RĪGAS EKONOMIKAS AUGSTSKOLA
STOCKHOLM SCHOOL OF ECONOMICS IN RIGA

Bachelor Thesis

Behavioural Biases of the Disposition Effect and Overconfidence and their Impact on the Estonian Stock Market

Authors:
Karolis Čekauskas
Vytautas Liatukas

Supervisor:
Michel Verlaine

Associate supervisor:
Tālis Putniņš

April 2011
Riga

Abstract

Challenging the three underlying propositions of the EMH we analyze the disposition effect, overconfidence, systematic trading, and disposition prone and overconfident investors' impact on the Estonian stock market. We employ Odean's (1998a) methodology and reveal that investors are more prone to realize gains than losses, i.e. exhibit the disposition effect. In line with overconfidence hypothesis, using Odean's (1999) method we find that investors' purchases underperform their sales. We apply methods of Barber, Odean, and Zhu (2009) and conclude that investors' buying decisions are correlated and persistent. Following the method by Goetzman and Massa (2008) we witness some evidence of disposition prone investors' impact on the stock prices. Although using Statman, Thorley, and Vorkink (2006) method we find evidence of positive association between returns and turnover, the relationship is short lived and results are statistically insignificant. We come to three main implications. First, resting on the evidence of disposition effect and overconfidence we see a space for improving investor sophistication in Estonia. Second, we imply that the limits to arbitrage are an important issue. Market quality could be improved by providing better tools of arbitrage. Third, the soundness of the underlying mechanisms of the EMH is questionable.

Contents

I. Introduction

Traditional finance analyses financial markets by assuming rational participants. Baltussen (2009) says that "rationality means that economic agents make the best choices possible for themselves". Although still being the foundation of the finance, traditional view has been questioned by a new paradigm – behavioural finance. Behavioural finance challenges the rationality assumption and aims to improve the understanding of the financial markets by applying knowledge form psychology and sociology (Baltussen, 2009). However, behavioural finance does not have one unifying theory and is best defined by its objections to the traditional finance. The major subject of disagreement is the efficient markets hypothesis (EMH).

Fama (1970), the father of the EMH, defines efficient financial market as one in which prices are informationally efficient – instantly reflect all relevant information. Prices represent fundamental value and resources are directed to their most efficient uses. Fama (1970) also presents empirical evidence that U.S. common stock market is efficient. The EMH rests on three main propositions. First, investors are assumed to be rational utility maximizing agents. Second, if some investors are not rational, their trades are random and cancel each other out. Third, even if some irrational investors trade systematically, there are rational arbitrageurs that eliminate deviations from fundamental value. Validity of any one of these propositions is sufficient for the market to be informationally efficient.

Starting from 1980s contradicting studies emerged that challenged theoretical foundations of the efficient markets. All three theoretical propositions have been under attack. Black (1986) states that individual investors trade on noise rather than information. Kahneman and Tversky (1979; 1973) model investors that deviate from rationality in a consistent fashion. Finally, Shleifer (2000) argues that arbitrage in real life is risky and therefore limited.

Recently, a lot of empirical evidence on the irrational investor behaviour emerged from individual investors' trading patterns. These studies challenge the first proposition of the EMH by finding that investors' decisions contradict the expected utility theory of Von Neumann and Morgenstern (1944), which states that people faced with risk apply probabilities with the aim of maximizing their final wealth. Odean (1999), Barber and Odean (2000), Grinblatt and Keloharju (2009) find that individual investors are overconfident in trading; they trade too much and thus are decreasing their wealth. Shefrin and Statman (1985), Odean (1998a) find that individual investors hold losing investments too long and sell

winning investments too soon, i.e. exhibit the disposition effect. Kaniel, Saar, and Titman (2008), Hirshleifer, Myers, and Teoh (2008) discover that individual investors sell stocks that announce positive news and buy stocks that announce negative news. Griffin, Harris, and Topaloglu (2003) and Grinblatt and Keloharju (2000) find that individual investors follow contrarian trading strategies with regard to past returns. Finally, many studies (Blume and Friend, 1975; Barber and Odean, 2000; Polkovnichenko, 2005; Goetzmann and Kumar, 2008) find evidence of serious under-diversification of investors in the financial markets. Barber, Odean, and Zhu (2009) among others test the second proposition of the EMH and find that trading of individuals is highly correlated and persistent. Goetzmann and Massa (2008) and Statman, Thorley, and Vorkink (2006) tackle the third proposition by investigating disposition prone and overconfident investors' (respectively) impact on stock market. Scholars find evidence of return and turnover movements.

