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THE INFLUENCE OF EDUCATION AND OTHER SOCIOECONOMIC AND TRADING RELATED FACTORS ON THE DISPOSITION EFFECT ON THE TALLINN STOCK EXCHANGE

Master's Thesis

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I declare I have written the master's thesis independently.

All works and major viewpoints of the other authors, data from other sources of literature and elsewhere used for writing this paper have been referenced.

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ABSTRACT

This master's thesis studies the influence of education and other investor characteristics on the disposition effect. The disposition effect is investor's tendency to sell winning stocks too soon and hold on to losing stocks too long. The aim of this thesis is to study how education and other socioeconomic characteristics affect the disposition effect. The data used includes trades made by individual investors on the Tallinn Stock Exchange in the period from 2004 to 2010 and it is unique in the context of behavioural finance because it is the first data about one economic cycle to be linked with explanatory characteristics about the investor's education and experience. Logit method was used in order to measure the disposition effect and the influence of different characteristics. The studied characteristics were: investor gender, age, educational degree and high school final state organized exam results, number of trades and number of stocks in the portfolio. The influence of education was smaller than expected; educational degree and most of the specialities do not influence the disposition effect. High school final state organized exam results as a measure of intelligence did not show consistent results and therefore adequate conclusions about educational influence to the disposition effect could not be made. On the other hand gender, age and the number of trades showed reliable results. Men perform better in terms of the disposition effect, older investors experience the disposition effect less than younger investors and the number of trades made as a measure of experience helps to decrease the influence of the disposition effect.

Keywords: behavioural finance, disposition effect, individual investor, investor behaviour, education, the Tallinn Stock Exchange.

INTRODUCTION

Investors are constantly faced with the decision to buy or sell stocks in order to maximize their wealth. They are faced with risk and sometimes make mistakes and act irrationally. This means that they do not always act as expected utility maximizers. The disposition effect is one of the examples. It is described as a tendency to sell winners too soon and hold losers too long. It cannot be explained by traditional finance theories and is therefore the most unexplained phenomenon in the behaviour of investors.

The reason why the disposition effect exists is not completely clear. It is questionable how much it is caused by preferences, beliefs and psychological bias and therefore it is important to study different factors that can be associated with this behavioural bias. Education, knowledge and also different socioeconomic factors influence the investors' behaviour and therefore these factors can limit the disposition effect on stock markets.

The aim of this thesis is to study how education and other socioeconomic factors together with trading related factors affect the disposition effect. The main research question is set up as follows: How do education and other socioeconomic factors influence the existence of the disposition effect? The aim is to study how different educational achievements and other factors, as well as trading knowledge influence the disposition effect and whether education plays an important role in eliminating it. An attempt is made to evaluate the importance of education in the context of investing. Education is a new field to be studied in connection with the disposition effect, but the thesis also focuses on other factors.

The data used includes trades of individual investors on the Tallinn Stock Exchange in the period from 2004 to 2010. The sample consists of investors about whom it was possible to collect educational characteristics. The educational indicators were obtained from Estonian Ministry of Education and Research, which has collected data since the 1990-s. Therefore, the sample largely consists of young investors. In total, there is information about 6851 investors. Every day when an investor holds or sells the stock, it is recorded as one observation, resulting in the total number of observations of 5 138 758.

This data set is unique in the context of behavioural finance because it is the first data about one economic cycle to be linked with explanatory characteristics about the investor's education and experience. The method used to study the effect of different educational indicators is logistical regression.

The studied characteristics were: investor gender, age, educational degree, high school exam results, number of trades and number of stocks in the portfolio.

It is expected that investors on the Tallinn Stock Exchange are prone to the disposition effect in general. In connection with socioeconomic factors it is expected that men are less prone to the disposition effect than women and that the disposition effect decreases with age. In connection with educational indicators it is expected that graduates from economics related specialities and from mathematics and statistics are less prone to the disposition effect. Besides, better results in high school final state organized exams are expected to make investors less prone to the disposition effect. In connection with trading related factors it is expected that the more stocks in the portfolio and the more trades an investor makes, the less he or she is prone to the disposition effect.

The paper is organised as follows. The first part of the thesis deals with the theoretical background of the disposition effect and an overview of recent studies and their results on the same topic. The second part concentrates on the methodology and data used. Also the hypotheses are explained in greater detail in the second part of the thesis. The last part of the thesis is about the results of the empirical study, together with discussion, suggestions and conclusion.

I would like to thank my supervisor Tõnn Talpsepp for the patience, support and his valuable advice and comments.

1. THE DISPOSITION EFFECT ON STOCK MARKETS

The first part of this master’s thesis focuses on the theoretical background of the disposition effect and gives an overview of the disposition effect and how it is connected to the prospect theory. It also explains why it is sometimes believed not to have a connection. An overview of previous studies is given, which makes a good starting point for testing the connection between various investor characteristics and their sensitivity towards the disposition effect.

1.1. The Prospect theory as a starting point

The prospect theory of investments is the backbone of the disposition effect and it is a contribution from Kahneman and Tversky (1979). It was developed to criticize the expected utility theory and was presented as an alternative model to account for choices under risk. It is a normative model of rational choice and therefore widely applied as a descriptive model of economic behaviour. The prospect theory on the other hand presents choice problems in which people’s preferences systematically violate the axioms of the expected utility theory that all reasonable people are assumed to follow. The prospect theory value function is depicted in figure 1.

In the figure it is seen that under the prospect theory people behave as if maximising this “S”-shaped value function. The difference compared to the standard utility function is that it is defined rather on gains and losses than on the final value of assets. The function is concave for gains and convex in the domain of losses, and also steeper for losses than for gains, which proves that people are generally risk averse. (Odean 1998, 1776) It shows that people are risk averse in the gains region and risk seeking in the loss region.

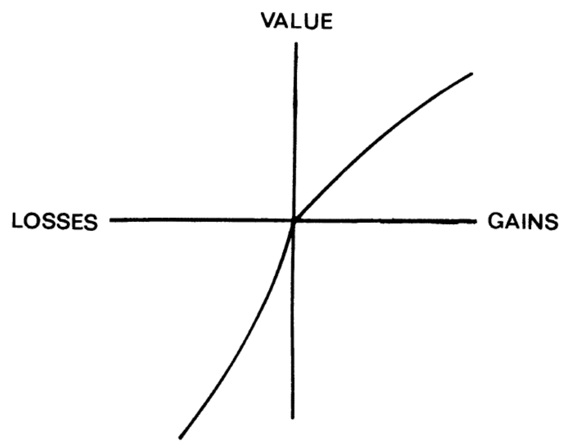

Figure 1. The prospect theory value function.
Source: (Kahneman and Tversky 1979, 279)

Under the prospect theory people normally evaluate outcomes as potential gains and losses, rather than as final states of wealth. These gains and losses are defined on the basis of a specific reference point of the investor, which is usually the initial asset price that the investor paid to buy the asset.

Another key component of the prospect theory is the loss aversion of investors. When there is the same variation of absolute value away from the reference point, there is a bigger impact on losses because the utility function is steeper in the loss region. Therefore investors care more about potential losses than potential gains. It indicates that losses hurt more than gains of the same magnitude increase utility. (Dichtl, Drobetz 2011, 44)

The prospect theory can also be characterized by probability weighting, which means that people tend to overweight events with low probabilities (Ibid.). The basic insight of the prospect theory is the certainty effect, which means that people overweight outcomes that are merely probable in comparison to the outcomes that are obtained with certainty (Kahneman and Tversky 1979, 263).

To sum up, the prospect theory has five important components. Investors are risk averse in the gains region and risk seeking in the loss region, which is presented with concave and convex utility functions respectively. When these two components are taken together a utility function around the reference point is formulated. The reference point shows that differences around it are more relevant than the aggregate levels of profit or loss. The prospect theory also presumes that investors in general are loss averse. This means that losses hurt more than gains of the same magnitude. This is explained by the steeper utility function in the losses region. Finally investors tend to overweight low probabilities. These aspects have an important role in the occurrence of the disposition effect.

1.2. The disposition effect as an implication of the prospect theory

The disposition effect was first labelled by Shefrin and Statman (1985). It is an extended implication of the prospect theory and it is defined as a tendency to sell winners too soon and hold losers too long (Shefrin, Statman 1985, 778). Investors may irrationally or rationally believe that the current losers in their portfolios will outperform their current winners in the future. This is the explanation why they sell winners in order to rebalance their portfolios. (Odean, 1998,1775)

The model used to explain the disposition effect by Shefrin and Statman (1985) consists of four major elements that are: the prospect theory, mental accounting, regret aversion and self-control. Each of these elements contributes something distinctive to the analysis of the disposition effect. (Shefrin, Statman 1985, 778) A rational investor is not affected by these elements in his decisions but an irrationally behaving investor will experience these elements and as a result will be subjected to the disposition effect.

The prospect theory predicts a disposition to sell winners and hold losers. This disposition comes from a combination of several features. Decision makers frame all choices in terms of potential gains and losses relative to a fixed reference point and employ the “S”-shaped valuation function. This reflects risk aversion in the gain region and risk seeking in the loss region. (Ibid., 779)

The reference point is a very important element of the disposition effect and it is certainly a link between the disposition effect and the prospect theory. If many investors buy a stock at a particular price, that price may become their reference point. It can affect supply and thus the disposition effect may contribute to market stability near prices at which substantial trading has previously taken place. (Odean, 1998,1796)

On the other hand, if stock falls below this reference point, these investors will be averse to selling for a loss and thus reducing the supply of potential sellers, which leads to slowing down in price decreases. The opposite effect happens when the investors sell the stock above their reference point. It is critical because, if investors who have negative private information about the stock do not sell at the price below their reference point, this information is not signalled in the market and there will be a delay when this is reflected in prices. (Ibid.) Although the disposition effect affects prices, its influence is the highest for individual investors.

The extent to which the disposition effect affects market prices depends on the trading activities of other market participants such as traders and institutional investors. If the disposition effect holds in aggregate, it may contribute to the positive relationship between the price change and volume. (Ibid.,1795) The main reason why the market does not collapse or become illiquid in the face of the disposition effect is the coexistence of momentum and contrarian traders (Dacey, Zielonka 2008, 49), who balance the market with their different approaches towards making investments, which are more clearly explained later in this work.

Mental accounting is another major element of the disposition effect and clarifies conditions under which the disposition effect holds. The main idea of mental accounting is that decision making investors tend to segregate different types of decisions faced into separate accounts and apply prospect theoretic decision rules to each account by ignoring possible interactions. It explains why an investor is likely to refrain from readjusting his reference point of a stock. A new purchase brings a new mental account in which the reference point stands as the price paid for the asset. (Shefrin, Statman 1985, 780) Investors should learn to unite their losses and gains and look at them together not separately from the point of view of their reference point.

Aversion to regret provides an important framework why investors have difficulties realizing gains as well as losses. Investors do not want to realize losses because it stands as a proof that their first judgement was wrong and it is even harder to admit the mistake to others. Since regret is a negative emotional feeling that the previous knowledge was wrong, the positive side of it is pride. While closing a stock account at loss it induces regret, but closing at gain induces a positive emotion – pride. The quest for pride and the avoidance of regret lead to a disposition to realize gains and defer losses. (Ibid., 782)

Self-control is used to explain the rationale for methods investors use to force them realize their losses. It is an interpersonal conflict between a rational part and the emotional part. Since investors hold losers to postpone regret and sell winners too fast because they want the feeling of pride, it is the emotional part that embodies the reaction associated to regret and pride. To cope with their resistance to realizing losses, investors have developed some techniques in order to control the losses. One of the examples is having stop-loss order at a certain percentage when the downwards movement has occurred. In this case it is easier to find willpower to realize a loss. (Ibid., 783)

Dacey and Zielonka (2008) prove that the disposition effect is an application of the prospect theory. They say that an investor does not always follow the disposition effect by keeping the stock after a downtrend and selling the stock after an uptrend. If after an upward movement the investor expects further growth, then he does not sell the stock. The same goes for the downward movement. It shows that probability weighting is an important aspect of experiencing the disposition effect. (Kubińska et al 2012, 214)

For example, the increased volume of trading in the month of December relative to the volume of trading all year around is part of the disposition effect. It occurs because of tax-motivated transactions. There is a high volume of trading especially in stocks that have declined in price during the year and it reflects the end of the year tax loss selling. (Shefrin, Statman 1985, 783) The same result was found by Odean (1998), who found out that individual investors do exhibit the disposition effect, which means that they realize their profitable stock investments at a much higher rate than their unprofitable ones, except in December because of tax motivated selling (Odean, 1998,1795).

To sum up, there are three rational reasons why investors may hold their losers and sell their winners. First of all, investors may respond to large price increases by selling some of their appreciated stock in order to restore diversification in their stocks. Secondly, when people know some favourable information and when the price goes up, they may sell the stock believing that the price reflects their information. Finally, investors refrain from selling losers in order to avoid higher trading costs that are present for lower priced stocks. (Ibid.,1779)

1.3. The disposition effect not explained by the prospect theory

As seen earlier some theorists say the disposition effect is the implication of the prospect theory, but there is also adverse empirical evidence saying that the disposition effect cannot be explained by the prospect theory.

Barberis and Xiong (2009) have investigated if prospect theory preferences can predict a disposition effect. They consider two implementations. The first one is to apply the prospect theory to annual stock-level trading profits. It means that over the year the investor trades the stock and at the end of the year he receives prospect theory utility based on his trading profit. The second implementation is to apply the prospect theory to realized gains and losses. In this case the investor buys some shares at the beginning of the year and a few months later sells some of them and receives a jolt of prospect theory utility right at the moment of the sale. (Barberis, Xiong 2009, 752)

They also found out that when it comes to annual gains or losses, the opposite of the disposition effect is experienced. It means that an investor has a greater propensity to sell shares after a drop in the stock price rather than after a rise. It shows that investors are more inclined to sell stocks with prior losses than stocks with prior gains. (Ibid., 762) As a result, the annual gain or loss implementation of the prospect theory does not support the disposition effect.

According to the prospect theory, the investor is loss-averse and the stock must have a reasonably high expected return for him to buy it at all in the first place. The investor takes more risk after a gain than after a loss. The propensity is therefore lower after a gain than after a loss, which is contrary to the disposition effect. After a gain the investor gambles to the edge of the concave region, which shows that the expected stock return is high and this shows that if it was not, then the investor would not have bought the stock in the first place (Ibid., 770).

Hens and Vlcek (2011) consider probability weighting and study ex-post and ex-ante disposition effects. They also show that the disposition effect cannot be explained by the prospect theory. The reason for it is that investors who sell winning stocks too early and hold losing stocks too long would not have invested in the stocks in the first place. (Hens, Vlcek 2011, 141) The ex-ante disposition effect is studied by adding the additional condition that an investor does not only have to sell a winning stock and buy a losing stock, but also has to buy the stock in the first place. This addition makes the definition of the disposition effect even more consistent. Their model also predicts that investors who sell winning stocks too early and hold losing stocks too long would not invest in the stock in the first place. Therefore they also find that the prospect theory cannot explain the ex-ante disposition effect. (Ibid., 154)

They find that an investor, who weights outcomes with their objective probabilities and who is quite risk-averse in the domain of gains and risk-seeking in the domain of losses never invests in the risky asset as long as he is loss-averse. This shows that the investor is not prone to the disposition effect. The investor, who is risk neutral in the gain and loss domains and weights outcomes with their objective probabilities, is never prone to the disposition effect because he either does not purchase the stock to begin with or if he does, he never sells it after a gain. (Ibid., 149)

On the other hand, the second implementation of Barberis and Xiong (2009) with realized gains and losses leads to the disposition effect. It assumes that in addition to the prospect theory, also investor preferences distinguish between paper and realized gains (Barberis, Xiong 2009, 753). Besides, the ex-post disposition effect studied by Hens and Vlcek (2011) is studied under the assumption that the investor sells the winning stock and buys the losing stock and already has a risky asset. They find that an investor who weights outcomes with the objective probabilities is quite risk-averse in the domain of gains and quite risk-seeking in the domain of losses, which means that the investor is prone to the ex-post disposition effect whenever the risky asset has a downside risk. (Hens Vlcek, 2011, 147)

An investor who is less loss-averse risks more eagerly in the risky asset. The less the potential loss hurts, the more the investor favours the risky asset. The disposition effect occurs more frequently for low coefficients of loss aversion. If an investor holds a risky asset and has a high downside risk, he is in a loss region after the loss in the first period. It means that he is risk-seeking and proves that he will prefer the risky asset to the risk-free asset and will hold the losing stock. On the other hand, after a gain in the first period, he will be in the gain region. This implies that there can be a possible loss at the end of the following period. Therefore, he prefers the safe investment to the risky stock and sells winners. (Ibid., 151)

Kaustia (2010) also found that the prospect theory does not explain the disposition effect. The prospect theory value function predicts that the propensity to sell winners will decline as the gain increases and propensity to sell in the loss region declines as the loss increases. Kaustia's research showed that propensity to sell increases or remains almost constant as gain increases and the propensity to sell in the domain of losses remains almost constant. (Kaustia 2010, 809)

1.4. Factors influencing the disposition effect

A very important question to be answered is what investor characteristics are correlated with the disposition effect. The importance of it is that it would give clear implications of the dynamics of asset prices in bubbles and crashes. Moreover, when it is known what type of an investor is more susceptible to biases, it will have implications on welfare. A rational investor may profit from a heuristic of irrational investor. (Dhar, Zhu 2006, 726)

The fact that the disposition effect exists on stock markets among individual investors has been studied a lot. The first to study the disposition effect were Shefrin and Statman (1985). Odean (1998) used the ratio method of proportion of realized gains and realized losses to show that individual investors experience the disposition effect on the stock market. Dhar and Zhu (2010) also found a significant disposition effect on average. About 80% of investors exhibit the disposition effect according to their study. Grinblatt and Keloharju (2001) found that large gains are realised and large losses are held onto. The disposition effect is a major determinant of the propensity to sell a stock that an investor holds. Barberis and Xiong (2009) showed that the disposition effect exists on realised gains and losses but not on annual gains and losses. Hens and Vleck (2011) also managed to find that investors are prone to the ex-post disposition effect but not to the ex-ante disposition effect. Shapira and Venezia (2001) showed that individual investors exhibit the disposition effect stronger than professional investors. Talpsepp (2011) showed that an average investor on the Tallinn Stock Exchange is prone to the disposition effect.

