clients of a major Israeli brokerage house. They show that both professional and individual investors exhibit the disposition effect, although the effect is stronger for individual investors.

Grinblatt and Keloharju (2000, 2001a, 2001b) find evidence that Finnish investors are reluctant to realise losses; engage in tax-loss selling activity; and that past returns and historical price patterns affect trading. They show that unsophisticated investors are more prone to the disposition effect than sophisticated investors. Their tests distinguish the disposition effect from the contrarian strategy by controlling for both the stock's pattern of past returns and the size of the holding-period capital loss. They show that past returns, reference price effects, the size of the holding period capital gain/loss, tax-loss selling and the smoothing of consumption over the life cycle are all determinants of trading.

Weber and Welfens (2007) analyse individual level disposition effects by using both account level German online broker data, as well as a controlled laboratory experiment. They find that the degree of the disposition effect varies considerably on an individual level, as most investors exhibit the disposition to some degree, although investors with a reverse effect exist. In an experiment setup, they find that investors who started with a positive disposition effect decreased their bias over time, while those investors with a negative initial disposition effect also drifted towards the no-disposition effect benchmark. The results show that investors with higher income, as well as more trading experience, are less prone to the disposition effect; whereas, investors with aggressive investment strategies tend to exhibit a relatively high disposition effect.

Leal et al. (2008) find strong evidence of the disposition effect on the Portuguese market. They report a higher degree of the disposition effect during the periods of a bull market than a bear market. They find that the disposition effect reduces, as investor sophistication increases.

2.3. Asia and Oceania

Using Chinese discount brokerage data from 1998 to 2002 Chen et al. (2004) find strong evidence that more experienced investors are more inclined toward making trading mistakes and suffering from representativeness bias. They conclude that investor sophistication does not mitigate behavioural biases, nor improve the trading performance.

Krause et al. (2006) use Chinese brokerage data from 1999 to 2003 to find evidence of the disposition effect for buy strategies, but they report a reverse disposition effect for sell strategies. They find that the disposition effect depends on the time horizon of a trading strategy; where short-term strategies yield the reverse disposition effect and long-term strategies the disposition effect.

Feng and Seasholes (2005) investigate investor sophistication and trading experience based on Chinese discount broker data from 1999 to 2000. They show that investor sophistication and trading experience eliminate the reluctance to realise losses; as sophisticated investors are clearly less susceptible to the disposition effect than the average investor in the sample. Feng and Seasholes (2008) also document that men hold larger portfolios, trade more intensively and make slightly larger trades than women, although they do not find difference in the performance of genders.

Choe and Eom (2006) show that Korean individual investors are much more susceptible to the disposition effect than institutional and foreign investors. They also found that investor sophistication and trading experience reduces the disposition effect, but does not eliminate it.

Brown et al. (2006) use a large Australian dataset from 1995 to 2000 and find that the disposition effect is pervasive across investor classes, although traders with larger investments tend to be less affected by the effect. They confirm that the disposition effect is not driven by diversification nor transaction cost motives.

3. Methodology

The paper uses two different approaches to measure the disposition effect, which enables to get more comparable results with different previous studies and can stand as a robustness check of the results. Thus, survival analysis (similarly to Feng and Seasholes, 2005 and Stoffman, 2008) is employed along with PGR-PLR ratio analysis of Odean (1998).

I use the Cox proportional hazard model with time-varying covariates to measure the probability that an investor will sell its current stock position. Survival analysis is used for measuring the disposition effect, as well as the trading activity of different investor groups.

An alternative approach would be to use logistic regressions (as used in Grinblatt and Keloharju, 2000). Both survival analysis and logistic regressions use binary outcome variables and allow for categorical or continuous predictor variables and are thus quite similar in their setup. The main difference and advantage of survival analysis comes from bringing in the time dimension to the analysis and thus allowing to examine the relationship of both timing and occurrence of outcomes to multiple predictors, rather than focusing only on occurrence. Another advantage of survival analysis is that it allows for censored observations, meaning that data can be analysed before all participants have experienced the terminal event. The same is true when the entry time for participants is not simultaneous.

The hazard rate, which is the probability of selling at time t conditional on holding a stock until time t-1, is calculated from Equation 1, where $p\lambda t^{p-1}$ denotes the baseline hazard which describes how hazard changes over time at baseline levels of covariates and the term $\exp(X\beta + Z_t\gamma + \varepsilon_t)$ allows for both fixed and time-varying covariates. Cox proportional hazard model assumes that covariates can multiply hazard, while the baseline hazard may vary. The hazard rate and coefficients for the covariates is obtained by maximum likelihood from the following equation:

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

For the different coefficients of covariates, I only report hazard ratios which are equal to $\exp(\beta)$ and $\exp(\gamma)$. Hazard ratio of covariates describes a relative risk in how the hazard varies in response to explanatory covariates, meaning that, for example, a hazard ratio for an independent binary covariate can be regarded as a change in the hazard rate when the variable changes from zero to one.

$$hazard\ ratio\ (\gamma) = \frac{h(t,p, X,Z_t = 1)}{h(t,p, X,Z_t = 0)} \quad (2)$$

The used hazard model does not impose any structure on the baseline hazard, and Cox's (1972) partial likelihood approach allows estimating the coefficients for covariates without estimating the baseline hazard. As no structure is imposed to the baseline hazard, no potentially unsure distributional assumptions about the hazard are made. As the data contains partial liquidations and positions that are not closed by the end of the viewed period, the advantage of the method is that it also allows for censored observations necessary for such a setup.