Mainstream of significant research on the individual investors' trading patterns has been conducted using the U.S. discount brokerage house data. Even less research outside the U.S. has been conducted on the systematic trading. Finally, to our knowledge the only researches that investigate the influence of behavioural biases on stock market were conducted using the same U.S. database. The aim of this paper is to close this gap by presenting new evidence from a different financial market on the extent to which behavioural biases exist, are coordinated, and influence the financial market.

To our knowledge, we are the first to test all three underlying mechanisms of the EMH in a single study using a single dataset. We are grateful to Tālis Putniņš and Estonian Central Securities Depository, who provided us with the unique and extensive data from the Estonian stock market. Having this exceptional opportunity, we perform a three step analysis. We research whether individual investors in the Estonian stock market suffer from behavioural biases of overconfidence and disposition effect, whether their actions are systematic and persistent, and what effects to the stock market, if any, investors suffering from these biases have.

The research is valuable in several important ways. First, the new evidence would allow re-evaluating the soundness of the three propositions on which the EMH rests. Second, it contributes to the evidence found in the U.S. by giving a thorough view on how a less developed financial market performs in terms of investor behaviour and its impact on stock prices. Third, such study indicates the level of investor sophistication and the potential need to improve it. Fourth, it sheds some light on whether market facilitators, governors or

regulators should take any action to improve the means of arbitrage, which could minimize the negative impact of behavioural biases. Answers to all these questions are an important step in determining the path to improve the quality of financial markets.

We chose to address overconfidence as such behaviour is strongly theoretically grounded. The consensus of the psychologists is that people are generally overconfident. The disposition effect, on the other hand is chosen as it is well documented, and is probably the most popular behavioural bias investigated in academia. Therefore, when examining these trading patterns we can employ trusted methodology and compare our results to the findings of other studies.

Employing Odean's (1998a) methodology we find that individual investors in Estonian stock market exhibit the disposition effect. Proportion of gains realized is 0.45, while proportion of losses realized is lower, equal to 0.33. Gap of 0.12 is statistically and economically significant. Using the method by Odean (1999) we identify that investors in Estonian stock market are overconfident in their ability to pick stocks and in precision of their information. Over 100 days' horizon the stocks they buy underperform the stocks they sell by 0.54% even before accounting for transaction costs. Investigating systematic trading using Barber, Odean, and Zhu (2009) method we find that investors' trading is indeed correlated and persistent. Correlation of buying decisions among two unrelated groups of investors is equal to 44% and positive correlation stretches for 10 months. We also borrow Goetzman and Massa (2008) and Statman, Thorley, and Vorkink (2006) methods to check stock market impact of disposition effect and overconfidence. We find some evidence that investors suffering from disposition effect have an impact on the Estonian stock market. Investigating overconfident investors' impact on the stock market we witness some evidence of positive association between returns and trading volume. However, the relationship is short lived and statistically insignificant, so we do not draw any conclusions.

We see three main implications of our study. First, we imply that there is space for improving investor sophistication. Second, market quality could be increased by providing investors with better tools of arbitrage. Third, the validity of the underlying mechanisms of the EMH is questionable.

The rest of the paper is structured as follows: section II reviews the literature about the disposition effect, overconfidence, systematic trading, and stock market impact of the aforementioned behavioural biases, section III explains methodology used in the three step

analysis, section IV presents findings, section V provides implications, and section VI concludes.

II. Literature review

We first review the literature on the two behavioural biases we are interested in, namely, the disposition effect and overconfidence. We then review the evidence on aggregate systematic trading of individual investors. Finally, we present literature that investigates the stock market impact of behaviourally biased investors.