Lee et al (2013) studied the disposition effect among mutual fund investors. They found that also fund investors exhibit the disposition effect. They showed that different market states can affect investor psychology differently, since investors have different hopes for the future (Lee et al 2013, 1340). Cici (2012) also found that mutual fund managers still exhibit the disposition effect (Cici 2012, 795). Also Shapira and Venezia (2001) showed that professional investors exhibit the disposition effect, but it is somewhat smaller than the disposition effect of individual investors (Shapira, Venezia 2001, 1573). It shows that even professional traders and fund managers exhibit the disposition effect, although it is found not to have an effect on the fund's performance.

The aim of this thesis is to examine the relationship between investor education, socioeconomic and trading related factors and the disposition effect. There are a numerous previous studies that have proved a significant relationship between investor characteristics and the disposition effect. The following sub-chapter gives an overview of what has been studied and what results have been found.

1.4.1. Age and gender

Age is an indicator of investor experience, which is not a factor a person can affect by himself. Feng and Seasholes (2005) show that age affects individual investment decisions. It is expected that different age groups vary in the disposition effect since sophistication increases with age. Older investors who grew up during times of highly centralized planning are not as sophisticated as those who grew up post 1980 switch to more open economy. They show that investors who are between 25 and 35 years old are less prone to the disposition effect. (Feng, Seasholes 2005, 318) Dhar and Zhu (2010) also showed that older investors have a smaller disposition effect (Dhar and Zhu 2010, 735). It gives an advantage to certain people, but it is also a factor that cannot be changed.

Gender is also shown to be part of the disposition effect. Men trade 45% more than women (Barber, Odean 2001, 261) and their trading costs reduce their returns more than for women. So Feng and Seasholes (2005) say that men are more confident than women and since trading frequency is greater for men they should experience less of the disposition effect. It was also confirmed by Rau (2014), who found that women buy less stock and are therefore more risk averse than men and also show significantly higher disposition effect than men, which is driven by women's reluctance to realize capital gains (Rau 2014, 35). On the other hand Da Costa Jr. et al (2008) find that women do not keep losing stock and sell winners. This shows that the disposition effect vanishes for women but remains for men (Da Costa Jr. et al 2008, 416). The success of men and women differs among geographical areas and also time periods. It could be the result of educational differences in investment activity on certain markets.

Talpsepp (2010) studied age and gender affect to disposition effect on the Tallinn Stock Exchange. His data set is somewhat different of the data set of this current study. His study covers all domestic and foreign investors. He found out that men trade more than women, but in terms of disposition effect, there is no difference between men and women, although women's portfolios perform better. On the other hand the disposition effect bias tends to decrease with age. (Talpsepp 2010, 89)

1.4.2. Education

Education is not much studied in relation to disposition effect. Mainly the reason is the lack of data. Goo et al (2010) show that the level of education is significantly connected to the disposition effect. They used surveys to get information about investor education. Investors with high school education or below experience the disposition effect more than university graduates. Investors holding college degrees or more advanced degrees have a lower disposition effect. This shows that the disposition effect is much stronger among those less educated. (Goo et al 2010, 111)

1.4.3. Trading frequency

Dhar and Zhu (2006) show that difference in investor knowledge of financial markets and trading frequency are partly responsible for the variation in the individual disposition effect.

They find a negative relationship between trading frequency and the magnitude of the disposition effect. Individuals who trade more often are more willing to sell their loser, which implies that trading frequency might help investors to get rid of the disposition effect. Using demographic and socioeconomic variables as proxies for investor literacy they found out that

20% of the investors who do not exhibit the disposition effect have a higher trading frequency, higher income and they work in professional occupations (Dhar, Zhu 2006, 732).

Experience is gained by doing something repeatedly, which also applies in trading and is shown by Seru et al (2010), who found that investor performance improves as investors become more experienced. Therefore, the disposition effect decreases, showing that investors learn by trading. They used cumulative trades rather than the years traded as investor experience. This also shows the importance of trading frequency and amount.

Feng and Seasholes (2005) also studied investing experience in connection to trading frequency, but found out that this alone does not eliminate the disposition effect bias. Trading experience alone reduces about 72% of the disposition effect, but does not eliminate it totally. Since experience changes over time they measured it by the number of positions an investor has taken. They found out that trading experience attenuates, but does not fully eliminate the disposition effect. On the other hand, a combination of investor sophistication and trading experience eliminate the reluctance of investors to realize losses. A sophisticated investor is no longer reluctant to realize losses by the time he initiates his 16^{th} stock position. (Feng, Seasholes 2005, 336) Therefore having gained a lot of experience and knowledge about stock markets by trading a lot, it is possible to get rid of the disposition effect.

Kumar and Lim (2008) also showed that investors who execute more clustered trades and hold better-diversified portfolios exhibit weaker disposition effects (Kumar, Lim 2008, 1052). Boolell-Gunesh et al (2012) showed that investors who trade more frequently are less influenced by the disposition effect (Boolell-Gunesh et al 2012, 35). Talpsepp (2010) showed that disposition effect is smaller for investors with less trading experience, which means 6-10 trades made. The disposition effect starts to decrease with more experienced investors (Talpsepp 2010, 89).

The opposite result was found by Kubińska et al (2012), who showed that investors with smaller average number of stocks in their portfolios and investors with higher number of conducted transactions have a higher propensity towards the disposition effect. This can be explained by the fact that people who make more transactions sell losers but also more winners since they have a smaller amount of stocks in their portfolios at the same time.

On the other hand Da Costa Jr. et al (2013) studied investing experience by using a computer program and two groups of investors and showed that investor experience is also gained with years traded. The two groups of investors are experienced investors and undergraduate students as unexperienced investors. The results show that both groups show the disposition effect but experienced investors are less affected. When investors have more than 5 years of experience on stock markets, the disposition effect is reduced. (Da Costa Jr. et al 2013, 1673) Having more experience makes investors familiar with stock markets and also sources of information. They have an understanding of market movements and they know how to make use of it in their own favour.

Ammann et al (2012) also found strong evidence for the presence of disposition effect among mutual fund managers. Investors who invest in larger equities, trade more, have a higher past performance and lower risk exhibit a lower disposition effect. They also found out that lower disposition effect does not necessarily decrease the fund performance. (Ammann et al 2012, 18)

1.4.4. Portfolio diversification

Feng and Seasholes (2005) also included portfolio diversification in their study as a part of investor sophistication. They found that more sophisticated investors tend to diversify their portfolios right from the start of their trading career and therefore the number of stocks in an investor's portfolio is looked at on the first day the investor trades. If at the beginning the investor has two or more stocks in his portfolio, his portfolio is diversified. (Feng, Seasholes 2005, 318) This finding is consistent with the results of Kubinska et al (2012) and Kumar and Lim (2008). Cici (2012) also found that holding a smaller number of stocks or highly concentrated portfolios makes investors more likely to sell gains than losses (Cici 2012, 815). Therefore portfolio diversification lowers the existence of disposition effect.

Feng and Seasholes (2005) also add the number of trading rights used to investment sophistication. They find out that sophisticated investors are generally more inclined to use more methods of investing and therefore have a reduced sensitivity to losses by at least 67%. They show an asymmetric relationship between sophistication and the disposition effect, which can be explained by mental accounting. Both mental accounting and the prospect theory suggest that losses should be combined and gains should be divided. Rather than focusing on whether or not to realize a loss of an individual stock, investors should be focusing on a bigger question as to whether or not to realize a loss at all. (Feng, Seasholes 2005, 322)

Boolell-Gunesh et al (2012) measured investor sophistication with trading with foreign assets, derivative assets, bonds and holding multiple accounts. They showed that financially sophisticated investors are less prone to the disposition effect (Boolell-Gunesh et al 2012, 35). More sophisticated investors are more willing to focus on the big picture of their portfolios and therefore they can move away from loss aversion.

1.4.5. Income and self-regard

Dhar and Zhu (2006) show that individual characteristics, such as income and occupational status, reduce the magnitude of the disposition effect. Individuals who are wealthier and work in more professional occupations show a significantly smaller disposition effect, amounting up to 20%. This is consistent with the notion that high-income individuals might get advice from financial planners and this tempers the bias regardless of their educational and investment knowledge. (Dhar, Zhu 2006, 733) Kubińska et al (2012) also showed that non-professionals revealed a higher propensity towards the disposition effect (Kubińska et al 2012, 221).

On the other hand Kadous et al (2014) associate investor sophistication with self-regard. They say that lower income individuals are treated as individuals with lower sophistication because they have a lower self-regard. These individuals make bad investment decisions because their self-regard is damaged by their low status. Investors with lower self-regard hold losing investments longer than investors with high self-regard. (Kadous et al 2014, 247) This shows that less sophisticated investors are more prone to the disposition effect than investors with higher self-regard. Kadous et al (2014) explained it by the fact that gain and loss sides of the disposition effect are driven by different biases.

They show that a belief in mean reversion does not drive the disposition effect. Since investors want to have a positive image of them, they do not want to recognize losses because it threatens their self-image. On the other hand, they trade off the financial gain for self-regard.

Investors with higher confidence have higher expectations regarding success and therefore they are more averse to threats to their self-image. Investors with higher investing confidence hold losing stocks longer than those with lower confidence. (Ibid., 236) In addition, Goo et al (2010) found that avoiding regret, maximising profits and seeking pride are highly correlated to each other. This reveals investor psychology, and it is important to know these connections in order to make rational investment decisions.

1.4.6. Investment strategies

Investment strategies also influence investors regarding the disposition effect. Kubińska et al (2012) ask whether investors' vulnerability to the disposition effect is related to their forecasting strategy. In particular they examine the contrarian strategy and the momentum strategy. The contrarian strategy is a tendency to take the opposite perspective and invest against market trends. The momentum strategy is a tendency of purchasing stocks recently rising in price and of selling stocks recently falling in price.

These two strategies should differ concerning assessments of the probability of the stock price changes. Momentum traders expect the stock to continue rising if the price has been growing previously and contrarian traders on the other hand expect a trend reversal. Contrarian investors are more prone to the disposition effect than momentum investors. Their primary explanation of the relationship between the disposition effect and the contrarian forecasting strategy is based on the assumption that the two components, the value and the probability of the prospect, determine investors' decisions. (Kubińska et al 2012, 222)

2. DATA, METHODOLOGY AND HYPOTHESES

The second part of the thesis gives an overview of the data and test method used in order to test how various characteristics influence the disposition effect. Also the hypotheses are formulated.

2.1. Data

The data used includes individual investor transactions on the Tallinn Stock Exchange during 2004 and 2010. Transactions cover all 22 companies that have been listed on the Tallinn Stock Exchange during that period. Also investors' educational and characteristic indicators are linked to the transactions. Information about transactions has been gathered from the Tallinn Stock Exchange and information about investors' educational indicators from the Ministry of Education and Research. This data set is unique in the context of behavioural finance because it is the first data about one economic cycle to be linked with explanatory characteristics about investors, such as education, experience, gender, age and portfolio volume.

Initially there was transactional information about 33 843 investors, but only data about individual investors who had educational indicators was used. The sample was narrowed because a lot of investors had completed their studies before the Ministry of Education and Research started to gather their data at the end of 1990s. The final sample is formed of individual investors who have at least one state examination result. This makes the final sample of 6851 individual investors. Every day when an investor holds or sells the stock, it is recorded as one observation, resulting in the total number of 5 138 758 observations.

2.1.1. Data description

First of all it is important to describe the data used. The factors that are studied in relation to the disposition effect are described and presented graphically in order to get better overview of the data.

The age distribution among investors is depicted in figure 2. The youngest investor in the data is 17 years old and the oldest is 53 years old. The most common age group on the Tallinn Stock Exchange is between 26 and 30, which is characteristic of 40% of investors. 32% of them are men and 8% are women. 37% of the investors are between 31 and 35, 29% of them men and 8% women. Only 5% of the investors are older than 36. This is because the sample includes investors who have educational data linked. Since the Ministry of Education and Research started gathering data at the end of the 1990-s, then it is logical that the majority of the sample consists of young investors. There are 16% of investors who are between 21 and 25 and only 2% of the investors are younger than 20.

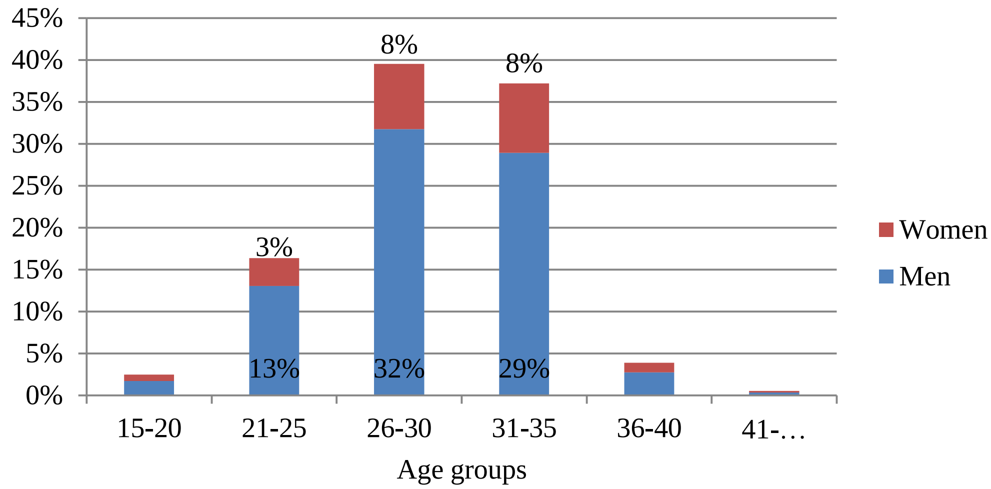

Figure 2. Age distribution between age groups by men and women

Source: Compiled by the author

Higher education has been acquired by 54.2% of investors. Thus, 3699 investors, which accounts for the 54%, have a bachelor`s or equivalent degree and only 16 investors that make up 0.2% have a master’s degree or a doctorate. How higher education is distributed among different specialities is depicted in figure 3.

In the figure it is seen that 68% of the investors have economics related education. It is somewhat expected since economics graduates often have an interest in stock markets and are therefore investors. This group includes graduates in economics and management, business, public administration and finance. It must be mentioned that the variation between economics and management, business and finance studies is relatively small. These categories were made solely based on the name of the speciality and therefore the content of the studies can be similar. Other popular specialities among investors are IT and law.

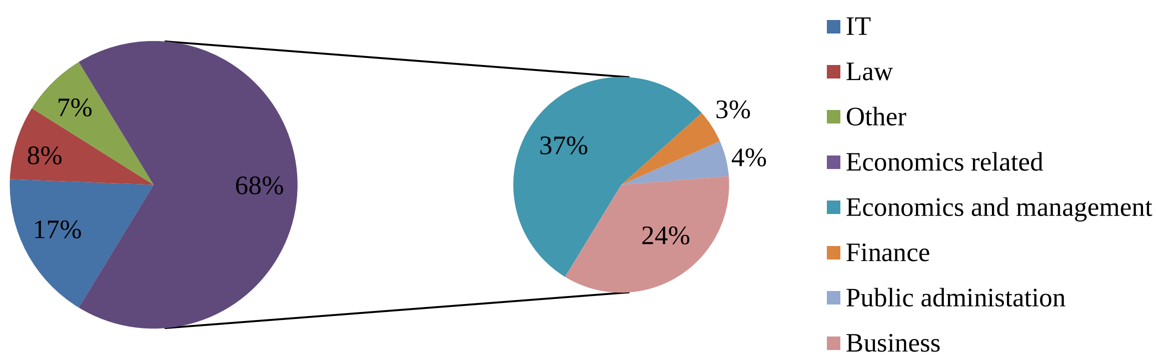

Figure 3. Distribution of specialities among investors
Source: Compiled by the author

In total 79% of the investors are men and only 21% are women. This can be because men are more risk seeking and entrepreneurial. On the other hand only 15.2% of the graduates in social sciences, business and law were men (Anspal et al 2010, 40). In this data set male graduates in economics make up 72% of the sample and accordingly 28% are women. It shows that finance graduates who invest on stock markets are mainly men. The difference can come from historical family models where men have to support the family and therefore they find more eagerly alternative ways to make money.

On the basis of statistics, economics is one of the most popular specialities in all universities as well as in this data set. In Tallinn University of Technology the most popular specialities were business, public sector economics and public administration (RE konkurss…). In University of Tartu the largest numbers of students were accepted to study in law, economics, and medicine (Kõrghariduse…). In Tallinn University the most popular specialities were business administration, IT and early childhood education teacher (Vastuvõtuarvud…). Although this statistics does not cover the graduates because the information about that is not publicly available, it shows that economics is one of the most popular specialities in all universities as well as in this data set. IT and law are also very popular as seen from the sample used on this thesis.

In figure 4, five of the most popular exam results are depicted in comparison with the actual average results in 2012. The percentage of investors who took the exams are depicted in comparison with male and female investors.