Survival analysis is accompanied with *PGR-PLR* ratio analysis that counts the number of realised gains and losses, as well as unrealised gains and losses on days when a selling transaction takes place for the portfolio. The counts are used to calculate the proportion of gains realised, labelled as *PGR*, and the proportion of losses realised, labelled as *PLR*. The *PGR* and *PLR* for the sample or an investor group are defined as:

$$PGR_i = \frac{RG_i}{RG_i + PG_i} \quad (3)$$

$$PLR_i = \frac{RL_i}{RL_i + PL_i} \quad (4)$$

where *RG* is the number of realised gains; *PG* is the number of paper gains; *RL* is the number of realised losses; *PL* is the number of paper losses. A positive difference between *PGR - PLR* indicates the disposition effect.

A t-test is used for testing the statistical significance of the differences in the proportions of *PGR* and *PLR*. The standard error for the difference in the proportions of *PGR* and *PLR* is given by:

$$\sqrt{\frac{PGR_i(1- PGR_i)}{RG_i + PG_i} + \frac{PLR_i(1- PLR_i)}{RL_i + PL_i}} \quad (5)$$

The data setup for survival analysis and *PGR - PLR* ratio analysis follows the procedures that accord to the methodology of Shapira and Venezia (2001), Feng and Seasholes (2005). I compile stock portfolios for each account according to all purchases and sales made after 1 January 2004. As accounts include stocks before January 1st, which enables them to seemingly sell more stock than my definition of the position, such transactions are discarded. A weighted average price is regarded as the reference price. Using a weighted average purchasing price for the reference price is similar to Feng and Seasholes (2005), who report that different approaches (highest, average, first, latest purchasing price) do not produce any differences in results.

For every trading day in the sample, for each stock in each investor's portfolio, I make a comparison of the reference price to the current market price of the stock to see whether the investor incurs realised or unrealised loss or profit for the specified stock on every day. When comparing the reference price to the market price, a loss is recorded only when the reference price is higher than the highest price of the day and a gain is recorded when the reference price is lower than the lowest price of the day. If no transactions have occurred, a closing price of the previous day is used for the market price. If a sale occurs, the selling price is used instead of the day's price range. For each position, regardless of whether it is still open or has been liquidated on the given day (a sell has occurred), respectively a paper or realised return is calculated for each day. For calculating the returns, the reference price and the closing price (or selling price) of the day is used.

Based on whether a loss or gain is recorded for a given position, I use two variables: the Trading gain indicator (TGI) and the Trading loss indicator (TLI), to capture the event for each position for every trading day. The TGI takes a value of 1 when a position is realised or trading at a gain on a given day or 0 otherwise. The TLI takes a value of 1 when a position is realised or trading at a loss on a given day or 0 otherwise.

Survival analysis is based on over 9 million observations, as observations are recorded for each position of each account (a total of about 21 thousand) and for every trading day (over 1000 days). As PGR-PLR analysis records observations only on days when a sale takes place, a total of about 800 thousand observations are employed under that methodology.

Portfolio return is measured as an aggregate of different investor groups by an annual money weighted return (IRR). Such an approach allows to weight periods of more invested funds more heavily and is justified over time-weighted average return, as most participants in the market can diversify the portfolio with foreign assets and, based on their market expectations, can control the amount of invested funds.

4. Individual Investor Account Data and Trading

I use a dataset provided by Nasdaq OMX Baltic. The data includes all transactions on Nasdaq OMX Tallinn (OMXT) for all domestic and foreign individual investors from 1 January 2004 till 30 June 2008. The data consists of 242 thousand transactions for 20,758 different accounts. The provided data is anonymous and includes the account ID-s, the transaction date, the price, the security and the type of investor. Individual investors can be classified by gender, age and nationality (classified as domestic and foreign).

4.1. Investor Age and Gender

The breakdown of the number of investors is presented in Table 1, by gender and age, which shows that 67.9% of investors are male and 32.1% female. Such a difference can be quite expected as the Barber and Odean (2001) sample of US investors consists of 78.7% of male investors, although Feng and Seasholes (2008) report that approximately only half of the Chinese investors are male.