Trading patterns

Disposition effect

Kahneman and Tversky (1979) in their seminal paper *Prospect theory: An analysis of decision under risk* challenge the expected utility theory of Von Neumann and Morgenstern (1944). They claim that basic assumptions of the theory are violated. People tend to underweight outcomes with miniscule probabilities as compared to outcomes with certainty. This certainty effect results in risk averse choices involving sure gains, and risk seeking choices involving certain losses. They also claim that people have inconsistent preferences. Authors presented prospect theory as an alternative theory to describe the decisions between alternatives involving risk. In their framework value is assigned to gains and losses relative to some reference point as compared to final wealth in expected utility theory. Probabilities are also replaced by decision weights. The value function takes S-shape and allows loss aversion – function is concave for gains, but convex and steeper for losses. Shefrin and Statman (1985) apply this intuition to the financial markets and model investors' tendency to sell and realize gains of winning stocks too quickly and hold on to losing stocks too long. They name such behaviour the disposition effect.

Odean (1998a) empirically tests the disposition effect in the U.S. stock market. He obtains a random sample of 10,000 accounts from discount brokerage house for the period 1987-1993. He compares the ratio of realized gains to total gains (PGR) with ratio of realized losses to total losses (PLR). If PGR ratio is higher than PLR it means that investors sell winners too soon and hold on to losers too long. When testing the difference in PGR and PLR on aggregate across all investors, Odean (1998a) finds that the difference is equal to 0.21 and hypothesis that PLR is equal or higher than PGR is strongly rejected with t-statistic greater than 35. The result is robust for testing the number of shares traded instead of simply checking for amount of trades as well as for different partitions of the sample based on period

or trading frequency. Odean (1998a) also presents a rough estimation of the costs of the disposition effect – if a person chooses to sell a winner instead of a loser he will have 4.4 percent lower return in one year's horizon. The costs might increase even more if the person defers the sale of a loser for a longer period.

There are other studies that investigate the disposition effect. Talpsepp (2010) investigates investor trading characteristics, the disposition effect and its relation to performance in Estonia. He finds that the disposition effect is associated with lower portfolio returns. Grinblatt and Keloharju (2000) find evidence of disposition effect using Finnish data. Chen, Kim, Nofsinger, and Rui (2007) investigate brokerage account data from China. They find that investors in China suffer from disposition effect and that the magnitude of the bias is higher than in the U.S. Odean (1999) and Barber and Odean (2000, 2001, 2002), while mainly interested in overconfidence, still repeatedly find evidence of the disposition effect. Weber and Camerer (1998) make an experiment in order to determine whether investors exhibit the disposition effect. Authors find that investors tend to keep losing and sell wining stocks. Weber and Zuchel (2001) also make an experiment in order to study whether prior outcomes affect risky choice. Authors find increased risky behaviour following a loss, which conform to the disposition effect. Fernandes, Pena, and Tabak (2008) perform the same experiment across countries and again find that prior outcomes affect risky choices in the form of loss aversion. Oehler, Heilmann, Volker, and Oberlande (2002) investigate 490 investors in 3 stock markets and conclude that majority of them demonstrate the disposition effect.

Tax-motivated selling is often contrasted to the disposition effect. Constantinides (1984) shows that investors should increase their tax motivated selling throughout the year and it should reach peak in December. Investors can gain from selling their securities at loss, in that way reducing their profit and thus taxes and re-buying them at the beginning of the next year to keep the desired compositions of their portfolios. Tax motivated selling should induce investors to realize losses and consequently mitigate the disposition effect. Odean (1998a) discovers that tax-motivated selling is indeed reducing the disposition effect and December is the only month during the year when PGR/PLR (a comparable alternative to PGR-PLR) is smaller than 1 (0.85). He confirms that the reluctance to realise losses decreases consistently throughout the year and reaches the bottom in December.

There are two main explanations of the disposition effect in line with the rational behaviour. First, the disposition effect might be caused by portfolio rebalancing. Second, it could be

justified by investors' expectations of mean reversion. Odean (1998a) finds that none of these explanations are plausible. He concludes that traders are systematically mistaken about their beliefs.