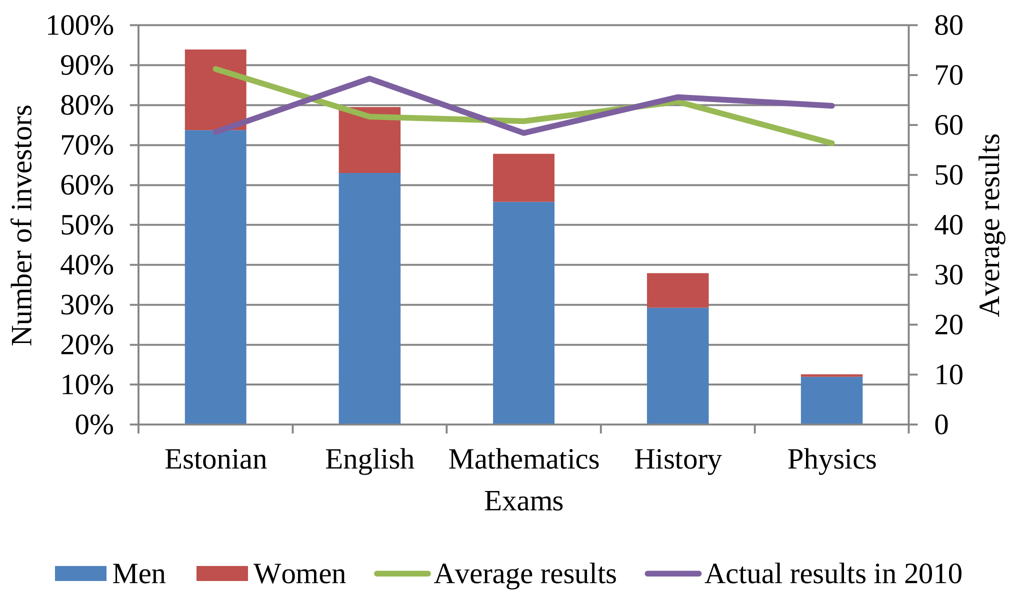

Figure 4. Distribution of specialities among investors and average results

Source: Compiled by the author

The most popular exam was Estonian, followed by English and mathematics. The percentage of investors who took these exams were 94%, 80% and 68% accordingly. The highest result was got in Estonian. To compare investors in the sample with the whole population of Estonia who took these exams the actual results in 2012 are also outlined. The actual results in 2010 (Riigieksamite statistika…) were lower in Estonian and mathematics than the average results in this sample.

Currently there are 13 stocks on the Tallinn Stock Exchange (Balti aktsiad) and the investment popularity is depicted in figure 5. The most popular stock in the data set is Tallink Grupp, where 56% of the investors have invested. The second popular stock is Olympic Entertainment Group with 37% of investors. The third biggest stock is Tallinna Kaubamaja Grupp with 23% of investors. The smallest stocks are Merko Ehitus, Harju Elekter, Premia Foods and Skano Group.

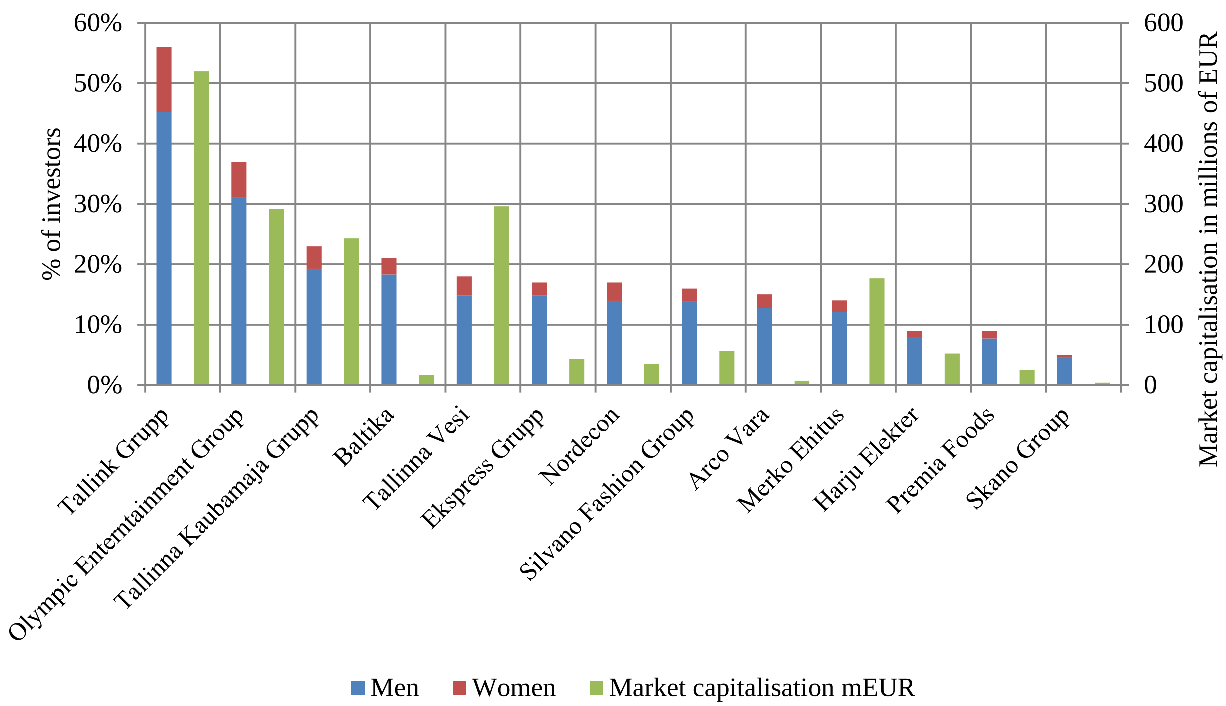

Figure 5. Stock popularity and market capitalisation on the Tallinn Stock Exchange
Source: Compiled by the author

The biggest stocks according to market capitalisation are Tallink Grupp, Tallinna Vesi and Olympic Entertainment Group (Turukapitalisatsioon). In general, stocks with the biggest market capitalisation are also the most popular stocks in the sample, with the exception of Baltika, which is rather popular but has a very small market capitalisation compared to other popular stocks.

The cumulative number of trades investors make on the Tallinn Stock Exchange are depicted in figure 6. It is seen that 30% of investors make 6-15 trades. 1-2 trades are made by 23% of the investors and 3-5 trades are made by 24% of investors. More than 16 trades are made by 22% of investors.

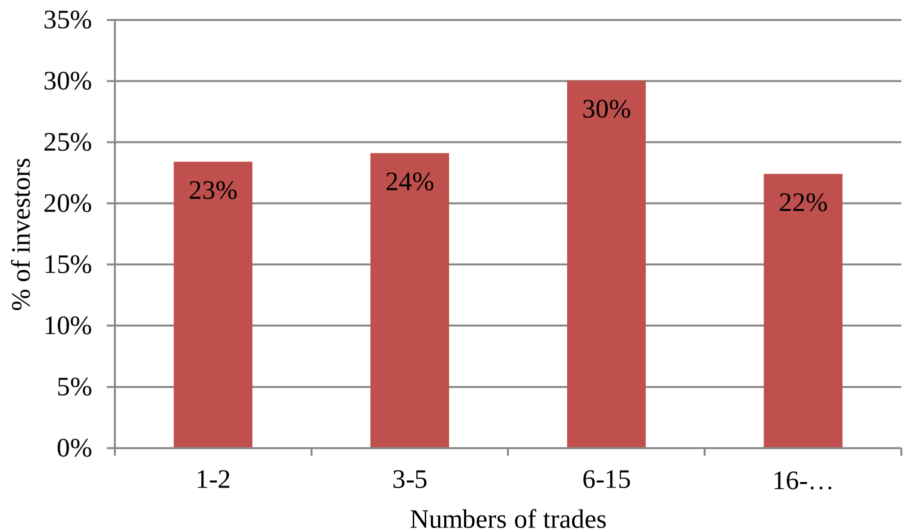

Figure 6. Numbers of trades
Source: Compiled by the author

The numbers of stocks investors hold in their portfolios are depicted in figure 7. It is seen that 33% of investors have only one stock in a portfolio, 23% have two stocks and 18% have 3 stocks. This shows that portfolios are not very diversified on the Tallinn Stock Exchange. This can be due to the small number of stocks on the market and their small volume.

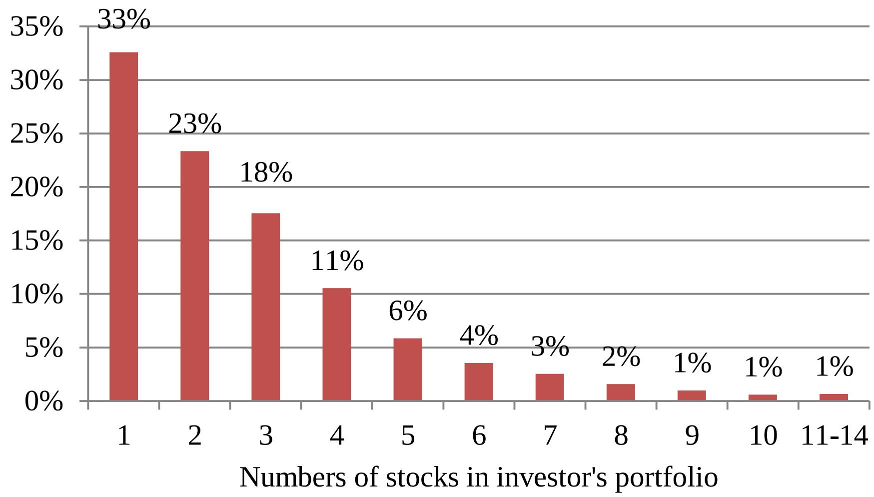

Figure 7.Number of stocks in investor’s portfolio on the Tallinn Stock Exchange

Source: Compiled by the author

2.2. Logit method

There are several methods used in order to measure the disposition effect. Studying the propensity to realize gains and reluctance to realise losses can show the general loss aversion of investors, which explains the existence of the disposition effect. Also studying trading volume can show the disposition effect. When the current volume is negatively correlated with the volume on previous days in which the stock price was higher than the current price on the aggregate level, the disposition effect is existent. (Goo et al 2010, 110)

The most widely used method of studying the disposition effect is the ratio analysis developed by Odean (1998). It depends on measuring various ratios of sales for gains and losses. The method is used by calculating the difference between potential gains realised and potential losses realised. If there is a positive difference, it shows the existence of the disposition effect. It is a very easy method, but it is good for measuring the disposition effect on average but not the best method for individual account level. For example this method was used by Kubinska et al (2012), Dhar and Zhu (2006), Dacey and Zielonka (2008), Barberis and Xiong (2009), and Rau (2014).

Another method to be used is survival analysis as Feng and Seasholes (2005), Talpsepp (2011), and Seru et al (2009) have done. Survival analysis is a statistical model showing how long stocks are typically held in a portfolio.

Logit methodology is the third method and it is also a statistical model. This thesis concentrates on studying the decision to sell and therefore Logit method is used. The advantage of logit methodology is that it allows testing for the disposition effect while at the same time controlling for educational and other factors that might be correlated with the disposition effect. This method was used by Grinblatt and Keloharju (2001), and Kaustia (2009).

Logit regression is a nonlinear regression model specifically designed for binary dependent variables. It models the probability for Y to be 1 and adopts a nonlinear formulation that forces the predicted values to be between 0 and 1. Since cumulative probability distribution functions produce probabilities between 0 and 1, they are used in logit regression. The population logit model with multiple regressors is depicted in the equation 1 (Stock, Watson 2011, 392).

$$Pr(Y = 1|X_1, X_2, \dots, X_k) = F(\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_k X_k) = \frac{1}{1+e^{-(\beta_0+\beta_1 X_1+\beta_2 X_2+\cdots+\beta_k X_k)}} \quad (1)$$

where
Y – Dependent binary variable,
F – Cumulative standard logistic distribution function,
X_1, X_2 *etc* – regressors,
β_1,β_2 etc – logit coefficients.

The application examined in this thesis is whether educational indicators and other socioeconomic factors influence the decision to sell a stock too early while being profitable and holding onto it too long while making a loss. The binary dependent variable is whether the stock is sold at that certain point in time. For testing the disposition effect, the decision to sell is a dependent variable. If the stock was sold at that time the variable equals 1 and if the stock was not sold, the variable equals 0.

It is important to test the decision to sell on both, the loss and the profit side. On loss side one independent variable is always a dummy variable showing if the position was in loss or not. Inversely on profit side one independent variable is a dummy showing if the position was in profit or not. Other independent variables are added.

In order to control for the disposition effect and how the selling decision is affected by different investor characteristics, two dummy variables about one characteristic are used. The first one is the control variable. The second variable is an interacted variable. All dependent variables under investigation are interacted with the variable showing whether the position is in loss or not. The interaction terms are of key interest since they directly answer the question of whether changes in the variables are correlated with changes in an investor's propensity to avoid losses and realize gains. The regular variables themselves act as controls because members of one characteristic group may have different results. (Feng, Seasholes 2005, 317) This way it is possible to control for different behaviour while at the same time it is possible to test cross-sectional differences in the disposition effect.

The models are made by using data analysis and a statistical software program Stata, which allows to test models easily. The results of the models are translated into odds ratios that are easier to interpret than coefficients. Odds ratio is an exponentiated coefficient and it shows how many times the independent variable is less likely or more likely to influence the dependent variable. The use and interpretation of odds ratios are described later in this thesis.

2.2. Formulation of hypotheses

The following sub chapter gives a short overview about the theoretical starting points for the empirical study carried out in the third chapter of this thesis. The expectations are stated based on previous findings in order to give an understanding of what is being studied.

2.2.1. General disposition effect

First of all whether the disposition effect is an issue on the Tallinn Stock Exchange or not is examined. Many previous studies have showed the existence of the disposition effect. For example Shefrin and Statman (1985) were the first to study the disposition effect, Odean (1998) developed their idea and showed that individual investors experience the disposition effect on stock markets, Grinblatt and Keloharju (2001) found that large gains are realised and large losses are held onto, which means that the disposition effect is a major determinant of the propensity to sell a stock that an investor holds. Feng and Seasholes (2005) also showed that the disposition effect is existent. Dhar and Zhu (2010) showed that investors experience a significant disposition effect on average. Talpsepp (2010) found that investors on the Tallinn Stock Exchange are prone to the disposition effect. Therefore before controlling various characteristics it is important to show that also investors on the Tallinn Stock Exchange experience the disposition effect. It is expected that investors are prone to the disposition effect in general.

2.2.2. Gender and age

After showing the existence of the disposition effect, the connection of other investor characteristics to the disposition effect is studied. The influences of investor gender and also age are checked. These two characteristics are something the investor cannot influence himself, so they are studied in order to get an overview of how congenital characteristics influence investor behaviour on stock exchanges. Gender has produced different results in previous studies as showed in chapter 1.4.1. For example Feng and Seasholes (2005) and Rau (2014) found that women show higher disposition effect than men, but Da Costa Jr. et al (2008) show that the disposition effect vanishes for women but remains for men. Talpsepp (2010) found that on the Tallinn Stock Exchange there is no difference between men and women as regards the disposition effect.

Feng and Seasholes (2005) also studied the influence of age. They showed that investors between 25 and 35 are less prone to the disposition effect since they are the most sophisticated. On the other hand Talpsepp (2010) showed that on the Tallinn Stock Exchange the disposition effect bias tends to decrease with age. This is also consistent with Dhar and Zhu (2010). This thesis investigates both gender and age and how they influence the disposition effect. It is expected that men are less prone to the disposition effect. Since the data includes mostly young investors it is expected that the disposition effect decreases with age.

2.2.3. University education

Educational factors are not much studied previously because of the lack of information. This data set is therefore unique and helps to check how higher educational degrees and also high school final state exam results influence the existence of the disposition effect. Previously Goo et al (2010) have showed that investors with college degrees or more advanced degrees have a lower disposition effect. So it is expected that investors with a bachelor`s and master`s degree have lower disposition effect. Education is a measure of investor intelligence and therefore investors with higher education should make better decisions.

Besides degrees also different specialities are studied. There was information about graduating in finance, mathematics and statistics, economics and management, law, IT, medicine, public administration, business, chemistry, physics and biology and psychology. The first expectation about university specialities is that graduates in finance and economics related specialities should perform better in terms of the disposition effect because it is expected that they have studied and are aware of different biases and are able to avoid them. The second expectation is that mathematicians and statisticians are also expected to perform better because these specialities are generally quite difficult and not a lot of people are good at maths. Therefore knowledge in mathematics should help increase the skill on stock markets. The third expectation is that other specialities do not to have any significant influence on the disposition effect.

2.2.4. High school final state organized exams

Besides university specialities, also high school final state organized exam results should influence the disposition effect. The following exams were tested: Estonian, history, physics, English and mathematics. It is expected that higher exam results mean that investors are less influenced by the disposition effect and lower exam results mean that investors are more influenced. Better results show better academic abilities but also higher intelligence, which are expected to lower the disposition effect.

2.2.5. Portfolio diversification and number of trades

The number of stocks in the portfolio shows portfolio diversification. According to Feng and Seasholes (2005) portfolio diversification is part of investor sophistication. They showed that when an investor has two or more stocks in his portfolio, his portfolio is diversified and therefore he is less prone to the disposition effect. Therefore it is expected that the more stocks in the portfolio, the less the investor is prone to the disposition effect.

The number of trades made has also been showed to have an influence on the disposition effect. Dhar and Zhu (2006) showed that the more investors trade, the less they are influenced by the disposition effect. On the other hand Kubińska et al (2012) found that investors with a greater number of transactions have a higher propensity towards the disposition effect. It is expected that the more trades an investor makes, the less he or she is prone to the disposition effect. How trading frequency influences the disposition effect on the Tallinn Stock Exchange is shown later in this thesis.

2.2.6. All formulated hypotheses

The hypotheses are based on previous literature. To sum up what is expected, the hypotheses are the following:

- investors on the Tallinn Stock Exchange are prone to the disposition effect in general;
- men are less prone to the disposition effect than women;
- the disposition effect decreases with age;
- investors with higher education are less prone to the disposition effect;
- graduates in economics related specialities are expected to be less prone to the disposition effect;
- graduates in mathematics and statistics are expected to be less prone to the disposition effect;
- better results in high school final state exams are expected to make investors less prone to the disposition effect;

- the more stocks in the portfolio, the less an investor is prone to the disposition effect;
- the more trades an investor makes, the less he or she is prone to the disposition effect.

3. EMPIRICAL EVIDENCE OF THE DISPOSITION EFFECT ON THE TALLINN STOCK EXCHANGE

The third part of this master's thesis focuses on the empirical work. First of all the results of the empirical study are presented. After that the discussion about the results and the conclusion follows together with recommendations.

3.2. Results

First of all results from all dependent variables are presented individually in a relationship to the decision to sell and after that the final model is created by using statistically significant variables. The variables chosen to be tested are based on earlier studies and the expectations set up in the formulation of hypotheses. All the statistically significant variables are added into one model to see the aggregate effect of the variables tested on the disposition effect. The effects of important variables are presented as follows.