Table 1. Trading and Account Statistics of the Estonian Market

	Number of accounts		Average portfolio size (EUR)		Average portfolio beta		Average annual return	
	Female	Male	Female	Male	Female	Male	Female	Male
Total	6,673	14,085	5,573	7,278	1.027	1.019	23.0%	15.0%
Age under 21	377	714	4,469	2,637	1.178	1.134	19.8%	6.0%
Age 21-30	931	3,657	2,890	2,115	1.063	1.063	3.6%	-0.1%
Age 31-40	1,482	4,195	4,060	4,518	1.105	1.037	13.3%	7.4%
Age 41-50	1,063	2,163	7,200	11,762	0.988	0.992	22.4%	16.3%
Age 51-60	1,015	1,367	5,795	11,932	1.056	1.000	19.8%	17.7%
Age 61-70	1,028	1,076	4,728	13,083	0.945	0.916	31.2%	16.3%
Age over 70	771	909	4,052	10,226	1.084	0.988	35.9%	22.7%
	Average amount of a purchase (EUR)		Average amount of a sale (EUR)		Average num. of puchases per account		Average num. of sales per account	
	Female	Male	Female	Male	Female	Male	Female	Male
Total	1,985	2,017	2,292	2,284	3.3	7.0	3.7	6.7
Age under 21	1,340	900	1,684	1,127	2.7	2.8	2.5	2.5
Age 21-30	1,136	1,377	1,439	1,483	3.0	6.9	3.0	6.7
Age 31-40	1,681	1,823	2,042	2,013	3.0	7.5	3.4	7.3
Age 41-50	2,537	2,565	2,720	2,697	4.6	8.4	5.0	7.9
Age 51-60	2,122	2,802	2,652	3,576	3.8	7.3	3.9	6.8
Age 61-70	2,073	2,644	2,271	3,181	3.0	6.3	3.5	6.3
Age over 70	2,301	2,626	2,447	3,365	2.7	4.6	3.9	5.0
	Average holding period		Average stock days per account		Stock days/avg holding period			
	Female	Male	Female	Male	Female	Male		
Total	91.0	61.7	384.1	468.0	4.2	7.6		
Age under 21	90.2	73.6	370.6	368.2	4.1	5.0		
Age 21-30	75.5	46.2	299.8	342.6	4.0	7.4		
Age 31-40	99.9	56.8	378.5	457.1	3.8	8.1		
Age 41-50	68.4	70.5	385.8	579.3	5.6	8.2		
Age 51-60	104.6	78.9	483.5	565.8	4.6	7.2		
Age 61-70	108.6	79.1	427.5	559.2	3.9	7.1		
Age over 70	94.7	107.5	307.3	579.3	3.2	5.4		

Source: Author´s calculations

Investor age is measured at the end of the sample time, so that trades of one investor can belong only to one subgroup. The largest subgroup (27.3%) of investors belongs to the age bracket 31-40 years. Very clear differences between the number of male and female investors emerge among younger investors up to 50 years of age, where the number of male investors almost exceeds female investors up to three times, depending on the age bracket. The general tendency is that the younger the investors, the greater the proportion of male investors. The only exception is the age bracket below 21, which mainly includes accounts that have been opened by parents for their under 18 year old children (current age grouping dictates that during most of the time of the sample, this age group has not been able to make their own trades, which by law is allowed after turning 18).

4.2. Investor Portfolios and Performance

The provided data includes starting portfolios for all accounts with the date of 1 January 2004, as well as portfolios with monthly intervals. This enables the calculating of the monthly average market value of all portfolios grouped by investor gender and age (see Table 1). Although the average portfolio size for men somewhat exceeds female portfolios (7,278 EUR vs. 5,573 EUR), interesting patterns can be observed among different age groups. For the investors at the age of 21-40 years, the portfolio size for male and female investors is quite similar. For male investors the portfolio size seems to increase with the increase of age, which can be logically affected by the fact that before retirement individual investor wealth should generally be growing. Female investors, on the other hand, do not exhibit such a pattern and their portfolio size starts to decrease after the age of 50, which can be affected by women being less overconfident (see Barber and Odean, 2001), which makes them more conservative towards approaching retirement time and decreases their exposure to the stock market.

Another interesting pattern can be seen in the youngest age group; where the female investor portfolio size is almost double the male portfolio size. Although it can be affected by a much bigger number of young men turning 18 and opening trading accounts with their allowances, but can also imply that when parents open accounts for their children, they tend to fund their daughters' accounts more generously than their sons' accounts.

Although it could be expected that male investors would generally hold portfolios with higher beta due to being more overconfident and risk seeking, this seems not to be the case for Estonian investors.[1] Mostly all betas for male and female investors are in a similar range and there does not seem to be a clear pattern regarding the risk level depending on the investor age. Only the youngest investors have clearly above average portfolio betas.