Overconfidence

Psychologist Jarome D. Frank (1935) showed that most people are generally overconfident about their abilities. Scholars investigating subjective probabilities find that people tend to overestimate the precision of their knowledge (Alpert and Raiffa, 1982; Fischhoff, Slovic, and Lichtenstein, 1977). Such overconfidence applies to many professional fields, not only economics (Barber and Odean, 2001). It is greatest for difficult tasks, and stock selection is exactly of such type.

Odean (1998b) develops overconfidence model in financial securities market. Investors overestimate their ability to asses value of security more precisely than others. Individuals believe in their own valuation, which in turn causes differences in opinion that motivate trading (Varian, 1989; Harris and Raviv, 1993). However, individuals should only trade if doing so increases their expected utility (Grossman and Stiglitz, 1980). Odean (1998b) finds that the more investor is overconfident the more he trades, and the lower his expected utility is. This is because investors possess unrealistic beliefs about how precise the returns can be estimated and spend too much resources on gathering information. Overconfident investors also hold riskier portfolios than rational investors. Author notes that there are exceptions to the rule, and some investors do not exhibit overconfidence. For example, Annaert, Heyman, Vanmaele, and Van Osselaer (2008) find that trades of mutual funds do not erode performance, thus do not exhibit overconfidence.

Note that Odean (1998b) models overconfidence about the precision of assessing information signals. Therefore, the worst expected outcome for such investor is zero gross profit and expected net loss equal to transaction costs. These models do not take into account systematic misinterpretation of information. Barber and Odean (2005) state that in addition to investors being overconfidence about the precision of their information they are also overconfident in their ability to interpret information. Investors, being overconfident in the interpretation of information, hold mistaken beliefs about the mean, instead of (or in addition to) the precision of the probabilistic distribution of their information. In this case, investors on average incur losses beyond transaction costs.

Odean (1999), using the U.S. discount brokerage data, finds that trading volume is excessive for individual investors. Author tests whether securities investors buy outperform securities they sell by at least the amount to cover transaction costs. Strikingly, Odean (1999) finds that individual investors' buys underperform sells by as much as 3.3% in one year after the trade even before accounting for transaction costs. Author concludes that investors are overconfident in their ability to interpret information, not only about the precision of their information signals.

Barber and Odean (2000) studies the same phenomenon – whether individual investors trade excessively; however, they employ a different methodology. Authors take the same data from the discount brokerage firm, but they analyze the aggregate performance of all stocks held by individuals. Contrary to Odean (1999) they are not only able to tell that investors trade too much, but also can analyze how individual investors perform on aggregate. Their empirical evidence supports the view that overconfidence causes excessive trading. Those that trade the most frequently earn returns of 11.4% compared to the market returns of 17.9%. Those who trade infrequently earn 18.5% return. Authors also find that households underperform all benchmarks after accounting for transaction costs. Households earn returns before accounting for trading costs that are approximately equal to the market index.

There are other studies investigating overconfidence. Biais, Hilton, and Mazurier (2005) perform an experiment with 245 participants and find that investors are overconfident in the precision of their information and that such overconfidence reduces trading performance. Daeves, Luders, and Luo (2009) perform another experiment and analyze whether overconfidence induce more trading and find it to be true at the level of individuals and at the market level. Barber and Odean (2001) test overconfidence by partitioning investors by gender. Using Barber and Odean (2000) method, they find that men trade 45% more than women and trading reduces men's net returns by 2.65 p.p. as opposed to 1.72 p.p. for women. Barber and Odean (2002) investigate individual investors who switch to the internet trading. Authors hypothesize that because of access to more information and higher degree of control over their account investors should become more overconfident. They find that after switching to the internet trading investors trade more actively and perform worse. Hsu and Shiu (2010) investigate the investment performance of 6993 investors in IPO auctions in Taiwan stock market. They find that frequent bidders have lower returns and conclude that investors suffer from overconfidence.