3.2.2. The disposition effect on the Tallinn Stock Exchange

The disposition effect is the tendency to hold losing investments and sell winning investments (Shefrin, Statman 1985, 778). Before testing different educational aspects that affect an investor's selling decisions, it is important to test if investors on the Tallinn Stock Exchange are subjected to the disposition effect to begin with. The data used in this thesis helps to determine whether an investor sold his position or not and whether his position was in loss or in profit.

The dependent variable is the decision to sell. It equals zero for every day an investor holds the stock position and one if he sells the stock. The independent variable is a dummy variable showing whether the position is in loss or in profit. On the loss side the independent variable equals one when the position was sold for a loss or is traded at a paper loss and on the profit side it equals one if the position was sold for a gain. The loss side and the profit side should be tested with separate models. In order to confirm the disposition effect, the odds ratios on the loss and profit variable on both sides should be different. That is less than 1 on the loss side and bigger than 1 on the profit side. An odds ratio less than 1 means that investors are less likely to sell their position. It is expected that an investor holds onto the loosing stock on the loss side and sells the stock on the profit side. The results of the logit regression are presented in table 1.

Table 1. General disposition effect

Variable	Loss side		Profit side	
	odds ratio	standard error	odds ratio	standard error
Loss	0.3277***	0.0043		
Profit			2.9868***	0.0387
Constant	0.0088***	0.0001	0.0029***	0.0000

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

Source: Calculated by the author and compiled on the basis of data provided in Appendix 1.

As seen in table 1, the odds ratio for loss is 0.3277, which means that investors in loss are less likely to sell than investors in profit. The odds ratio for profit is 2.9868, which confirms the existence of the disposition effect on the Tallinn Stock Exchange. Loss and profit have different effects on the decision to sell. Investors sell 3 times more likely while they are in profit. Since p-value is 0 for all indicators, it means that the results are statistically significant and the investors on the Tallinn Stock Exchange experience the disposition effect. The findings are consistent with multiple previous studies.

3.2.3. The disposition effect among genders and age

The question whether men or women show more disposition effect has had controversial results in previous studies. Some authors have found that men sell more compared to women, but others found that the disposition effect vanished for women, but remained for men.

The first characteristic to be tested is the gender of the investor. As was shown in chapter 2.1.1 most investors on the Tallinn Stock Exchange are men. Two models are generated – one for the loss side and the other for the profit side. The dependent variable is the decision to sell as discussed earlier, but now the model has three independent variables. The first one is still a dummy variable showing whether the position is in loss or in profit. The second variable is the gender – male. The variable equals one if the investor is a man and zero if the investor is a woman. The third variable is the interacted variable that shows how much males who are in loss sell their position. On the profit side the second variable shows how much males who are in profit sell their position. The results on the profit and loss side are presented in table 2.

Table 2. Gender influence on the disposition effect

Variable	Loss side		Profit side	
	odds ratio	standard error	odds ratio	standard error
Loss	0.2766***	0.0107		
Profit			3.5741***	0.1374
Male	1.9658***	0.0490	2.4372***	0.0787
Male in loss	1.2316***	0.0504		
Male in profit			0.8030***	0.0328
Constant	0.0050***	0.0001	0.0014***	0.0000

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

Source: Calculated by the author and compiled on the basis of data provided in Appendix 2.

As seen in table 2, the odds ratio for loss is 0.2766 and for profit it is 3.5741. It shows that the disposition effect is still existent. The odds ratio for males on the loss side is 1.9658 and on the profit side 2.4372, meaning that men make more trades on both the loss side and the profit side. Compared to women, men have a higher probability of selling and this is consistent with the previous studies by Barber and Odean (2001) and also by Feng and Seasholes (2005) and Rau (2014).

To test for the disposition effect, it is important to study the odds ratios for males in loss and in profit on both the loss side and the profit side. The odds ratio for males who are in loss is 1.2316, meaning that men in loss are more likely to sell than women in loss. The profit side shows that men in profit are less likely to sell than women in profit. The odds ratio is 0.8030. The results show that men experience less disposition effect than women. This result is consistent with Rau (2014) and Feng and Seasholes (2005), but opposite to Da Costa Jr. et al (2008) findings.

In order to test the age influence on the disposition effect, 4 dummy variables are constructed according to figure 2 in chapter 2.1.1. The first age group is investors until the age of 25, because this is the age when young people still study. From 26 till 30 is the second age group, which is the period while people concentrate on increasing their wealth. The third group is investors from 31 to 35 and the fourth group is for older investors. Interacted variables are added to the model and the results are given in table 3.

Table 3. Age influence on the disposition effect

Variable	Loss side		Profit side	
	odds ratio	standard error	odds ratio	standard error
Loss	0.3156***	0.0061		
Profit			3.1070***	0.0600
Age till 25	0.6387***	0.0182	0.6026***	0.0215
Age from 26 to 30	1.0747 ***	0.0190	1.1843***	0.0263
Age from 36	0.9778	0.0325	1.2334***	0.0515
Age till 25 in loss	0.9421	0.0432		
Age till 25 in profit			1.0587	0.0484
Age from 26 to 30 in loss	1.0981***	0.0313		
Age from 26 to 30 in profit			0.9050***	0.0257
Age from 36 in loss	1.2693***	0.0679		
Age from 36 in profit			0.7958***	0.0425
Constant	0.0091***	0.0001	0.0030***	0.0000

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

Source: Calculated by the author and compiled on the basis of data provided in Appendix 3.

The omitted category is investors between ages 31 to 35 because there are a lot of investors between ages 26 to 30 and ages 31 to 25 and in order to remove the multicollinearity problem, one of them should be omitted.

In the table it is seen that the disposition effect is still existent and that investors who are younger than 25 have an odds ratio of 0.6387, which means that they tend to have a lower probability of selling and therefore they trade less than other investors on both the loss and profit side. Investors older than 36 trade less on the loss side (odds ratio 0.9788) and more on the profit side (odds ratio 1.2334). Since the loss side is statistically insignificant, no conclusions can be drawn. Investors between the ages 26 to 30 trade the most, but also investors from 31 to 35 trade more than the youngest investor group. Younger investors may trade less because they are more inexperienced and that they probably have less money to make the trades with. Experience is gained with age and more experienced investors are more confident and therefore not reluctant to trade. Confidence comes with experience.

The results show that investors from 26 to 30 and older than 36 are less prone to the disposition effect than investors younger than 25 and also investors from 31 to 35. It is somewhat unexpected that investors from 26 to 30 and from 31 to 35 behave differently, especially considering the fact that investors from 26 to 30 act similarly to investors older than 36. On the Tallinn Stock Exchange investors over 36 are the least prone to the disposition effect. The disposition effect is strongest for investors younger than 25 but these results are statistically insignificant.

3.2.4. University specialities and the disposition effect

Since more educated people are expected to have a lower disposition effect according to Goo et al (2010), the influence of university degrees on the disposition effect is tested. It is expected that investors with university degrees tend to sell more in the loss region and sell less in the gains region than less educated people. The data includes information about a bachelor’s or an equivalent degree and a master’s or a doctoral degree. Testing for both educational degree categories while being in loss and in profit shows that a bachelor’s degree is statistically insignificant. Therefore no effect with a bachelor’s degree can be found.

Having a master’s or a doctoral degree is, on the other hand associated with the disposition effect. The results for a master’s and a doctoral degree are depicted in table 4. The loss and the profit variables show that the disposition effect is existent.

Table 4. The influence of master degree and doctorate on the disposition effect

Variable	Loss side		Profit side	
	odds ratio	standard error	odds ratio	standard error
Loss	0.3279***	0.0043		
Profit			2.9851***	0.0387
Master or doctor	0.4324***	0.0695	0.1567***	0.0593
Master or doctor loss	0.3672**	0.1509		
Master or doctor profit			2.7828**	1.1434
Constant	0.0088***	0.0001	0.0029***	0.0000

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

Source: Calculated by the author and compiled on the basis of data provided in Appendix 4.

Since only 0.2% of the sample has a master's degree or a doctoral degree, it is very hard to draw reliable conclusions. Nevertheless, it is shown that a higher educational degree makes investors trade less than less educated investors. Masters and doctors sell less likely in both the loss and the profit region. On the other hand they sell more likely in the profit region when they are in profit and less likely in the loss region when they are in loss. It shows that masters and doctors are more likely to be influenced by the disposition effect than less educated investors. This is inconsistent with the findings of Goo et al (2010), but the results of this thesis concerning this aspect are not reliable.

As for educational indicators, the data included various university specialities. There was information about graduates in finance, mathematics and statistics, economics and management, law, IT, medicine, administrative studies, business, chemistry, physics and biology, and psychology. The distribution among investors was shown in figure 3 in chapter 2.1.1. All of these indicators were tested for the disposition effect and the results are the following.

Finance related education is expected to decrease the disposition effect because in this case investors are more aware of different biases and should be able to act rationally and avoid biases they are aware of. The results are somewhat different and are depicted in table 5. The table shows the disposition effect is existent and that those investors with a degree in finance trade more on the loss side and less on the profit side than investors with other degrees.

As to the disposition effect, financially educated people are less likely to sell when the position is in loss and more likely to sell when the position is in profit. Therefore the investors with financial degrees are more likely to be affected by the disposition effect. This is contrary to what could have been expected.

Table 5. The influence of financial education on the disposition effect

Variable	Loss side		Profit side	
	odds ratio	standard error	odds ratio	standard error
Loss	0.3309***	0.0043		
Profit			2.9577***	0.0386
Finance	1.2135***	0.0718	0.5757***	0.0624
Finance loss	0.4696***	0.0585		
Finance profit			2.1108***	0.2609
Constant	0.0088***	0.0001	0.0029***	0.0000

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

Source: Calculated by the author and compiled on the basis of data provided in Appendix 5.

The same models are made for other specialities. For example graduates in mathematics and statistics show a lower tendency to sell in both the profit and the loss region, but the variables are insignificant. Mathematicians in loss are more likely to sell in the loss region and mathematicians in profit are less likely to sell in the profit region. But the variables showing the disposition effect remain insignificant. Variables are insignificant also for other specialities: economics and management, law, medicine, administrative studies, business, chemistry, physics and biology, and psychology. Therefore the results are not presented.

IT graduates is the only group besides finance graduates that shows some statistically significant results, which are depicted in table 6. The disposition effect is still existent. IT graduates sell less on the loss side and more on the profit side. On the other hand they sell more when they are in loss and less when in profit. It shows that IT graduates are less influenced by the disposition effect.

Table 6. The influence of IT education on the disposition effect

Variable	Loss side		Profit side	
	odds ratio	standard error	odds ratio	standard error
Loss	0.3245***	0.0044		
Profit			3.0194***	0.0408
IT	0.9926	0.0287	1.1409***	0.0428
IT loss	1.1402***	0.0543		
IT profit			0.8663***	0.0411
Constant	0.0088***	0.0001	0.0029***	0.0000

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

Source: Calculated by the author and compiled on the basis of data provided in Appendix 6.

3.2.5. High school final state organized exam results

Besides university specialities, also five of the most popular high school state exam results were tested. The following exams were tested: Estonian, mathematics, physics, English and history. The percentage of investors who had results in these exams is given in figure 4 in chapter 2.1.1. together with the average results and the actual results.

The results of the exams were transformed into dummy variables. The variables were constructed according to quartiles. Therefore four different categories were constructed. The first quartile was 25% of the weakest results, second quartile was from 26 to 50, the third from 51 to 75 and the last quartile was 76 to 100, which showed 25% of the highest results. The fifth category is investors who have not taken the exam and is therefore omitted from all models except Estonian because the number of investors who have not taken the exam is rather small.

The exam results show investor intelligence and academic abilities. Previous studies have found clear correlation between intelligence and educational abilities (Deary, Johnson 2010, 1363). Therefore it is assumed that investors who are smarter, get better results. The first quartile can be stated as least intelligent investors, the second quartile as investors who are less intelligent than average and the third quartile as investors who are more intelligent than average. The investors who get the highest results are the most intelligent. All subjects were tested separately and investors who had not taken the exam were omitted.

Estonian high school exam results are statistically insignificant and therefore do not influence investor behaviour regarding the disposition effect. History exam results are significant and depicted in table 7. Testing history exam results showed that the least intelligent investors sell less than investors who have not taken the exam. The same effect occurs with investors who are smarter than the average and also with investors who are the most intelligent. Investors who are less intelligent than average sell more likely in both the loss side and the profit side. Based on these results it is not possible to draw adequate conclusions because a pattern in not established.

Table 7. The influence of history high school final state organized exam results on the disposition effect

Variable	Loss side		Profit side	
	odds ratio	standard error	odds ratio	standard error
Loss	0.3362***	0.0056		
Profit			2.9050***	0.0482
History exam 0-25	0.7202***	0.0361	0.9161**	0.0474
History exam 26-50	1.3483***	0.0372	1.1681***	0.0420
History exam 51-75	0.8728***	0.0244	0.8346***	0.0291
History exam 76-100	0.9804	0.0215	0.8902***	0.0254
History exam 0-25 in loss	1.2908***	0.0931		
History exam 0-25 in profit			0.7934***	0.0572
History exam 26-50 in loss	0.8713***	0.0396		
History exam 26-50 in profit			1.1590***	0.0526
History exam 51-75 in loss	0.9622	0.0431		
History exam 51-75 in profit			1.0498	0.0469
History exam 76-100 in loss	0.9054***	0.0327		
History exam 76-100 in profit			1.1004***	0.0397
Constant	0.0088***	0.0001	0.0030***	0.0000

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

Source: Calculated by the author and compiled on the basis of data provided in Appendix 7.

To find out how history exam results influence the disposition effect, interacted variables are looked at. As it is seen in the table, the least intelligent investors are more likely to sell when their position is in loss and less likely to sell when their position is in profit. This means that getting poor results in history exam results in being less influenced by the disposition effect. All investors who are more intelligent are prone to the disposition effect, although the results for more intelligent than average are statistically insignificant and do not have any effect on the disposition effect. The most influenced investors are less intelligent than average. This finding is unexpected and interesting since least intelligent perform the best and a little bit more intelligent perform the worst. The line between the intelligence is quite indistinguishable and therefore the reliability of the results is questionable.

The results for physics exam are depicted in table 8. The least intelligent and the most intelligent investors sell less likely than other investors. Average investors sell more. The interacted variables for the least intelligent and the most intelligent investors are statistically insignificant and therefore very good or very bad results do not have an impact on the disposition effect. Investors who are less intelligent than average are less prone to the disposition effect and investors more intelligent than average are more prone to the disposition effect than investors who have not taken physics exam. It also complies with the pattern that less intelligent investors are less prone to the disposition effect.

Table 8. The influence of physics high school final state organized exam results on the disposition effect

Variable	Loss side		Profit side	
	odds ratio	standard error	odds ratio	standard error
Loss	0.3278***	0.0046		
Profit			2.9862***	0.0417
Physics exam 0-25	0.7589***	0.0701	0.9134	0.0997
Physics exam 26-50	1.0280	0.0512	1.3506***	0.0802
Physics exam 51-75	1.3110***	0.0469	0.9743	0.0483
Physics exam 76-100	0.8201***	0.0285	0.8753***	0.0398
Physics exam 0-25 in loss	1.1912	0.1715		
Physics exam 0-25 in profit			0.8240	0.1183
Physics exam 26-50 in loss	1.3179***	0.1024		
Physics exam 26-50 in profit			0.7623***	0.0591
Physics exam 51-75 in loss	0.7390***	0.0454		
Physics exam 51-75 in profit			1.3440***	0.0823
Physics exam 76-100 in loss	1.0689	0.0614		
Physics exam 76-100 in profit			0.9385	0.0538
Constant	0.0088***	0.0001	0.0029***	0.0000

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

Source: Calculated by the author and compiled on the basis of data provided in Appendix 8.

The results for English exam are depicted in table 9. As can be seen in the table, less intelligent investors trade less as well as most intelligent investors. More intelligent investors than average trade more on the loss side but less on the profit side than investors who have not taken the exam. It is very hard to interpret the results because there is no pattern established.

Consistent with physics exam results the interacted variables for the least intelligent and the most intelligent investors are statistically insignificant and therefore do not have an impact on the disposition effect although the results show that less intelligent are less prone to the disposition effect. Investors more and less intelligent than average are both more prone to the disposition effect than investors who have not taken the exam. The most influenced investors are less intelligent than average.

Table 9. The influence of English high school final state organized exam results on the disposition effect

Variable	Loss side		Profit side	
	odds ratio	standard error	odds ratio	standard error
Loss	0.3427***	0.0092		
Profit			2.8667***	0.0772
English exam 0-25	0.9451**	0.0278	1.0089	0.0347
English exam 26-50	0.9260***	0.0240	0.7699***	0.0262
English exam 51-75	1.0168	0.0244	0.9502**	0.0288
English exam 76-100	0.7790***	0.0175	0.7521***	0.0217
English exam 0-25 in loss	1.0639	0.0483		
English exam 0-25 in profit			0.9320	0.0423
English exam 26-50 in loss	0.8301***	0.0357		
English exam 26-50 in profit			1.2022***	0.0515
English exam 51-75 in loss	0.9311**	0.0361		
English exam 51-75 in profit			1.0671**	0.0413
English exam 76-100 in loss	0.9634	0.0354		
English exam 76-100 in profit			1.0344	0.0379
Constant	0.0096***	0.0002	0.0033***	0.0001

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

Source: Calculated by the author and compiled on the basis of data provided in Appendix 9.

The results for mathematics exam are depicted in table 10. Investors who are less intelligent trade more, and more intelligent trade less than investors who have not taken mathematics exam. The results for the disposition effect are statistically significant and show that the least intelligent investors are least influenced by the disposition effect. Other investors are more prone to the disposition effect. Investors who are the most influenced by the disposition effect are less intelligent than average. It confirms earlier findings that less intelligent investors are less prone to the disposition effect.