A higher average beta of female investors can slightly explain better performance of female investors, but not to the extent that can be seen from average money-weighted returns for each investor group in Table 1. Female investors realised an average 23% annual return over the observed 4.5 year period, compared to the average 15% return of male investors (the market index grew at an average annual rate of 17.6% during that time). Female investors are shown to realise better returns (Barber and Odean, 2001) of US investors, although there does not seem to be any significant differences for Chinese investors (see Feng and Seasholes, 2008). There is not a single age group where men perform better than women. The worst performance can be seen among the age group that can be considered the youngest investors making independent trading decisions, which is the age group of 21-30. As for investors below 21, women show a much closer average return than very young men; this can also be affected by a larger number of just turned 18 young men who make similar not very profitable trading decisions as their slightly older counterparts. On the other hand, the youngest female investors do not enter the marketplace themselves and their return is more affected by decisions made by their parents (which should be mostly buy and hold strategies).

[1] It should be noted that beta calculations for the Estonian stock market can be problematic, as market index returns can be too greatly affected by a few larger capitalisation stocks and trading activity for some stocks is very low.

Older investors seem to show superior results for both female and male investors. This cannot be explained by more trading experience; as the Estonian stock market was opened in the second half of 1990's and before 1990's Estonian investors didn't even have a theoretical possibility of investing in foreign markets, nor the experience of a market economy. So there cannot be any differences in trading experiences among older than 40 year old investors. The main differences in performance can be affected by differences in trading intensity and holding period lengths as discussed in the next subsection.

4.3. Transaction and Trading Characteristics

There is detailed transaction data available for all accounts and trades during the observed 4.5 year period. Table 1 shows that the average size of purchases, as well as selling transactions, for male and female investors is very similar. As reported by Shapira and Venzia (2001), Barber and Odean (2000) and Feng and Seasholes (2008), selling transactions are generally larger than purchases. An average transaction size for the Estonian market is clearly less than reported for Israeli (about 3 times), the USA (about 4 times) and China (about 1.6 times). The difference is affected by clearly less liquidity and size of the Estonian market compared to the named countries and by Estonia's smaller GDP/capita compared to Israeli and the USA. Concerning the differences of the age groups, the average transaction size is in a clear positive correlation with the average portfolio size.

The clearest differences between genders emerge in trading intensity measured by the average number of trades made per account. Even when controlling for the portfolio size, men still trade almost twice as much as women (7.0 vs. 3.3 purchases and 6.7 vs. 3.7 sales per account). Higher trading intensity also affects holding periods for male investors, which is over 30% shorter than for females (61.7 days vs. 91 days). Women hold stocks clearly longer, which can be one of the factors that positively affect their trading performance, especially during periods when stocks, on average, increase in value.

Stock days per account and stock days divided by the average holding period show that men clearly hold more stocks in their portfolio, which more than compensates the shorter holding period and results in the higher number of stock days despite a shorter holding period (ceteris paribus, a longer average holding period should result in a greater number of stock days per account).

To further test the trading intensity of men and women, I use Cox proportional hazard model to statistically model the differences in trading intensity. The methodology is described in Section 3 and is also used to measure the disposition effect with results presented in the next section. The hazard model will provide the conditional probability of selling stock versus holding stock that will answer the question whether men or women are more likely to sell the same stock they hold. Including both fixed and time-varying covariates (gender, age, portfolio size, trading experience) I can test the cross sectional differences of gender and age groups, at the same time controlling for time series effects. The results of the trading intensity hazard model are presented in Table 2. The model (Equation 1) uses a dependent indicator variable that equals one for every day for each investor and the stock position that is sold on that day and zero if there is no sale of the stock, as a dependent variable.

Table 2. Hazard Model for Trading Intensity

	Individual investors		
Variable	Haz. Ratio	Z-stat	
Portf. size	1.094	31.06	***
No. of Stock	0.784	-91.65	***
Male	1.736	11.29	***
Age 21-30* male	1.135	2.21	**
Age 31-40* male	1.014	0.25	
Age 41-50* male	0.645	-7.97	***
Age 51-60* male	0.760	-4.80	***
Age 61-70* male	0.715	-5.64	***
Age over 70* male	0.451	-12.26	***
Age 21-30	1.773	12.32	***
Age 31-40	1.240	4.98	***
Age 41-50	1.444	8.52	***
Age 51-60	1.075	1.62	
Age 61-70	0.987	-0.28	
Age over 70	1.103	1.95	*
Exper. 6-10 trades	1.471	29.00	***
Exper. 11-20 trades	2.996	62.27	***
Exper. 21-30 trades	4.419	67.23	***
Exper. 31-40 trades	5.211	85.31	***
Exper. 41-50 trades	7.249	87.71	***
Exper. over 50 trades	15.911	214.54	***

***significant at 1% level; **significant at 5% level; *significant at 10% level

Note: The model presents hazard ratios associated with different variables that can affect selling decisions.
Source: Author´s calculations