Table 10. The influence of mathematics high school final state organized exam results on the disposition effect

Variable	Loss side		Profit side	
	odds ratio	standard error	odds ratio	standard error
Loss	0.3428***	0.0078		
Profit			2.8627***	0.0652
Mathematics exam 0-25	1.0594**	0.0319	1.2577***	0.0456
Mathematics exam 26-50	1.2303***	0.0324	1.0914***	0.0354
Mathematics exam 51-75	0.9747	0.0234	0.8698***	0.0261
Mathematics exam 76-100	0.9610**	0.0201	0.8769***	0.0234
Mathematics exam 0-25 in loss	1.1899***	0.0563		
Mathematics exam 0-25 in profit			0.8436***	0.0398
Mathematics exam 26-50 in loss	0.8813***	0.0370		
Mathematics exam 26-50 in profit			1.1231***	0.0471
Mathematics exam 51-75 in loss	0.8887***	0.0343		
Mathematics exam 51-75 in profit			1.1187***	0.0430
Mathematics exam 76-100 in loss	0.9104***	0.0309		
Mathematics exam 76-100 in profit			1.0961***	0.0372
Constant	0.0087***	0.0001	0.0030***	0.0001

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

Source: Calculated by the author and compiled on the basis of data provided in Appendix 10.

To sum up, the influence of intelligence based on high school exam results is the following: the least intelligent investors are least prone to the disposition effect, although two models showed that this is statistically insignificant. History, English and mathematics exam results as a proxy for intelligence show similar results. Least intelligent investors are least prone to the disposition effect and all other investors are prone to it. The most influenced investors are investors who are less intelligent than average. Physics exam showed a little different pattern. The least and the most intelligent were insignificant but less intelligent are less prone to the disposition effect. These results in general were unexpected. As regards the likelihood to sell a pattern was not established and it is hard to draw any conclusions how intelligence and academic abilities influence the decision to sell.

3.2.6. Number of trades and portfolio diversification

According to literature there have been some controversial findings about trading frequency. For example Dhar and Zhu (2006) found that the more investors trade, the less they are influenced by the disposition effect. Feng and Seasholes (2005) found that a sophisticated investor is no longer reluctant to realize losses by the time he initiates his 16th stock position. On the other hand Kubinska et al (2012) found that investors who make more trades have a higher propensity towards the disposition effect. Therefore the number of trades is an important indicator to be studied and the results are showe in table 11.

Table 11. The influence of the number of trades on the disposition effect

Variable	Loss side		Profit side	
	odds ratio	standard error	odds ratio	standard error
Loss	0.4038***	0.0077		
Profit			2.4289***	0.0465
1-2 trades	0.3306***	0.0085	0.2787***	0.0083
3-5 trades	0.3550***	0.0086	0.2425***	0.0076
6-15 trades	0.4698***	0.0092	0.3836***	0.0096
1-2 trades in loss	0.8406***	0.0332		
1-2 trades in profit			1.1808***	0.0465
3-5 trades in loss	0.6810***	0.0271		
3-5 trades in profit			1.4617***	0.0580
6-15 trades in loss	0.8156***	0.0261		
6-15 trades in profit			1.2238***	0.0391
Constant	0.0160***	0.0002	0.0065***	0.0001

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

Source: Calculated by the author and compiled on the basis of data provided in Appendix 11.

The distribution of the number of trades investors have made is depicted in figure 6 in chapter 2.1.1. The number of trades is divided into four categories. Having made 1-2 trades makes an investor inexperienced. The second group is 3-5 trades, which shows that investors are a little more experienced and have a little more knowledge about stock markets. The third group makes 6-15 trades and the most experienced investors make more than 16 trades. The results show that making more than 15 trades means that investors are more likely to sell. This result is expected and shows that the results are logical. When coming to the disposition effect, it influences investors who make 3-5 trades the most. Investors who make more than 15 trades are the least influenced by the disposition effect.

According to Feng and Seasholes (2005) and Kubinska et al (2012) having more than two stocks in the portfolio already makes the portfolio diversified and therefore the investor should be less prone to the disposition effect. In order to test the effect of portfolio diversification, the number of stocks in the portfolio has been allocated into dummy variables. Having 1 stock in the portfolio depicts an undiversified portfolio, 2-4 stocks shows a diversified portfolio, 5-7 a more diversified and 8-14 stocks show a lot diversified portfolio. The model shows that the number of stocks in a portfolio is statistically insignificant. Therefore on the Tallinn Stock Exchange portfolio diversification does not help you escape the disposition effect.

3.2.7. All tested variables

In order to test the aggregate effect of all variables tested before, a new model with all statistically significant results was compiled. The statistically significant results of the final model are depicted in table 12. High school final state organized exam results were not added to the final model since the variables did not establish a pattern and it did not show the existence of the disposition effect. Therefore educational results do not have a reliable impact on the existence of the disposition effect based on this thesis as adding other control variables to the model, decreases the effect further.

As can be seen from the results, the disposition effect is still existent on the Tallinn Stock Exchange. The results confirm that men trade more than women and that they are less prone to disposition effect. Investor age also influenced the disposition effect as was seen earlier.

The results still show that investors younger than 25 trade less than older investors. They are also more influenced by the disposition effect, but this result was statistically insignificant. Investors in the age between 26 to 30 and also investors older than 36 experience disposition effect less than investors in the age between 31 to 35. The model shows that investors who are the least influenced by the disposition effect are older than 36.

Table 12. The influence of all tested variables on the disposition effect

Variable	Loss side		Profit side	
	odds ratio	standard error	odds ratio	standard error
Loss / profit	0.3409***	0.0158	2.9146***	0.1350
Male	1.648***	0.0433	1.9343***	0.0640
Male in loss / profit	1.1651***	0.0493	0.8479***	0.0359
Age till 25	0.8188***	0.0237	0.7918***	0.0287
Age from 26 to 30	1.1187***	0.0198	1.231***	0.0274
Age from 36	1.0122	0.0342	1.2288***	0.0517
Age till 25 in loss / profit	0.9659	0.0449	1.0332	0.048
Age from 26 to 30 in loss / profit	1.0968***	0.0313	0.9065***	0.0258
Age from 36 in loss / profit	1.2209***	0.0660	0.8265***	0.0447
Master or doctor	0.4340***	0.0707	0.1353***	0.0515
Master or doctor loss / profit	0.3134***	0.1298	3.2233***	1.3350
Finance	1.612***	0.0981	0.9492	0.1043
Finance loss / profit	0.5813***	0.0737	1.6978***	0.2134
1-2 trades	0.3608***	0.0094	0.3185***	0.0096
3-5 trades	0.3851***	0.0095	0.2677***	0.0085
6-15 trades	0.4921***	0.0097	0.4009***	0.0101
1-2 trades in loss / profit	0.8796***	0.0352	1.1276***	0.0450
3-5 trades in loss / profit	0.693***	0.0280	1.4359***	0.0579
6-15 trades in loss / profit	0.8136***	0.0261	1.2265***	0.0393
Constant	0.0098***	0.0003	0.0034***	0.0001

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

Source: Calculated by the author and compiled on the basis of data provided in Appendix 12

Investors with master’s degree or doctoral degree trade less than less educated and are more prone to the disposition effect, but since only 0.2% of the sample has a master’s degree or a doctoral degree, it is very hard to draw reliable conclusions. Graduates from finance experience disposition effect more than graduates from other specialities. All the other specialities were insignificant and therefore not added to the final model.

The number of trades made also influences the disposition effect. The more trades an investor makes, the less is he influenced by the disposition effect. Investors who make 3-5 trades are the most influenced by the disposition effect and investors who make more than 16 are less influenced.

The final model was tested for the goodness of fit, which is measured by the pseudo R^2. The pseudo R^2 is around 5% for the final model on both the loss side and the profit side. It means that 5% of the decision to sell is explained by the different variables tested. The model was also tested for the specification error. The results of the test are depicted in appendix 13. The value of *_hatsq* is statistically insignificant, which shows that the specification of the model is correct. Therefore the model fits data relatively well and the results are creditable. The model was also tested for multicollinearity and VIF coefficients are depicted in appendix 14. The test showed that the only variable with a multicollinearity problem is the variable loss and also the variable profit. It is somewhat logical because all other variables are interacted with it. Therefore it has no multicollinearity problem. The problem with heteroscedasticity was eliminated by using a model with robust standard errors.

3.3. Discussion

This part of the master's thesis concentrates on the discussion of the results and finding reasons why the results occurred. First of all the existence of the disposition effect was the basis of this research and it showed to be existent on the Tallinn Stock Exchange as was expected. This finding gave a starting point to studying different characteristics that ought to have influence on the disposition effect. This thesis confirmed the findings of Shefrin and Statman (1985), Odean (1998), Dhar and Zhu (2010), Grinblatt and Keloharju (2001), Feng and Seasholes (2005), Talpsepp (2010) and others and the hypothesis set up in chapter 2.2.1.

The reason why the disposition effect exists is not completely identified. It is questionable how much it is caused by preferences, beliefs and psychological biases. Education as a measure of investor intelligence and other socioeconomic factors as well as investor experience can influence investor behaviour and decision making. Therefore this thesis tries to find out how these factors influence the disposition effect.

The first factors studied were the gender of an investor and the age. They are indicators that investors cannot influence themselves, but they should be aware of the effect. Gender has had different results in previous studies. Feng and Seasholes (2005) and Rau (2014) showed that men are less prone to the disposition effect but on the other hand Da Costa Jr. et al (2008) showed the opposite. Talpsepp (2010) showed that men and women are similarly affected. The findings of this thesis are consistent with Feng and Seasholes (2005) and Rau (2014) and therefore the hypothesis set up in chapter 2.2.2. is confirmed. The disposition effect is existent for women and not for men. Barber and Odean (2001) showed that men are more overconfident than women and they trade 45% more, but perform worse in terms of common stock investment turnover by having higher turnover as they make more trades.

This study also found that men trade more, but in terms of the disposition effect men perform better. The difference can come from trading experience. Since men trade more, they are more experienced. The reason why men are more confident and also take more risks may be because of historical family models, where men were the ones who had to ensure economic stability to the family.

Feng and Seasholes (2005) associated age with investor sophistication, because with age they become more experienced in life. They found that investors between 25 and 35 are less prone to the disposition effect. This thesis on the other hand showed that investors older than 36 are the least prone to the disposition effect. On the other hand the findings were consistent with Dhar and Zhu (2010) and Talpsepp (2010), who showed that older investors have a smaller disposition effect. Therefore the hypothesis set up in chapter 2.2.2. is confirmed.

The difference with Feng and Seasholes study can be caused by the time difference. The investors who were 25 to 35 in his study would be older than 35 in this study. The difference between different age groups can also be caused by Estonian history. Older investors grew up during the Soviet occupation and therefore they may be more careful in their decision making. Investors, younger than 35 years, have lived most of their lives in the Republic of Estonia. The difference may be due to the experience gained during life, caused by different education received and the different economic regime while growing up.

When testing the influence of higher education on the disposition effect it was unexpected that a bachelor's or an equivalent degree was statistically insignificant. Unexpected was also the finding that a master's or a doctoral degree makes investors more prone to the disposition effect. This not consistent with the study about education by Goo et al (2010), who showed that investors with higher educational degrees are less influenced by the disposition effect. Masters and doctors also make fewer trades than less educated people and this can be the result of more thoroughly considered decisions. Since only 0.2% of investors have a master's or a doctoral degree, reliable conclusions cannot be made based upon this data set. Therefore the effect of higher education is insignificant in terms of the disposition effect. Therefore the first hypothesis set up in chapter 2.2.3. is not confirmed.

The effect of graduating in finance, mathematics and statistics, economics and management, law, IT, medicine, administrative studies, business, chemistry, physics and biology, and psychology was tested. All other specialities besides finance and IT were statistically insignificant and have no effect towards investor behaviour in relation to their decision to sell. Therefore the second hypothesis about university specialities set up in chapter 2.2.3. is not confirmed, but the third hypothesis is confirmed.

Financially educated people are more prone to the disposition effect. The first hypothesis about university specialities set up in chapter 2.2.3. is not confirmed. It was an unexpected finding, since finance speciality concentrates a lot on stock exchanges and how to make right decisions using various analytical methods. It seems that on the Tallinn Stock Exchange investors do not really use what they have learned and are more biased than other specialities when it comes to the disposition effect. This result can be biased because the distinction between different economics related specialities is based on the name of the speciality. Actually it can be hard to distinguish between different specialities since they may have similar content. Therefore it is hard to tell if the results are reliable.

IT graduates were less influenced by the disposition effect, but together with other investor characteristics IT education did not have an influence on the disposition effect. Having IT education can be beneficial towards trading on stock exchanges due to the ability to use different programs that make trading easier. For example one way to decrease the disposition effect is to set certain limits when the stock is automatically sold. IT graduates may have better knowledge how to do it and more confidence to trust technology.

Good high school final state organized exam results should show investor intelligence. More intelligent investors should get better results. Based on the unreliable results it can be said that education does not really influence individual investor propensity towards the disposition effect and other characteristics play a more important part in investor’s skills on stock markets regarding the disposition effect.

Some models showed that intelligence measured by the educational level and academic results influence investor’s propensity towards the disposition effect the opposite way as was expected. The hypothesis set up in chapter 2.2.4. is therefore not confirmed. In fact it was shown that intelligence makes investors more prone to the disposition effect. The most influenced investors are less intelligent than average and the least influenced investors are the least intelligent. There is a thin distinction between these two and therefore the results are not very reliable. Besides the final model did not show any adequate results for these variables. Therefore reliable conclusions cannot be made about education as a measure of intelligence as a factor influencing the disposition effect.

Feng and Seasholes (2005) added trading frequency and portfolio diversification as part of investor sophistication. According to them an investor is no longer prone to the disposition effect by the time he initiates his 16th stock position. Investors who trade more can be regarded as more experienced since they have made a lot of trades and it can be assumed that they are the most familiar with the Tallinn Stock Exchange. The findings of this thesis are consistent with Feng and Seasholes (2005). Experience and knowledge increases with the number of trades made and the disposition effect disappears when an investor has made more than 16 trades.

Dhar and Zhu (2006) also showed that 20% of investors who have a higher trading frequency do not exhibit the disposition effect. Investors who trade less also sell less likely compared to those who trade more. This result is very logical because trading less also results in making fewer sales. Less experienced investors are less likely to sell while on the loss side and more likely to sell while on the profit side. This means that the less experienced are more influenced by the disposition effect.

Trading more also helps investors sell their losing stocks more easily. They are constantly following stock markets and the events that cause stock movements. Therefore it can be said that they are more sophisticated about stock markets. According to this study less experienced investors are more prone to the disposition effect and this can be because they do not have a clear understanding about stock markets yet and they do not know how the economic cycle works. The real experience and understanding comes much later. Therefore the first hypothesis set up in chapter 2.2.5. is confirmed.

Seru et al (2010) show that investor performance improves with experience and therefore also with the number of trades made. Also Kumar and Lim (2008) showed that investors who execute more clustered trades exhibit weaker disposition effects. Boolell-Gunesh et al (2012) showed that trading frequency helps to avoid the disposition effect. Therefore this study is consistent with most of the earlier findings that show that trading helps to decrease the disposition effect.

Portfolio diversification shows investor sophistication according to Feng and Seasholes (2005). They showed that more sophisticated investors diversify their portfolios from the beginning of their career. If an investor has two or more stocks in their portfolio then their portfolio is diversified and it helps to escape the disposition effect. This is also consistent with Kubiska et al (2012) and Kumar and Lim (2008). The results of this thesis are contrary to previous studies. Therefore the second hypothesis set up in chapter 2.2.5. is not confirmed. On the Tallinn Stock Exchange portfolio diversification does not help you to escape the disposition effect. This may be because of the small number of stocks on the stock exchange or the small volume of trades.

To sum up, based on the sample used, the investor who is less prone to the disposition effect on the Tallinn Stock Exchange is a man, who is older than 36 years old, does not have a master's or a doctoral degree, and trades a lot.

For further studies it would be wise to try other methods such as Odean's ratio analysis or survival analysis to study the influence of education and other socioeconomic factors on the disposition effect on the Tallinn Stock Exchange. Different methods can change the results and show if education influences the disposition effect or not. Studying the risk and the return with regard to the disposition effect could show how different investors are influenced by the disposition effect and if the disposition effect decreases the return of the portfolio. Since this thesis covers the time period of 2004-2010, it is already possible to extend the time period. In this case there are more investors with a master’s degree and also the sample of high school final state exams is bigger.

CONCLUSION

The aim of this master's thesis was to study how education and other socioeconomic factors influence investor's tendency to sell winning stocks too soon and hold on to losing stocks too long. This is one of the investor's irrational behaviours and it is called the disposition effect. Investors believe that current loser stocks in their portfolio outperform their current winners in the future. Therefore they sell winners in order to rebalance their portfolios.

The influence of investor characteristics has been studied previously, but the reason why the disposition effect exists and why investors are influenced by it, has not yet been completely found. It is said to be caused by preferences, beliefs and psychological bias. Education and socioeconomic factors are the characteristics that are likely to influence investor behaviour and decision making. It is not much studied because of the lack of data. Therefore this study is remarkable with a thorough data set about all individual investor transactions in the period from 2004 to 2010 linked with educational characteristics.

The characteristics that were studied were: investor gender, age, educational degree, high school final state organized exam results, number of trades and number of stocks in the portfolio. The disposition effect was studied by using logit regression method, which helps to study the decision to sell and what causes it when being in profit and as well in loss.

The influence of education was somewhat different than was expected. Having a bachelor's or an equivalent degree was statistically insignificant and therefore doesn't have any effect on the disposition effect. On the other hand having a master's or a doctoral degree makes investors more prone to the disposition effect. Since only 0.2% of investors in the data set have a master's or a doctoral degree, reliable conclusions cannot be made based upon this data set. Therefore, on the basis of the present thesis we can conclude that the effect of higher education is insignificant in terms of the disposition effect.

From among different specialties only finance had an effect on the disposition effect. Finance related education made investors more prone to the disposition effect. This result was unexpected. Financially educated people should know how to make right decisions by using various analytical methods studied, but it seems that they do not use their knowledge when making decisions on stock exchange. The effect of high school final state organized exam results was statistically insignificant. This is certainly something that should be studied in the future by using a different method. The study showed that education does not really influence individual investor propensity towards the disposition effect and other characteristics play a more important part in an investor's skills on stock markets regarding the disposition effect

Portfolio diversification was also studied, but unlike previous studies, this remained insignificant. The reason can be the small amount of stocks on the Tallinn Stock Exchange and also the small volume.

There were also characteristics that gave expected and significant results. Men perform better than women in terms of the disposition effect. They also trade more and are therefore more experienced. The age of an investor is associated with experience as well as trading frequency. They both showed statistically significant results. The older the investors get, the less they are influenced by the disposition effect. One influencing factor can be the social regime while growing up. People who have grown up during the Soviet occupation make different decisions than younger investors who have lived most of their lives in the Republic of Estonia.

The number of trades made is also a measure of investor experience. By experience investors develop their knowledge about stock markets. Less experienced investors are more influenced by the disposition effect. It can be because they do not have a clear understanding about stock markets yet and they do not know how the economic cycle works. The real knowledge and understanding comes with experience. These results confirm the earlier findings.

For further studies it would be wise to extend the data set. In this case there would be more investors with a master's degree. It would also be useful to try different methods, such as Odean's ratio analysis or survival analysis. In order to make the study more complex, risk and return can be added to the model to see how the disposition effect affects investor performance.

REFERENCES

Ammann, M., Ising, A., Kessler, S. (2012). Disposition effect and mutual fund performance. – *Applied Financial Economics*, Vol. 22, pp. 1-19.

Anspal, S., Kraut, L., Rõõm, T. (2010). Sooline palgalõhe Eestis. Talinn: Eesti Rakendusuuringute Keskus CENTRAL, Poliitikauuringute Keskus PRAXIS. https://www.sm.ee/sites/default/files/content-editors/Ministeerium_kontaktid/Uuringu_ja_analuusid/Sotsiaalvaldkond/2_raport.pdf (10.04.2015)

Balti aktsiad. Nasdaq. http://www.nasdaqomxbaltic.com/market/?pg=mainlist&lang=et (03.05.2015)

Barber, B. M., Odean, T. (2001). Boys Will Be Boys: Gender, Overconfidence and Common Stock Investment. – *The Quarterly Journal of Economics*, February 2001, pp. 261-292.

Barberis, N., Xiong, W. (2009). What Drives the Disposition Effect? An Analysis of a Long-Standing Preference-Based Explanation. – *The Journal of Finance*, Vol. LXIV, No. 2, pp. 751-784.

Boolell-Gunesh, S., Broihanne, M-H., Merli, M. (2012). Sophistication of Individual Investors and Disposition Effect Dynamics. - *Revue de l'association française de finance*, Vol. 33, pp. 9-37.

Cici, G. (2012). The Prevalence of the Disposition Effect in Mutual Fund's Trades. – *Journal of Financial and Quantitative Analysis*, Vol. 47, No. 4, pp. 795-820.

Dacey, R., Zielonka, P. (2008). A Detailed Prospect Theory Explanation of the Disposition Effect. – *The Journal of Behavioral Finance*, Vol. 9, pp. 43-50.

Da Costa Jr., N., Mineto, C., Da Silca, S. (2008). Disposition effect and gender. – *Applied Economics Letters*, Vol. 15, pp. 411-461.

Da Costa Jr., N., Goulart, M., Cupertino, C., Macedo Jr., J., Da Silva, S. (2013). The disposition effect and investor experience. – *Journal of Banking and Finance*, Vol. 37, pp. 1669-1675.

Deary, I. J., Johnson, W. (2010). Intelligence and education: causal perceptions drive analytic processes and therefore conclusions. – *International Journal of Epidemiology*, Vol. 39, pp. 1362-1369.

Dhar, R., Zhu, N. (2006). Up Close and Personal: Investor Sophistication and the Disposition Effect. – *Management Science*, Vol. 52, No. 5, pp. 726-740.

Dichtl, H., Drobetz, W. (2011). Dollar-Cost Averaging and Prospect Theory Investors: An Explanation for a Popular Investment Strategy. – *The Journal of Behavioral Finance*, Vol. 12, pp. 41-52.

Feng, L., Seasholes, M. S. (2005). Do Investor Sophistication and Trading Experience Eliminate Behavioural Biases in Financial Markets? – *Review of Finance*, Vol. 9, pp. 305-351.

Goo, Y .J., Chen, D. H., Chang, S. H. S., Yeh, C.F. (2010). A study of the Disposition Effect for Individual Investors in the Taiwan Stock Market. – *Emerging Markets Finance & Trade*, Vol. 46, No. 1, pp. 108-119.

Grinblatt, M., Keloharju, M. (2001). What makes investors trade? – *The Journal of Finance*, Vol. LVI, No. 2, pp. 589-616.

Hens, T., Vlcek, M. (2011). Does Prospect Theory Explain the Disposition Effect? – *The Journal of Behavioral Finance*, Vol. 12, pp. 141-157.

Kadous, K., Tayler, W. B., Thayer, J. M., Young, D. (2014). Individual Characteristics and the Disposition Effect: The Opposing Effects of Confidence and Self-Regard. – *The Journal of Behavioral Finance*, Vol. 15, pp. 235-250.

Kahneman, D., Tversky, A. (1979). Prospect Theory: An Analysis of Decision under Risk. – *Econometrica*, Vol. 47, No. 2, pp. 263-292.

Kaustia, M. (2010). Prospect Theory and the Disposition Effect. – *Journal of Financial and Quantitative Analysis*, Vol. 45, No. 3, pp. 791-812.

Kubińska, E., Markiewicz, L., Tyszka, T. (2012). Disposition Effect Among Contrarian and Momentum Investors. – *The Journal of Behavioral Finance*, Vol. 13, pp. 214-225.

Kumar, A., Lim, S. S. (2008). How Do Decision Frames Influence the Stock Investment Choices of Individual Investors? – *Management Science*, Vol. 54, No. 6, pp. 1052-1064.

Kõrghariduse esimese astme ja integreeritud õppe vastuvõtt 2010. aastal. Vastuvõtustatistika. Tartu Ülikool.
http://www.ut.ee/sites/default/files/ut_files/stat_bak%202010.htm (03.05.2015)

Lee, J-S., Yen, P-H., Chan, K. C. (2013). Market states and disposition effect: evidence from Taiwan mutual fund investors. – *Applied Economics*, Vol. 45, pp. 1311-1342.

Odean, T. (1998). Are Investors Reluctant to Realize their Losses? – *The Journal of Finance*, Vol. LIII, No. 5, pp. 1775-1798.

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

RE konkurss 2010. Statistika. Tallinna Tehnikaülikool http://www.ttu.ee/sisseastujale/uldinfo-6/statistika/ (03.05.2015)

Riigieksamite statistika 2010. Riiklik Eksami- ja Kvalifikatsioonikeskus http://www.ekk.edu.ee/kiirelt-leitav/statistika/riigieksamite-statistika-2010 (03.05.2015)

Seru, A., Shumway, T., Stoffman, N. (2009). Learning by Trading. – *The Review of Financial Studies*, Vol. 23, No. 2, pp. 705-739.

Shapira, Z., Venezia, I. (2001). Patterns of behaviour of professionally managed and independent investors. – *Journal of Banking & Finance*, Vol. 25, No. 8, pp. 1573-1587.

Shefrin, H., Statman, M. (1985). The Disposition to Sell Winners Too Early and Ride Losers Too Long: Theory and Evidence. – *The Journal of Finance*, Vol. XL, No. 3, pp. 777-790.

Stock, J. H., Watson, M. W. (2011). Introduction to Econometrics. 3rd ed. Boston: Pearson Education.

Talpsepp, T. (2010). Does Gender and Age Affect Investor Performance and the Disposition Effect? – *Research in Economics and Business: Central and Eastern Europe*, Vol 2, No. 1, pp. 76-93.

Talpsepp, T. (2011). Reverse Disposition Effect of Foreign Investors. – *The Journal of Behavioral Finance*, Vol. 12, pp. 183-200.

Turukapitalisatsioon. Nasdaq. http://www.nasdaqomxbaltic.com/market/?pg=capital&lang=et (03.05.2015)

Vastuvõtuarvud 2013-2014. Vastuvõtustatistika. Tallinna Ülikool. http://www.tlu.ee/et/sisseastuja/kasulik-teada/vastuvotustatistika (03.05.2015)

RESÜMEE

HARIDUSE JA MUUDE SOTSIAALMAJANDUSLIKE JA KAUPLEMISEGA SEOTUD TEGURITE MÕJU DISPOSITSIOONI EFEKTILE TALLINNA BÖRSIL

Teele Talpsepp

Dispositsiooni efekt on investorite kalduvus müüa kasumis aktsiapositsioone liiga vara ning hoida kahjumis aktsiapositsioone liiga kaua. See on üks levinud investorite irratsionaalse käitumise vorme, mille põhjuseid ei ole veel täielikult leitud. Investorid usuvad, et nende kahjumis positsioonid edestavad tulevikus tootmisnäitajate osas nende praeguseid kasumis positsioone. Et oma portfelli tasakaalustada, realiseerivad nad kasumis aktsiad selle asemel, et nende pealt tulevikus veel suuremat kasumit teenida. Dispositsiooni efekt on mõjutatud investori eelistustest, uskumustest ja psühholoogilistest omadustest.

Uuringus kasutatud andmed sisaldasid individuaalsete investorite tehinguid Tallinna Börsil aastatel 2004 kuni 2010. Informatsioon tehingute kohta oli seotud investorite hariduslike näitajatega. Kuna haridusnäitajaid hakati koguma alates 1990-ndatest, siis on valdav osa investoreid, kes valimisse kuuluvad just noored. Kokku oli informatsioon 6851 investori kohta. Vaatluseks oli iga päev kui investor hoidis või müüs aktsiat. Vaatluste arv kokku oli 5 138 758.

Kasutatavaks meetodiks oli logistiline regressioon, mis võimaldas uurida otsust aktsiat müüa ning erinevaid faktoreid, mis seda mõjutavad. Uuritavateks faktoriteks oli investori sugu, vanus, haridustase, eriala, keskkooli lõpueksamite tulemused, aktsiate arv portfellis ning tehingute hulk.

Hariduse mõju dispositsiooni efektile oli oodatust väiksem. Haridustaseme poolest bakalaureusekraad dispositsiooni efekti ei mõjuta ning kuna magistri- või doktorikraadiga investoreid oli valimist vaid 0,2%, siis on see liiga väike maht, et üldistavaid järeldusi teha. Seetõttu võib öelda, et haridustaseme mõju dispositsiooni efektile on ebaoluline.

Erialadest osutus oluliseks vaid finantsalane haridus, mis mõjutas dispositsiooni efekti vastupidiselt oodatule. Finantsharidusega investorid on dispositsiooni efekti suhtes avatumad. Järelikult haridus ei aita kaasa börsidel otsuste tegemisele. Keskkooli lõpueksamite tulemused, kui intelligentsuse mõõdik, näitasid väga erinevaid tulemusi, mis lõppkokkuvõttes olid suures osas statistiliselt ebaolulised. Seega keskkooli lõpueksamite tulemused antud töö kontekstis usaldusväärseid tulemusi ei andnud. Hariduse mõju osutus oodatust väiksemaks ning seetõttu võib öelda, et investorite otsuseid mõjutavad pigem muud tegurid kui haridus.

Portfelli diversifitseerimine osutus samuti ebaoluliseks, kuigi varasemates uuringutes on see olnud väga levinud tegur mida on uuritud ning mis vähendab dispositsiooni efekti. Selle põhjuseks võib olla Tallinna Börsil kaubeldavate aktsiate väike arv ning samuti turu väike maht.

Hoolimata hariduse väikesest mõjust dispositsiooni efekti suhtes, oli ka tegureid, mis mõjutasid dispositsiooni efekti oodatult. Näiteks mehed on dispositsiooni efekti suhtes vähem avatud kui naised ning vanusega väheneb dispositsiooni efekti mõju. Põhjused võivad peituda Eesti ajaloos. Mehed on ajalooliselt harjunud perekonda ülal pidama ning seetõttu on nende käitumine erinev naiste omast. Samas vanemad investorid on üles kasvanud Nõukogude režiimi ajal, mis võib mõjutada nende otsuseid.

Väga oluliseks tulemuseks oli tehingute arvu mõju dispositsiooni efektile. Mida rohkem tehinguid investor teeb, seda kogenum ta on ning seda vähem on ta mõjutatud dispositsiooni efektist. See on kooskõlas paljude varasemate töödega.

Käesoleva uuringu põhjal mõjutavad dispositsiooni efekti eelkõige investori sugu, vanus ning kogemus ehk tehtud tehingute arv. Edasisteks uuringuteks võiks andmete mahtu suurendada ning uurida hariduslike tegurite mõju kasutades teisi uurimismeetodeid. Samuti võiks arvesse võtta investorite tootlust ning riski ning seeläbi vaadelda kuidas dispositsiooni efekt mõjutab investorite tootlikkust.

APPENDICES

Appendix 1. Stata output of logit model for general disposition effect

```
logit sold loss, or vce(robust)
Iteration 0:   log pseudolikelihood =  -159309.4
Iteration 1:   log pseudolikelihood = -155892.27
Iteration 2:   log pseudolikelihood = -155481.15
Iteration 3:   log pseudolikelihood = -155480.76
Iteration 4:   log pseudolikelihood = -155480.76

Logistic regression                               Number of obs   =    5138758
                                                  Wald chi2(1)    =    7381.10
                                                  Prob > chi2     =     0.0000
Log pseudolikelihood = -155480.76                 Pseudo R2       =     0.0240

------------------------------------------------------------------------------
             |               Robust
        sold | Odds Ratio   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        loss |   .3276844   .0042554   -85.91   0.000     .3194491    .3361319
       _cons |   .0088077   .0000709  -588.02   0.000     .0086698    .0089477
------------------------------------------------------------------------------

logit sold profit, or vce(robust)
Iteration 0:   log pseudolikelihood =  -159309.4
Iteration 1:   log pseudolikelihood = -156003.77
Iteration 2:   log pseudolikelihood = -155622.28
Iteration 3:   log pseudolikelihood = -155621.86
Iteration 4:   log pseudolikelihood = -155621.86

Logistic regression                               Number of obs   =    5138758
                                                  Wald chi2(1)    =    7134.84
                                                  Prob > chi2     =     0.0000
Log pseudolikelihood = -155621.86                 Pseudo R2       =     0.0231

------------------------------------------------------------------------------
             |               Robust
        sold | Odds Ratio   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
      profit |   2.986822   .0386917    84.47   0.000     2.911942    3.063627
       _cons |   .0029247   .0000296  -576.28   0.000     .0028673    .0029834
------------------------------------------------------------------------------
```

Appendix 2. Stata output of logit model for gender influence

```
logit sold loss male male_loss,or vce(robust)
Iteration 0:   log pseudolikelihood =  -159309.4
Iteration 1:   log pseudolikelihood = -155455.82
Iteration 2:   log pseudolikelihood = -154584.37
Iteration 3:   log pseudolikelihood = -154580.91
Iteration 4:   log pseudolikelihood = -154580.91

Logistic regression                               Number of obs   =    5138758
                                                  Wald chi2(3)    =    8590.57
                                                  Prob > chi2     =     0.0000
Log pseudolikelihood = -154580.91                 Pseudo R2       =     0.0297

------------------------------------------------------------------------------
             |               Robust
        sold | Odds Ratio   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        loss |   .2765623   .0106502   -33.38   0.000     .2564565    .2982443
        male |   1.965835   .0490063    27.11   0.000     1.872093    2.064271
   male_loss |   1.231601   .0503805     5.09   0.000     1.136712    1.334411
       _cons |   .0049899   .0001168  -226.42   0.000     .0047661    .0052241
------------------------------------------------------------------------------

logit sold profit male male_profit ,or vce(robust)
Iteration 0:   log pseudolikelihood =  -159309.4
Iteration 1:   log pseudolikelihood = -155544.46
Iteration 2:   log pseudolikelihood = -154721.75
Iteration 3:   log pseudolikelihood = -154718.53
Iteration 4:   log pseudolikelihood = -154718.53

Logistic regression                               Number of obs   =    5138758
                                                  Wald chi2(3)    =    8341.08
                                                  Prob > chi2     =     0.0000
Log pseudolikelihood = -154718.53                 Pseudo R2       =     0.0288

------------------------------------------------------------------------------
             |               Robust
        sold | Odds Ratio   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
      profit |   3.574047   .1374235    33.13   0.000       3.3146    3.853801
        male |   2.437239   .0787244    27.58   0.000     2.287725    2.596525
 male_profit |    .802968   .0327925    -5.37   0.000     .7412009    .8698823
       _cons |   .0013902   .0000424  -215.94   0.000     .0013096    .0014758
------------------------------------------------------------------------------
```

Appendix 3. Stata output of logit model for age influence

```
logit sold loss age25  age25_loss age26_30 age26_30_loss age36 age36_loss ,or vce(robust)

Iteration 0:   log pseudolikelihood =  -159309.4
Iteration 1:   log pseudolikelihood = -155707.82
Iteration 2:   log pseudolikelihood = -155090.46
Iteration 3:   log pseudolikelihood = -155089.76
Iteration 4:   log pseudolikelihood = -155089.76

Logistic regression                               Number of obs   =    5138758
                                                  Wald chi2(7)    =    7946.24
                                                  Prob > chi2     =     0.0000
Log pseudolikelihood = -155089.76                 Pseudo R2       =     0.0265

--------------------------------------------------------------------------------
              |               Robust
         sold | Odds Ratio   Std. Err.      z    P>|z|     [95% Conf. Interval]
--------------+-----------------------------------------------------------------
         loss |   .3156396   .0061103   -59.57   0.000       .303888    .3278457
        age25 |   .6386942   .0181764   -15.75   0.000      .6040445    .6753315
   age25_loss |   .9421467   .0432223    -1.30   0.194      .8611294    1.030786
     age26_30 |   1.074749   .0190113     4.08   0.000      1.038126    1.112664
age26_30_loss |    1.09808   .0313181     3.28   0.001      1.038382    1.161211
        age36 |   .9778311   .0325278    -0.67   0.500      .9161118    1.043709
   age36_loss |   1.269294   .0679438     4.45   0.000      1.142874    1.409698
        _cons |   .0090709   .0001078  -395.83   0.000      .0088621    .0092846
--------------------------------------------------------------------------------
```

```
logit sold profit age25  age25_profit age26_30 age26_30_profit age36 age36_profit ,or vce(robust)

Iteration 0:   log pseudolikelihood =  -159309.4
Iteration 1:   log pseudolikelihood = -155808.11
Iteration 2:   log pseudolikelihood = -155230.51
Iteration 3:   log pseudolikelihood =  -155229.9
Iteration 4:   log pseudolikelihood =  -155229.9

Logistic regression                               Number of obs   =    5138758
                                                  Wald chi2(7)    =    7702.40
                                                  Prob > chi2     =     0.0000
Log pseudolikelihood =  -155229.9                 Pseudo R2       =     0.0256
```