It can be seen that the hazard ratio for male investors is clearly (1.736) greater than the baseline value (which is always 1), which shows that men trade clearly more than women. The difference is still present when controlling for portfolio size (which increases trading intensity - hazard ratio of 1.094) and age. We can also see a decreasing trading intensity for older investors. As the male dummy variable is also interacted with age dummies, we can make a better distinction between male and female age groups. From the interaction terms of males over 40 years of age, we can see a reduced propensity to trade, which is almost reduced to the level of women (e.g. the difference of the total hazard ratio for a 41 year old male and female investor is 1.736*0.645=1.120, which is clearly smaller than for younger men and women). As can be expected, experience (measure in the number of trades made) increases the probability of trading further. Surprisingly a larger number of stocks in the portfolio seem to decrease the baseline trading intensity. Conclusions drawn from survival analysis support the conclusions made based on trading statistics presented in Table 1.

5. Disposition Effect Results

I use the same dependent variable (an indicator variable) to ascertain whether a sale has taken place, as for trading intensity calculations. The most important independent variables to capture the disposition effect is the Trading loss indicator (TLI) and the Trading gain indicator (TGI), which show whether the investment position is in loss or has gained in value. Altogether over 20 different demographic, market or stock specific, mostly indicator variables, are used as fixed and time-varying covariates of the hazard model. Most of the variables are market return specific to see how and which intervals of previous returns affect trading decisions. The choice of variables is based on previous studies and different variables that have been reported to either affect the disposition effect bias or the trading decision are included in the current study. Similarly to Feng and Seasholes (2005), I interact demographic variables with the TLI (TGI) and include the interaction terms in the regressions as independent variables that increase the total number of used variables under different setups to over 30. The interaction terms help to identify whether changes in demographic variables are correlated with changes in an investor's reluctance to realise losses and the propensity to realise gains early. I still include demographic variables by themselves to act as controls, as different demographic groups may have different holding times, on average, as shown by the trading intensity analysis.

Different variables for the regressions include the TLI (or the TGI); an indicator for male investors; indicators for the experience of an investor measured by the trades made since the beginning of the dataset; indicators for different age brackets; variables for the gain/loss in the stock price for previous intervals; a variable for the portfolio size of an investor; a variable for the number of stocks in the portfolio; a variable for the current return on the position or indicators for different return intervals; and indicators for different stock. For survival analysis, I pool all investors together and estimate hazard ratios of different variables to capture the average effect across investors. The hazard ratio below zero for the Trading loss indicator (TLI), along with the hazard ratio of above zero for the Trading gain indicator (TGI), indicate the presence of the disposition effect (i.e. decreased probability to sell a losing stock and an increased probability to sell a winning stock). Hazard ratios for other variables show an increased or decreased probability of selling the position resulting from that variable. The probabilities are measured against the baseline hazard rate of a sale.

For the disposition effect calculations, I construct portfolios with purchasing prices for all accounts, discarding the existing positions before 1 January 2004, where the purchasing price is not known. Such an approach still enables to calculate the reference price needed for testing for the disposition effect and is consistent with the methodology used e.g. in Odean (1998), Grinblatt and Keloharju (2001a). The average purchasing price of the position is used as the reference price and it is compared to the closing market price of each security in the portfolio for each trading day for each account. All prices are adjusted for stock splits and dividends.

5.1. The Disposition Effect Bias

To study the effect of different variables on the selling decision, I use a model with both fixed and time-varying covariates. To compare survival analysis and PGR-PLR results that are later correlated with performance measures, I use sub-sampling of the data and only one covariate (either the TLI or the TGI) to test whether investors in the sample exhibit the disposition effect on average. All PGR-PLR results are obtained by sub-sampling the dataset filtered by investor age and gender. Comparison between survival analysis and PGR-PLR ratio analysis is shown in Table 3. There is a discrepancy between survival and PGR-PLR analysis results for all gender groups (survival analysis shows that women are slightly more affected by the disposition effect and PGR-PLR ratio analysis proves the opposite). When controlling for different other trading related variables and market related variables (as presented in Table 4), also survival analysis yields that men are more affected by the disposition effect (the interaction term for the male indicator variable with the TLI is below one (0.947) and the interaction term with the TGI is above one (1.052).