Appendix 3 continuing

sold	Odds Ratio	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
profit	3.106994	.0600026	58.70	0.000	2.991589	3.226851
age25	.6025769	.0215376	-14.17	0.000	.5618087	.6463034
age25_profit	1.058693	.048449	1.25	0.213	.9678688	1.15804
age26_30	1.184341	.0263103	7.62	0.000	1.133881	1.237048
age26_30_profit	.9049574	.025743	-3.51	0.000	.8558827	.9568459
age36	1.233369	.0515474	5.02	0.000	1.136365	1.338653
age36_profit	.795762	.0425419	-4.27	0.000	.7166011	.8836677
_cons	.0028983	.000044	-384.68	0.000	.0028133	.0029859

Appendix 4. Stata output of logit model for master and doctoral influence

```
logit sold loss master_doctor master_doctor_loss ,or vce(robust)
Iteration 0:   log pseudolikelihood =  -159309.4
Iteration 1:   log pseudolikelihood = -155868.85
Iteration 2:   log pseudolikelihood =  -155440.3
Iteration 3:   log pseudolikelihood = -155438.43
Iteration 4:   log pseudolikelihood = -155438.39
Iteration 5:   log pseudolikelihood = -155438.39

Logistic regression                               Number of obs   =    5138758
                                                  Wald chi2(3)    =    7414.41
                                                  Prob > chi2     =     0.0000
Log pseudolikelihood = -155438.39                 Pseudo R2       =     0.0243

------------------------------------------------------------------------------------
                   |               Robust
              sold | Odds Ratio   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------------+----------------------------------------------------------------
              loss |   .3278666   .0042608   -85.81   0.000     .3196209    .3363249
     master_doctor |   .4324378   .0694651    -5.22   0.000     .3156386    .5924577
master_doctor_loss |   .3671692   .1508652    -2.44   0.015     .1641037    .8215128
             _cons |   .0088366   .0000712  -586.87   0.000     .0086981    .0089773
```

```
logit sold profit master_doctor master_doctor_profit, or vce(robust)
Iteration 0:   log pseudolikelihood =  -159309.4
Iteration 1:   log pseudolikelihood = -155979.85
Iteration 2:   log pseudolikelihood = -155581.35
Iteration 3:   log pseudolikelihood = -155579.45
Iteration 4:   log pseudolikelihood = -155579.41
Iteration 5:   log pseudolikelihood = -155579.41

Logistic regression                               Number of obs   =    5138758
                                                  Wald chi2(3)    =    7167.76
                                                  Prob > chi2     =     0.0000
Log pseudolikelihood = -155579.41                 Pseudo R2       =     0.0234
--------------------------------------------------------------------------------------
                     |               Robust
                sold | Odds Ratio   Std. Err.      z    P>|z|     [95% Conf. Interval]
---------------------+----------------------------------------------------------------
              profit |   2.985081    .038697    84.36   0.000     2.910192    3.061898
       master_doctor |   .1566811   .0592543    -4.90   0.000      .074663    .3287967
master_doctor_profit |    2.78279   1.143411     2.49   0.013      1.24375    6.226265
               _cons |    .002936   .0000297  -575.69   0.000     .0028783    .0029949
--------------------------------------------------------------------------------------
```

Appendix 5. Stata output of logit model financial education influence

```
logit sold loss finance finance_loss ,or vce(robust)
Iteration 0:   log pseudolikelihood =  -159309.4
Iteration 1:   log pseudolikelihood = -155885.46
Iteration 2:   log pseudolikelihood = -155460.33
Iteration 3:   log pseudolikelihood = -155459.81
Iteration 4:   log pseudolikelihood = -155459.81

Logistic regression                               Number of obs   =    5138758
                                                  Wald chi2(3)    =    7400.48
                                                  Prob > chi2     =     0.0000
Log pseudolikelihood = -155459.81                 Pseudo R2       =     0.0242

------------------------------------------------------------------------------
             |               Robust
        sold | Odds Ratio   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        loss |   .3309364   .0043251   -84.61   0.000     .3225671    .3395229
     finance |   1.213495   .0718282     3.27   0.001     1.080573    1.362767
finance_loss |   .4695747   .0585235    -6.07   0.000     .3678058    .5995021
       _cons |   .0087784   .0000713  -582.87   0.000     .0086397    .0089193
------------------------------------------------------------------------------
```

```
logit sold profit finance finance_profit ,or vce(robust)
Iteration 0:   log pseudolikelihood =  -159309.4
Iteration 1:   log pseudolikelihood = -155996.69
Iteration 2:   log pseudolikelihood = -155601.68
Iteration 3:   log pseudolikelihood = -155601.14
Iteration 4:   log pseudolikelihood = -155601.14

Logistic regression                               Number of obs   =    5138758
                                                  Wald chi2(3)    =    7154.89
                                                  Prob > chi2     =     0.0000
Log pseudolikelihood = -155601.14                 Pseudo R2       =     0.0233

--------------------------------------------------------------------------------
               |               Robust
          sold | Odds Ratio   Std. Err.      z    P>|z|     [95% Conf. Interval]
---------------+----------------------------------------------------------------
        profit |   2.957669   .0385608    83.18   0.000     2.883049    3.034221
       finance |   .5757028   .0624112    -5.09   0.000     .4655011    .7119934
finance_profit |   2.110842   .2609267     6.04   0.000     1.656672    2.689521
         _cons |   .0029437   .0000299  -573.10   0.000     .0028856    .0030029
--------------------------------------------------------------------------------
```

Appendix 6. Stata output of logit model for IT education influence

```
logit sold loss it it_loss, or vce(robust)
Iteration 0:   log pseudolikelihood =  -159309.4
Iteration 1:   log pseudolikelihood = -155888.12
Iteration 2:   log pseudolikelihood = -155475.95
Iteration 3:   log pseudolikelihood = -155475.57
Iteration 4:   log pseudolikelihood = -155475.57

Logistic regression                               Number of obs   =    5138758
                                                  Wald chi2(3)    =    7384.82
                                                  Prob > chi2     =     0.0000
Log pseudolikelihood = -155475.57                 Pseudo R2       =     0.0241

------------------------------------------------------------------------------
             |               Robust
        sold | Odds Ratio   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        loss |   .3244775   .0043957   -83.08   0.000     .3159755    .3332083
          it |    .992591   .0286718    -0.26   0.797     .9379565    1.050408
     it_loss |   1.140156   .0542886     2.75   0.006     1.038566    1.251682
       _cons |   .0088132   .0000741  -562.46   0.000     .0086691    .0089597
------------------------------------------------------------------------------

logit sold profit it it_profit,or vce(robust)
Iteration 0:   log pseudolikelihood =  -159309.4
Iteration 1:   log pseudolikelihood = -155998.93
Iteration 2:   log pseudolikelihood = -155616.23
Iteration 3:   log pseudolikelihood = -155615.82
Iteration 4:   log pseudolikelihood = -155615.82

Logistic regression                               Number of obs   =    5138758
                                                  Wald chi2(3)    =    7139.50
                                                  Prob > chi2     =     0.0000
Log pseudolikelihood = -155615.82                 Pseudo R2       =     0.0232

------------------------------------------------------------------------------
             |               Robust
        sold | Odds Ratio   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
      profit |   3.019363   .0408077    81.76   0.000     2.940431    3.100414
          it |   1.140924   .0427543     3.52   0.000      1.06013    1.227875
   it_profit |   .8663344   .0410801    -3.03   0.002     .7894471    .9507102
       _cons |   .0028961   .0000306  -553.89   0.000     .0028368    .0029566
------------------------------------------------------------------------------
```

Appendix 7. Stata output of logit model for history high school final exam results

```
logit  sold  loss  history_exam_0_25  history_exam_25_50  history_exam_50_75  history_exam_75_100
history_exam_0_25_loss  history_exam_25_50_loss  history_exam_50_75_loss  history_exam_75_100_loss,
or vce(robust)
Iteration 0:   log pseudolikelihood =  -159309.4
Iteration 1:   log pseudolikelihood = -155942.19
Iteration 2:   log pseudolikelihood = -155347.38
Iteration 3:   log pseudolikelihood = -155344.13
Iteration 4:   log pseudolikelihood = -155344.13

Logistic regression                               Number of obs   =    5138758
                                                  Wald chi2(9)    =    7698.15
                                                  Prob > chi2     =     0.0000
Log pseudolikelihood = -155344.13                 Pseudo R2       =     0.0249

-----------------------------------------------------------------------------------------
                         |               Robust
                    sold | Odds Ratio   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------------------+---------------------------------------------------------------
                    loss |   .3362005   .0055986   -65.46   0.000     .3254047    .3473545
       history_exam_0_25 |    .720159    .036113    -6.55   0.000      .652746    .7945342
      history_exam_25_50 |   1.348328   .0372197    10.83   0.000     1.277317    1.423286
      history_exam_50_75 |     .87277   .0243923    -4.87   0.000     .8262478    .9219117
     history_exam_75_100 |   .9803922   .0215088    -0.90   0.367     .9391293    1.023468
  history_exam_0_25_loss |   1.290824    .093065     3.54   0.000     1.120721    1.486744
 history_exam_25_50_loss |   .8712546   .0395904    -3.03   0.002     .7970138    .9524107
 history_exam_50_75_loss |   .9622136   .0430906    -0.86   0.390     .8813579    1.050487
history_exam_75_100_loss |    .905358   .0327456    -2.75   0.006     .8433998    .9718679
                   _cons |   .0088275   .0000913  -457.15   0.000     .0086503    .0090084
-----------------------------------------------------------------------------------------
logit  sold  profit  history_exam_0_25  history_exam_25_50  history_exam_50_75  history_exam_75_100
history_exam_0_25_profit            history_exam_25_50_profit            history_exam_50_75_profit
history_exam_75_100_profit, or vce(robust)
Iteration 0:   log pseudolikelihood =  -159309.4
Iteration 1:   log pseudolikelihood = -156048.63
Iteration 2:   log pseudolikelihood = -155488.91
Iteration 3:   log pseudolikelihood = -155485.85
Iteration 4:   log pseudolikelihood = -155485.85

Logistic regression                               Number of obs   =    5138758
                                                  Wald chi2(9)    =    7450.76
                                                  Prob > chi2     =     0.0000
Log pseudolikelihood = -155485.85                 Pseudo R2       =     0.0240
```

Appendix 7 continuing

sold	Odds Ratio	Robust Std. Err.	z	P>|z|	[95% Conf. Interval]	
profit	2.904972	.0482454	64.21	0.000	2.811935	3.001087
history_exam_0_25	.9161184	.0474348	-1.69	0.091	.8277098	1.01397
history_exam_25_50	1.16811	.0419592	4.33	0.000	1.0887	1.253312
history_exam_50_75	.834576	.0290686	-5.19	0.000	.7795037	.8935391
history_exam_75_100	.8901943	.0253824	-4.08	0.000	.8418103	.9413593
history_exam_0_25_profit	.7933589	.057191	-3.21	0.001	.6888251	.9137563
history_exam_25_50_profit	1.158984	.0525602	3.25	0.001	1.060413	1.266717
history_exam_50_75_profit	1.049762	.0469332	1.09	0.277	.9616895	1.1459
history_exam_75_100_profit	1.100357	.0396598	2.65	0.008	1.025308	1.1809
_cons	.0030113	.000039	-448.18	0.000	.0029358	.0030887

Appendix 8. Stata output of logit model for physics high school final exam results

```
logit sold loss physics_exam_0_25 physics_exam_25_50 physics_exam_50_75 physics_exam_75_100
physics_exam_0_25_loss physics_exam_25_50_loss physics_exam_50_75_loss physics_exam_75_100_loss,
or vce(robust)
Iteration 0:   log pseudolikelihood =  -159309.4
Iteration 1:   log pseudolikelihood = -155909.09
Iteration 2:   log pseudolikelihood = -155413.15
Iteration 3:   log pseudolikelihood = -155411.77
Iteration 4:   log pseudolikelihood = -155411.77

Logistic regression                               Number of obs   =    5138758
                                                  Wald chi2(9)    =    7542.41
                                                  Prob > chi2     =     0.0000
Log pseudolikelihood = -155411.77                 Pseudo R2       =     0.0245

------------------------------------------------------------------------------------------
                         |               Robust
                    sold | Odds Ratio   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------------------+----------------------------------------------------------------
                    loss |    .327805   .0045885   -79.68   0.000      .318934    .3369227
       physics_exam_0_25 |   .7588843   .0701113    -2.99   0.003     .6331918    .9095275
      physics_exam_25_50 |   1.028042   .0511791     0.56   0.579     .9324715    1.133408
      physics_exam_50_75 |    1.31102   .0469054     7.57   0.000     1.222236    1.406253
     physics_exam_75_100 |    .820093   .0284829    -5.71   0.000     .7661252    .8778624
  physics_exam_0_25_loss |   1.191242   .1715357     1.22   0.224     .8983163    1.579686
 physics_exam_25_50_loss |   1.317923   .1023963     3.55   0.000     1.131764    1.534703
 physics_exam_50_75_loss |   .7390247   .0454493    -4.92   0.000      .655105    .8336946
physics_exam_75_100_loss |   1.068906   .0613667     1.16   0.246     .9551491     1.19621
                   _cons |   .0088204   .0000768  -543.32   0.000     .0086712    .0089722
------------------------------------------------------------------------------------------
logit sold profit physics_exam_0_25 physics_exam_25_50 physics_exam_50_75 physics_exam_75_100
physics_exam_0_25_profit           physics_exam_25_50_profit           physics_exam_50_75_profit
physics_exam_75_100_profit, or vce(robust)
Iteration 0:   log pseudolikelihood =  -159309.4
Iteration 1:   log pseudolikelihood = -156016.43
Iteration 2:   log pseudolikelihood = -155554.92
Iteration 3:   log pseudolikelihood = -155553.66
Iteration 4:   log pseudolikelihood = -155553.66

Logistic regression                               Number of obs   =    5138758
                                                  Wald chi2(9)    =    7294.36
                                                  Prob > chi2     =     0.0000
Log pseudolikelihood = -155553.66                 Pseudo R2       =     0.0236
```

Appendix 8 continuing

sold	Odds Ratio	Robust Std. Err.	z	P>|z|	[95% Conf. Interval]	
profit	2.986188	.0416991	78.34	0.000	2.905568	3.069046
physics_exam_0_25	.9134407	.0997063	-0.83	0.407	.7375097	1.13134
physics_exam_25_50	1.350629	.0801527	5.06	0.000	1.202325	1.517226
physics_exam_50_75	.9743309	.048288	-0.52	0.600	.8841395	1.073723
physics_exam_75_100	.8752759	.0397772	-2.93	0.003	.8006853	.9568152
physics_exam_0_25_profit	.8240364	.1182556	-1.35	0.177	.6220028	1.091693
physics_exam_25_50_profit	.7622518	.0591319	-3.50	0.000	.6547361	.8874229
physics_exam_50_75_profit	1.343979	.0822833	4.83	0.000	1.192007	1.515326
physics_exam_75_100_profit	.938489	.0537467	-1.11	0.268	.8388444	1.04997
_cons	.0029296	.0000319	-535.72	0.000	.0028677	.0029928

Appendix 9. Stata output of logit model for English high school final exam results

```
logit sold loss english_exam_0_25 english_exam_25_50 english_exam_50_75 english_exam_75_100
english_exam_0_25_loss english_exam_25_50_loss english_exam_50_75_loss english_exam_75_100_loss,
or vce(robust)
Iteration 0:   log pseudolikelihood =  -159309.4
Iteration 1:   log pseudolikelihood = -155845.23
Iteration 2:   log pseudolikelihood = -155308.05
Iteration 3:   log pseudolikelihood = -155307.65
Iteration 4:   log pseudolikelihood = -155307.65

Logistic regression                               Number of obs   =    5138758
                                                  Wald chi2(9)    =    7686.21
                                                  Prob > chi2     =     0.0000
Log pseudolikelihood = -155307.65                 Pseudo R2       =     0.0251
```

sold	Odds Ratio	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
loss	.3426758	.0092441	-39.70	0.000	.3250284	.3612814
english_exam_0_25	.9450522	.027781	-1.92	0.055	.8921413	1.001101
english_exam_25_50	.926004	.0240392	-2.96	0.003	.8800666	.9743393
english_exam_50_75	1.016782	.0243851	0.69	0.488	.9700934	1.065717
english_exam_75_100	.7790467	.0175176	-11.10	0.000	.7454585	.8141484
english_exam_0_25_loss	1.06385	.0483435	1.36	0.173	.9731955	1.162949
english_exam_25_50_loss	.8301272	.0356861	-4.33	0.000	.7630493	.9031017
english_exam_50_75_loss	.9311307	.0361213	-1.84	0.066	.8629588	1.004688
english_exam_75_100_loss	.9633884	.0353625	-1.02	0.310	.8965136	1.035252
_cons	.0096385	.000159	-281.31	0.000	.0093318	.0099554

```
logit sold profit english_exam_0_25 english_exam_25_50 english_exam_50_75 english_exam_75_100
english_exam_0_25_profit english_exam_25_50_profit english_exam_50_75_profit
english_exam_75_100_profit, or vce(robust)
Iteration 0:   log pseudolikelihood =  -159309.4
Iteration 1:   log pseudolikelihood = -155950.45
Iteration 2:   log pseudolikelihood = -155448.94
Iteration 3:   log pseudolikelihood = -155448.58
Iteration 4:   log pseudolikelihood = -155448.58

Logistic regression                               Number of obs   =    5138758
                                                  Wald chi2(9)    =    7440.69
                                                  Prob > chi2     =     0.0000
Log pseudolikelihood = -155448.58                 Pseudo R2       =     0.0242
```

Appendix 9 continuing

sold	Odds Ratio	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
profit	2.866729	.0771599	39.13	0.000	2.719418	3.022019
english_exam_0_25	1.008916	.0347288	0.26	0.796	.9430945	1.079332
english_exam_25_50	.7699083	.0262207	-7.68	0.000	.7201944	.8230539
english_exam_50_75	.9502475	.0287845	-1.68	0.092	.8954729	1.008372
english_exam_75_100	.7521146	.021688	-9.88	0.000	.7107857	.7958465
english_exam_0_25_p~t	.9319672	.0422768	-1.55	0.120	.852683	1.018624
english_exam_25_50_~t	1.202178	.0515468	4.29	0.000	1.105277	1.307575
english_exam_50_75_~t	1.067077	.0412931	1.68	0.093	.9891368	1.151158
english_exam_75_100~t	1.034388	.0378769	0.92	0.356	.9627518	1.111354
_cons	.0033401	.0000709	-268.68	0.000	.003204	.0034819

Appendix 10. Stata output of logit model for mathematics high school final exam results

```
logit sold loss math_exam_0_25 math_exam_25_50 math_exam_50_75 math_exam_75_100 math_exam_0_25_loss math_exam_25_50_loss math_exam_50_75_loss math_exam_75_100_loss, or vce(robust)
Iteration 0:   log pseudolikelihood =  -159309.4
Iteration 1:   log pseudolikelihood = -155873.21
Iteration 2:   log pseudolikelihood = -155370.02
Iteration 3:   log pseudolikelihood = -155369.03
Iteration 4:   log pseudolikelihood = -155369.03

Logistic regression                               Number of obs   =    5138758
                                                  Wald chi2(9)    =    7563.27
                                                  Prob > chi2     =     0.0000
Log pseudolikelihood = -155369.03                 Pseudo R2       =     0.0247

-----------------------------------------------------------------------------------
                      |               Robust
                 sold | Odds Ratio   Std. Err.      z    P>|z|     [95% Conf. Interval]
----------------------+------------------------------------------------------------
                 loss |   .3427666   .0078262   -46.89   0.000     .3277656    .3584541
       math_exam_0_25 |   1.059433   .0319013     1.92   0.055     .9987172     1.12384
      math_exam_25_50 |   1.230339   .0324075     7.87   0.000     1.168433    1.295525
      math_exam_50_75 |   .9747107   .0233745    -1.07   0.285     .9299575    1.021618
     math_exam_75_100 |   .9609971   .0200549    -1.91   0.057     .9224833    1.001119
  math_exam_0_25_loss |   1.189926   .0562649     3.68   0.000     1.084604    1.305474
 math_exam_25_50_loss |   .8813101   .0370248    -3.01   0.003     .8116502    .9569486
 math_exam_50_75_loss |   .8887438   .0342702    -3.06   0.002      .824051    .9585154
math_exam_75_100_loss |   .9103998   .0309402    -2.76   0.006     .8517337    .9731067
                _cons |   .0086837   .0001259  -327.35   0.000     .0084404     .008934
-----------------------------------------------------------------------------------
logit sold profit math_exam_0_25 math_exam_25_50 math_exam_50_75 math_exam_75_100 math_exam_0_25_profit math_exam_25_50_profit math_exam_50_75_profit math_exam_75_100_profit, or vce(robust)
Iteration 0:   log pseudolikelihood =  -159309.4
Iteration 1:   log pseudolikelihood = -155979.58
Iteration 2:   log pseudolikelihood = -155512.79
Iteration 3:   log pseudolikelihood = -155511.91
Iteration 4:   log pseudolikelihood = -155511.91

Logistic regression                               Number of obs   =    5138758
                                                  Wald chi2(9)    =    7314.29
                                                  Prob > chi2     =     0.0000
Log pseudolikelihood = -155511.91                 Pseudo R2       =     0.0238
```

Appendix 10 continuing

sold	Odds Ratio	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
profit	2.862711	.0652439	46.15	0.000	2.737649	2.993486
math_exam_0_25	1.257725	.0456332	6.32	0.000	1.171392	1.350421
math_exam_25_50	1.091442	.0354352	2.70	0.007	1.024154	1.163151
math_exam_50_75	.8697907	.0260806	-4.65	0.000	.8201468	.9224396
math_exam_75_100	.8768982	.0233724	-4.93	0.000	.8322652	.9239248
math_exam_0_25_profit	.8435903	.0398283	-3.60	0.000	.7690311	.9253781
math_exam_25_50_profit	1.123108	.0470508	2.77	0.006	1.034574	1.219217
math_exam_50_75_profit	1.118689	.0430257	2.92	0.004	1.037461	1.206278
math_exam_75_100_profit	1.096117	.0371589	2.71	0.007	1.025654	1.171421
_cons	.0030104	.0000528	-331.04	0.000	.0029087	.0031157

Appendix 11. Stata output of logit model for number of trades

```
logit sold loss trades1_2 trades3_5 trades6_15 trades1_2_loss trades3_5_loss trades6_15_loss,or
vce(robust)
Iteration 0:   log pseudolikelihood =  -159309.4
Iteration 1:   log pseudolikelihood = -158049.47
Iteration 2:   log pseudolikelihood = -152241.87
Iteration 3:   log pseudolikelihood =  -152175.7
Iteration 4:   log pseudolikelihood = -152175.51
Iteration 5:   log pseudolikelihood = -152175.51

Logistic regression                               Number of obs   =    5138758
                                                  Wald chi2(7)    =   13404.41
                                                  Prob > chi2     =     0.0000
Log pseudolikelihood = -152175.51                 Pseudo R2       =     0.0448

--------------------------------------------------------------------------------
                |               Robust
           sold | Odds Ratio   Std. Err.      z    P>|z|     [95% Conf. Interval]
----------------+---------------------------------------------------------------
           loss |    .403822   .0077464   -47.27   0.000     .3889212    .4192937
      trades1_2 |   .3305808   .0084937   -43.08   0.000     .3143458    .3476544
      trades3_5 |   .3550293   .0085898   -42.80   0.000     .3385864    .3722706
     trades6_15 |   .4697594   .0092088   -38.54   0.000     .4520527    .4881595
 trades1_2_loss |   .8405961   .0331554    -4.40   0.000     .7780611    .9081572
 trades3_5_loss |   .6810315   .0270844    -9.66   0.000     .6299633    .7362395
trades6_15_loss |   .8155559   .0260932    -6.37   0.000     .7659846    .8683352
          _cons |   .0159682   .0001888  -349.89   0.000     .0156024    .0163426
--------------------------------------------------------------------------------

logit sold profit trades1_2 trades3_5 trades6_15 trades1_2_profit trades3_5_profit
trades6_15_profit,or vce(robust)
Iteration 0:   log pseudolikelihood =  -159309.4
Iteration 1:   log pseudolikelihood =  -157932.9
Iteration 2:   log pseudolikelihood = -152367.52
Iteration 3:   log pseudolikelihood = -152308.06
Iteration 4:   log pseudolikelihood = -152307.91
Iteration 5:   log pseudolikelihood = -152307.91

Logistic regression                               Number of obs   =    5138758
                                                  Wald chi2(7)    =   13204.53
                                                  Prob > chi2     =     0.0000
Log pseudolikelihood = -152307.91                 Pseudo R2       =     0.0439
```

Appendix 11 continuing

sold	Odds Ratio	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
profit	2.428912	.0464845	46.37	0.000	2.339491	2.52175
trades1_2	.2787279	.0082815	-43.00	0.000	.2629601	.2954413
trades3_5	.2425357	.0076	-45.21	0.000	.2280882	.2578983
trades6_15	.3836218	.0096375	-38.14	0.000	.3651902	.4029837
trades1_2_profit	1.180813	.0464915	4.22	0.000	1.093118	1.275542
trades3_5_profit	1.461673	.0579583	9.57	0.000	1.352378	1.579799
trades6_15_profit	1.22376	.0390533	6.33	0.000	1.149561	1.302747
_cons	.0065265	.000098	-335.14	0.000	.0063373	.0067214

Appendix 12. Stata output of logit model for all variables

```
logit sold loss male male_loss age25 age26_30 age36 age25_loss age26_30_loss age36_loss
master_doctor master_doctor_loss finance finance_loss trades1_2 trades3_5 trades6_15
trades1_2_loss trades3_5_loss trades6_15_loss,or vce(robust)

Iteration 0:   log pseudolikelihood =  -159309.4
Iteration 1:   log pseudolikelihood = -157994.38
Iteration 2:   log pseudolikelihood = -151548.78
Iteration 3:   log pseudolikelihood = -151465.49
Iteration 4:   log pseudolikelihood = -151465.15
Iteration 5:   log pseudolikelihood = -151465.15

Logistic regression                               Number of obs   =    5138758
                                                  Wald chi2(19)   =   14331.93
                                                  Prob > chi2     =     0.0000
Log pseudolikelihood = -151465.15                 Pseudo R2       =     0.0492

------------------------------------------------------------------------------------
                   |               Robust
              sold | Odds Ratio   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------------+----------------------------------------------------------------
              loss |   .3409006   .0158077   -23.21   0.000     .3112842    .3733348
              male |   1.647972   .0432522    19.03   0.000     1.565343    1.734964
         male_loss |   1.165084   .0493494     3.61   0.000     1.072267    1.265936
             age25 |   .8188048   .0236588    -6.92   0.000     .7737231    .8665133
          age26_30 |   1.118712   .0198103     6.33   0.000      1.08055    1.158221
             age36 |   1.012214   .0341886     0.36   0.719     .9473759     1.08149
        age25_loss |   .9658625   .0449489    -0.75   0.455     .8816627    1.058104
     age26_30_loss |   1.096774   .0313445     3.23   0.001     1.037028    1.159961
        age36_loss |   1.220889   .0660407     3.69   0.000     1.098077    1.357437
     master_doctor |   .4339972   .0706956    -5.12   0.000     .3153779    .5972314
master_doctor_loss |   .3134166    .129819    -2.80   0.005     .1391712     .705821
           finance |   1.612048   .0981087     7.85   0.000     1.430784    1.816276
      finance_loss |   .5813439   .0736786    -4.28   0.000     .4534748     .745269
         trades1_2 |   .3608195   .0094033   -39.11   0.000     .3428521    .3797286
         trades3_5 |   .3851115   .0095109   -38.64   0.000     .3669145    .4042111
        trades6_15 |   .4921362    .009704   -35.96   0.000     .4734796     .511528
    trades1_2_loss |   .8795992   .0351552    -3.21   0.001     .8133259    .9512729
    trades3_5_loss |   .6930345   .0280086    -9.07   0.000     .6402565     .750163
   trades6_15_loss |    .813611   .0261119    -6.43   0.000     .7640089    .8664333
             _cons |   .0098298   .0002826  -160.80   0.000     .0092913    .0103996
------------------------------------------------------------------------------------
```

Appendix 12 continuing

```
logit sold profit male male_profit age25 age26_30 age36 age25_profit age26_30_profit age36_profit master_doctor master_doctor_profit finance finance_profit trades1_2 trades3_5 trades6_15 trades1_2_profit trades3_5_profit trades6_15_profit,or vce(robust)

Iteration 0:   log pseudolikelihood =  -159309.4
Iteration 1:   log pseudolikelihood = -157843.72
Iteration 2:   log pseudolikelihood = -151669.56
Iteration 3:   log pseudolikelihood = -151594.95
Iteration 4:   log pseudolikelihood = -151594.67
Iteration 5:   log pseudolikelihood = -151594.67

Logistic regression                               Number of obs   =    5138758
                                                  Wald chi2(19)   =   14124.84
                                                  Prob > chi2     =     0.0000
Log pseudolikelihood = -151594.67                 Pseudo R2       =     0.0484
```

sold	Odds Ratio	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
profit	2.914649	.1349594	23.10	0.000	2.661781	3.191539
male	1.934327	.0640461	19.93	0.000	1.812785	2.064018
male_profit	.8478848	.0358623	-3.90	0.000	.7804307	.9211692
age25	.7918239	.0286832	-6.44	0.000	.7375552	.8500856
age26_30	1.230991	.0274119	9.33	0.000	1.178421	1.285907
age36	1.228788	.0517359	4.89	0.000	1.131458	1.334489
age25_profit	1.033174	.0479566	0.70	0.482	.9433292	1.131575
age26_30_profit	.9065419	.0258381	-3.44	0.001	.8572887	.9586249
age36_profit	.8264829	.0446504	-3.53	0.000	.7434437	.9187971
master_doctor	.1352818	.0515143	-5.25	0.000	.064137	.285345
master_doctor_profit	3.223336	1.33504	2.83	0.005	1.431381	7.258651
finance	.9492466	.1042982	-0.47	0.635	.7653385	1.177347
finance_profit	1.697766	.2134288	4.21	0.000	1.327003	2.172119
trades1_2	.3184761	.0095809	-38.03	0.000	.3002408	.3378188
trades3_5	.267736	.0085004	-41.51	0.000	.2515833	.2849258
trades6_15	.4009319	.0100857	-36.33	0.000	.3816437	.4211949
trades1_2_profit	1.1276	.0449869	3.01	0.003	1.042787	1.219312
trades3_5_profit	1.435948	.0578572	8.98	0.000	1.326912	1.553944
trades6_15_profit	1.226542	.0392634	6.38	0.000	1.151951	1.305962
_cons	.0033653	.000122	-157.13	0.000	.0031346	.003613

Appendix 13. Stata output of specification error test

```
Loss side
linktest,nolog

Logistic regression                               Number of obs   =    5138758
                                                  LR chi2(2)      =   15688.95
                                                  Prob > chi2     =     0.0000
Log likelihood = -151464.93                       Pseudo R2       =     0.0492

------------------------------------------------------------------------------
        sold |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        _hat |   .9332668   .1006241     9.27   0.000     .7360472    1.130486
      _hatsq |  -.0064215     .00965    -0.67   0.506     -.025335    .0124921
       _cons |  -.1694912   .2581829    -0.66   0.512    -.6755204     .336538
------------------------------------------------------------------------------

Profit side
linktest,nolog

Logistic regression                               Number of obs   =    5138758
                                                  LR chi2(2)      =   15429.89
                                                  Prob > chi2     =     0.0000
Log likelihood = -151594.45                       Pseudo R2       =     0.0484

------------------------------------------------------------------------------
        sold |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        _hat |   .9331712   .1020237     9.15   0.000     .7332084    1.133134
      _hatsq |  -.0064301   .0097835    -0.66   0.511    -.0256053    .0127452
       _cons |  -.1698168   .2618719    -0.65   0.517    -.6830764    .3434427
------------------------------------------------------------------------------
```

Appendix 14. Stata output of collinearity diagnostics

```
collin sold loss male male_loss age25 age26_30 age36 age25_loss age26_30_loss age36_loss master_doctor master_doctor_loss finance finance_loss trades1_2 trades3_5 trades6_15 trades1_2_loss trades3_5_loss trades6_15_loss
(obs=5138758)
```

Collinearity Diagnostics

Variable	VIF	SQRT VIF	Tolerance	R-Squared
sold	1.00	1.00	0.9964	0.0036
loss	10.13	3.18	0.0987	0.9013
male	3.21	1.79	0.3115	0.6885
male_loss	6.91	2.63	0.1447	0.8553
age25	3.55	1.89	0.2814	0.7186
age26_30	3.35	1.83	0.2988	0.7012
age36	2.85	1.69	0.3504	0.6496
age25_loss	3.80	1.95	0.2633	0.7367
age26_30_loss	3.93	1.98	0.2547	0.7453
age36_loss	2.90	1.70	0.3444	0.6556
master_doctor	2.56	1.60	0.3903	0.6097
master_doctor_loss	2.57	1.60	0.3889	0.6111
finance	2.88	1.70	0.3477	0.6523
finance_loss	2.89	1.70	0.3455	0.6545
trades1_2	4.68	2.16	0.2136	0.7864
trades3_5	4.55	2.13	0.2199	0.7801
trades6_15	4.35	2.09	0.2300	0.7700
trades1_2_loss	5.49	2.34	0.1821	0.8179
trades3_5_loss	5.30	2.30	0.1885	0.8115
trades6_15_loss	5.20	2.28	0.1923	0.8077
Mean VIF	4.11			

Appendix 14 continuing

```
collin sold profit male male_profit age25 age26_30 age36 age25_profit age26_30_profit
age36_profit master_doctor master_doctor_profit finance finance_profit trades1_2 trades3_5
trades6_15 trades1_2_profit trades3_5_profit trades6_15_profit
(obs=5138758)
```

Collinearity Diagnostics

Variable	VIF	SQRT VIF	Tolerance	R-Squared
sold	1.00	1.00	0.9965	0.0035
profit	10.13	3.18	0.0987	0.9013
male	1.58	1.26	0.6325	0.3675
male_profit	5.51	2.35	0.1813	0.8187
age25	1.73	1.32	0.5773	0.4227
age26_30	1.80	1.34	0.5549	0.4451
age36	1.79	1.34	0.5579	0.4421
age25_profit	1.92	1.39	0.5208	0.4792
age26_30_profit	2.41	1.55	0.4147	0.5853
age36_profit	1.88	1.37	0.5313	0.4687
master_doctor	1.73	1.32	0.5776	0.4224
master_doctor_profit	1.73	1.32	0.5774	0.4226
finance	1.58	1.26	0.6319	0.3681
finance_profit	1.60	1.26	0.6267	0.3733
trades1_2	2.55	1.60	0.3929	0.6071
trades3_5	2.57	1.60	0.3898	0.6102
trades6_15	2.68	1.64	0.3728	0.6272
trades1_2_profit	2.67	1.63	0.3744	0.6256
trades3_5_profit	2.79	1.67	0.3581	0.6419
trades6_15_profit	3.21	1.79	0.3111	0.6889
Mean VIF	2.64			