Table 3. Comparison of Survival Analysis and PGR-PLR Analysis

	Survival analysis				PGR-PLR ratio analysis			
Investor type	TLI		TGI		PGR	PLR	PGR-PLR	
Female total	0.774	***	1.274	***	0.407	0.379	0.028	***
Male total	0.799	***	1.226	***	0.421	0.371	0.051	***
Female age under 21	0.595	***	1.680	***	0.538	0.465	0.073	*
Female age 21-30	0.613	***	1.583	***	0.485	0.411	0.074	***
Female age 31-40	0.734	***	1.341	***	0.428	0.389	0.039	***
Female age 41-50	0.768	***	1.279	***	0.429	0.383	0.046	***
Female age 51-60	0.824	***	1.204	***	0.330	0.330	0.000	
Female age 61-70	0.990		0.997		0.451	0.427	0.024	
Female age over 70	0.673	***	1.488	***	0.335	0.300	0.036	*
Male age under 21	0.688	***	1.427	***	0.550	0.501	0.049	**
Male age 21-30	0.678	***	1.432	***	0.507	0.473	0.034	***
Male age 31-40	0.695	***	1.409	***	0.446	0.360	0.085	***
Male age 41-50	0.961	*	1.025		0.369	0.328	0.040	***
Male age 51-60	0.808	***	1.217	***	0.364	0.328	0.036	***
Male age 61-70	0.786	***	1.268	***	0.311	0.269	0.042	***
Male age over 70	1.005		0.981		0.363	0.307	0.056	***

***significant at 1% level; **significant at 5% level; *significant at 10% level

Note: Survival analysis presents hazard ratios for the Trading loss indicator (TLI) and the Trading gain indicator (TGI) used as the only covariate in filtered subsample regressions. PGR-PLR analysis presents the Proportion of gains realised (PGR) minus the Proportion of losses realised (PLR) for filtered subsamples.
Source: Author´s calculations

Table 4. Hazard Model for Selling the Stock for Individual Investors

	REG 1 Individual investors			REG 2 Local individual investors			REG 3 Individual investors			REG 4 Local individual investors		
Variable	Haz. Ratio	Z-stat		Haz. Ratio	Z-stat		Haz. Ratio	Z-stat		Haz. Ratio	Z-stat	
TLI	0.387	-14.30	***	0.340	-14.66	***						
TGI							2.468	13.65	***	2.823	14.15	***
Return of the position	1.000	-1.16		1.000	-1.15		1.000	-1.16		1.000	-1.16	
Portf. size*TLI (TGI)	1.123	18.76	***	1.114	16.67	***	0.894	-18.20	***	0.902	-16.08	***
Portf. size	1.037	10.37	***	1.024	6.53	***	1.162	29.85	***	1.138	24.49	***
No. of stock*TLI (TGI)	0.927	-13.20	***	0.929	-12.19	***	1.079	13.30	***	1.076	12.21	***
No. of stock	0.801	-70.25	***	0.808	-63.51	***	0.743	-62.58	***	0.751	-57.39	***
Male* TLI (TGI)	0.947	-2.26	**	0.960	-1.65	*	1.052	2.09	**	1.037	1.46	
Male	1.464	26.21	***	1.432	24.07	***	1.390	17.14	***	1.378	16.07	***
Age 21-30* TLI (TGI)	0.883	-2.32	**	1.031	0.48		1.120	2.12	**	0.955	-0.75	
Age 31-40* TLI (TGI)	0.840	-3.27	***	0.984	-0.26		1.186	3.20	***	1.007	0.11	
Age 41-50* TLI (TGI)	1.122	2.08	**	1.317	4.30	***	0.890	-2.11	**	0.753	-4.44	***
Age 51-60* TLI (TGI)	0.994	-0.11		1.160	2.22	**	1.005	0.09		0.856	-2.33	**
Age 61-70* TLI (TGI)	0.899	-1.77	*	1.079	1.11		1.121	1.90	*	0.927	-1.10	
Age over 70* TLI (TGI)	0.960	-0.60		1.142	1.78	*	1.046	0.67		0.873	-1.82	*
Age 21-30	2.238	24.31	***	1.969	17.73	***	1.989	16.41	***	2.049	14.69	***
Age 31-40	1.433	11.01	***	1.286	6.62	***	1.208	4.51	***	1.273	4.94	***
Age 41-50	1.018	0.52		0.925	-1.97	**	1.143	3.09	***	1.224	4.03	***
Age 51-60	0.912	-2.62		0.846	-4.10	***	0.907	-2.14	**	0.985	-0.28	
Age 61-70	0.841	-4.73	***	0.780	-5.95	***	0.753	-5.97	***	0.841	-3.20	***
Age over 70	0.644	-11.15	***	0.602	-11.49	***	0.617	-8.92	***	0.689	-6.23	***
6-10 trades* TLI (TGI)	1.051	1.80	*	1.067	2.26	**	0.953	-1.74	*	0.938	-2.23	**
11-20 trades* TLI (TGI)	0.945	-1.56		0.943	-1.56		1.071	1.89	*	1.074	1.90	*
21-30 trades* TLI (TGI)	0.842	-3.78	***	0.829	-3.94	***	1.194	3.91	***	1.211	4.02	***
31-40 trades* TLI (TGI)	0.900	-2.65	***	0.901	-2.50	**	1.110	2.66	***	1.108	2.48	**
41-50 trades* TLI (TGI)	0.768	-5.69	***	0.802	-4.51	***	1.285	5.41	***	1.238	4.37	***
Over 50 trades* TLI (TGI)	0.892	-4.33	***	0.908	-3.50	***	1.114	4.10	***	1.095	3.28	***
Exper. 6-10 trades	1.456	22.47	***	1.468	22.37	***	1.528	19.39	***	1.564	19.80	***
Exper. 11-20 trades	3.133	50.94	***	3.173	49.76	***	2.937	37.93	***	2.966	36.51	***
Exper. 21-30 trades	4.867	56.29	***	4.912	54.59	***	4.080	39.43	***	4.059	37.38	***
Exper. 31-40 trades	5.647	69.35	***	5.620	66.25	***	5.079	53.33	***	5.063	50.51	***
Exper. 41-50 trades	8.447	74.17	***	8.411	70.96	***	6.531	51.83	***	6.768	49.73	***
Exper. over 50 trades	17.489	173.75	***	17.596	167.11	***	15.639	134.13	***	16.013	128.49	***

***significant at 1% level; **significant at 5% level; *significant at 10% level

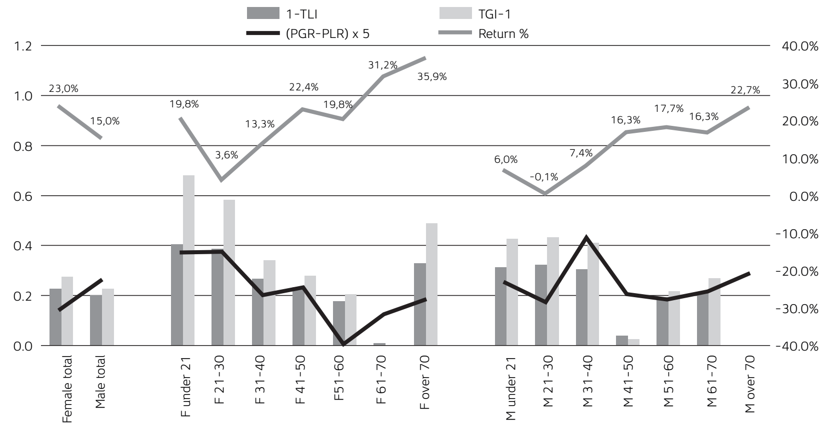
Note: Regressions 1 and 2 present the Trading loss indicator (TLI) as the main driver of the selling decision (all other variables are interacted with the TLI where indicated). Regressions 3 and 4 present the Trading gain indicator (TGI) as the main driver of the selling decision (all other variables are interacted with the TGI where indicated). Regressions 2 and 4 use the subsample of local individual investors and Regressions 1 and 3 use the whole sample of individual investors.

Source: Author´s calculations

My results support the finding of Odean (1998) in the sense that the control indicator for the gender clearly shows that men trade more frequently than women. The difference between men and women in respect to the disposition effect does not completely disappear even when adding different indicators to the regressions, but becomes qualitatively very small. This is quite consistent with the findings of Grinblatt and Keloharju (2001a) and Feng and Seasholes (2005), in which the difference between genders is not evident.

Both Table 3 and Table 4 show that the disposition effect bias tends to slightly decrease with the age, with only the youngest age group being an exception. Visual comparison of the age groups is presented in Figure 1.

Figure 1. Correlation between Portfolio Returns and the Disposition Effect



Source: Author´s illustration

Similarly to Feng and Seasholes (2005), I investigate whether investor sophistication can explain the differences in the level of the disposition effect that most investor classes exhibit. Feng and Seasholes (2005) discuss that the emerging market investor sophistication can be quantified by the number of trades they have made, age, portfolio size and diversification[2]. Results presented in Table 4 show that a larger portfolio size does seem to decrease the disposition effect bias, but holding more stocks in the portfolio tends to increase the bias. This is consistent with the statistics presented in Table 1, which show that investors holding positions for shorter time periods tend to trade more stocks, which can result in poor performance and also in a more noteworthy disposition effect bias. It can be argued that the number of stocks in the portfolio is not the best indicator for diversification (or sophistication); as the number of available investable companies is very small and low liquidity can reduce the investable universe even further for larger and more sophisticated investors.

The disposition effect seems to be smaller for investors with either a small trading experience (6-10 trades made) or starts to slightly decrease for more experienced traders, but still remains below the baseline. Control variables for trading experience show a clearly increased probability of selling the position if the person has already made a lot of trades in the past.

[2] Feng and Seasholes (2005) also included the number or trading rights that cannot be applied for current data.

Feng and Seasholes (2005) discuss that emerging market investors' sophistication can be affected by their age; where, investors in their mid twenties to mid thirties tend to be clearly less biased than older investors, as they have been more exposed to financial markets with improved education and training. Current results show that the less biased age group is 41-50 year olds. It cannot be said that this is somehow a differently educated subgroup, but those are the people who were in their prime age during the shift to a market economy in Estonia. The bias starts to increase with both decreasing and increasing age, but generally older people seem to be less affected by the disposition effect than the younger.

I control for feedback trading to see whether investors are contrarians and sell winning and buy losing stock that might have nothing to do with the disposition effect. I include the past returns for up to 60 trading days (about 3 months) before the transaction takes place. Although the hazard ratios indicate that investor selling decisions are affected by the past returns of the securities; whereas, most recent periods influence the selling decision the most; this does not eliminate the disposition effect. To further test whether investors are more momentum driven or contrarian, I used also positive and negative returns separately in the regressions for all investor types.[3]

Results of previous studies show that the disposition effect tends to decrease in December due to tax selling motivations. As usually the tax year ends with the calendar year and only realised profits are taxed (as it is in Estonia), it could be beneficial for investors to realise losses that could offset tax obligations from realised gains. Such an activity could be conducted throughout the year, but as Odean (1998) shows, for US investors it will increase in December.

In the Estonian sample, we can see reduced trading activity in December (which contradicts to the expectancy of seeing increased tax selling activities) and increased selling and buying activity in January. Under normal circumstances realising gains in January would be beneficial when rebalancing portfolios to take into account economic forecasts for the new year that tend to get more media coverage in January. Also a steadily decreasing income tax in Estonia during the past years can have its effect, as changes in tax laws get enforced in January and selling gains under lower taxes clearly affect performance results. Selling gains in January would also postpone the due date of the tax obligation by almost a year, compared to selling in December, but would not explain postponing the sale of losing positions. So there does not seem to be any clear logical explanation of selling more losing positions in January instead of December, except for market conditions.

5.2. The Disposition Effect and Performance

I use different measures of the disposition effect to control for the link between the disposition effect and investor performance. I calculate age group relevant disposition effect measures (the TLI and the TGI) using baseline and group specific interaction terms in Table 4. I also use sub-sampled results of both survival and PGR-PLR analysis, shown in Table 3. To normalise survival analysis hazard ratios, I subtract the TLI hazard ratios from 1 and subtract 1 from the TGI hazard ratios. A correlation matrix with the performance results is shown in Table 5.

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[3] Results for feedback trading are available upon request. The current paper investigates only sell decisions, and buy decisions are neglected.

Table 5. Correlation between Portfolio Returns and the Disposition Effect

	Return %	1-TLI*	TGI-1*	1-TLI	TGI-1
1-TLI*	-0.42				
TGI-1*	-0.40	0.99			
1-TLI	-0.43	0.18	0.16		
TGI-1	-0.37	0.15	0.13	0.98	
PGR-PLR	-0.37	0.24	0.26	0.43	0.49

Note: The TLI* and the TGI* is calculated based on baseline the TLI and the TGI values and corresponding interaction terms with age group dummies and the TLI and the TGI from Table 4.The TLI, the TGI and PGR-PLR is calculated from age group subsamples.
Source: Author´s calculations

There is a negative correlation between average returns over the period and the level of the disposition effect. Higher returns are shown by investor groups who exhibit less disposition effect. However, as can be seen visually in Figure 1, the correlation is not perfect and the age group performance can be influenced by other factors, as there are exceptions even in such a small sample. An alternative explanation for such a correlation is the differences in trading strategies that can also affect the disposition effect.

5. Conclusions

The current paper shows clear differences in investor group performance grouped by gender and age. The main findings include:

- The portfolios of female investors perform clearly better than the portfolios of male investors, even when adjusted for risk.
- Older investors clearly outperform younger investors in both female and male groups.
- A longer holding period, less trading intensity and fewer stocks in the portfolio is associated with female investors.
- The disposition effect bias is very similar for female and male investors when controlling for a different market, trading, performance and investor sophistication related variables.
- There is a negative correlation between the disposition effect and the portfolio performance, as less biased investors generally show better results.

The differences in trading and performance results of age groups can be explained by investor sophistication and experience, which was used in the disposition effect part of the paper. Poor performance is clearly associated with the higher trading intensity for younger age groups, as well as men in general. As men and younger investor groups tend to trade more, they harm their returns, which would explain the better performance of female or older investors. As Barber and Odean (2001) point out, the main cause of overtrading is overconfidence, but in the current case there is also the lack of experience of younger age groups. The negative effect of disposition effect bias to the returns that fades away with investor experience and sophistication reveals the problems of novice investors who could potentially improve their performance even simply by acknowledging the possibility of the bias. The differences in trading strategies and motivation can also yield different results, but this is not measurable or evident in a pure transaction data environment.

Further work in the area of studying investor attributes would include compiling and complementing trading data with survey data of investor attitudes towards risk-taking. Such data could shed more light into trading motivation and strategy setups. Additionally, the study could be extended to take into account attributes of the investments, such as news and financial data.

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