There are several standard explanations of overconfidence. Investors could trade for liquidity needs, in order to move to less or more risky investments, to realize tax losses, or to rebalance. Odean (1999) controls for these effects and still finds statistically significant effect of investors' overconfidence. Investors perform even worse – buys underperform sells by 5.8% over one year's horizon. Barber and Odean (2000) also check whether trading is caused by rational expectations, and find that liquidity, risk based rebalancing, and taxes can only explain some of the trading activity, but are unable to explain the annual turnover of 250% for the most frequently trading households.

Systematic trading

For the deviations from rational investor behaviour to have an effect on stock prices they have to be systematic and there must be limits to arbitrage. We start by reviewing the former condition here.

If investors are irrational in unsystematic way, their actions could offset each other (Fama, 1970). A recent approach to examine whether investors trade systematically was undertaken by Barber, Odean, and Zhu (2009). Resting on Shleifer's (2000) argument that "investor sentiment reflects common judgment errors made by substantial number of investors, rather than uncorrelated random mistakes", authors empirically test whether trading of individuals is correlated and persistent. They examine 66,000 investors at a discount broker and 665,000 investors at a retail broker. They find mean correlation of 73% between two randomly assigned investor groups and conclude that by knowing what one group of investors is doing you can also know much about the unrelated second group. Authors also find that the observed distribution of specific stock's proportion of trades that are purchases has fatter tails compared to the expected distribution when decisions to buy versus sell a specific stock are not correlated. This implies that the decisions of individual investors to buy (sell) a particular stock are correlated. Additionally, Barber, Odean, and Zhu (2009) test whether the correlation of individual investors' decisions is persistent. They find that stocks that are bought by individuals in one month are a lot more likely to be bought in the following months. Persistence is evident beyond one year, but gradually disappears.

However, as noted by Jackson (2003), the latter paper can be misleading to some extent. This is because authors investigate correlation within a single broker, so investment decisions can be affected by common advice or networks. Jackson (2003) takes a different approach and investigates 47 full-service and 9 internet brokerage firms in Australia. He tests whether

actions of investors are similar between the independent brokerage firms. Author finds that the cross-sectional correlation for weekly net flows into stocks for internet brokerage firms is 44% and for full-service firms – 24%. Nevertheless correlation for full-service firms is a lot lower, it is still strikingly robust. Author finds that correlation for every single unique pair of the full-service firms is positive.

Another remarkable work by Dorn, Huberman, and Sengmueller (2008) investigates systematic trading in Germany. Authors examine different types of retail trades for the three largest German discount brokers. They distinguish between speculative and other trades, and between limit orders and market orders. As suggested by some scholars, authors find that limit orders are responsible for some of the correlation that arise mechanically when price jump executes sell orders that could be set long time apart and artificially inflates correlation. However, authors conclude that limit orders and other mechanical reasons explain only a fraction of the trade co-movement. Taking speculative and non-speculative trades apart allows authors to tackle another problem. Non-speculative trades are often liquidity trades that could execute together and overstate level of systematic trading that should only reflect active traders. They indeed find that non speculative trades are correlated. This is not surprising as such trades are usually coordinated implicitly, for example, through automated investment plans. What is surprising, though, is that correlation among speculative trades is considerably higher than among the non-speculative trades. Authors conclude that retail investors trade systematically.

Kumar (2009) using the same database as Barber, Odean, and Zhu (2009) finds that investors systematically shift between different style portfolios, such as value versus growth. Kumar and Lee (2006) using the U.S. discount brokerage data find that investors are systematic in their money movements in and out of the stock markets.

Stock market impact

Even if one proves that individual investors exhibit the disposition effect and overconfidence and that investor behaviour is systematic, she still cannot make inferences about stock market impact and informational efficiency. For the irrational investors to have an impact on prices another vital condition must be satisfied – rational investors must be unable to return prices to the fundamentals. Many supporters of the EMH including Fama (1965) and Friedman (1953) argue that even if a group of investors in market is irrational and trade systematically, markets can still be efficient. If some investors are rational and bet against the market,

irrational investors' impact on prices is eliminated. Therefore, market remains efficient and prices fully reflect all available information.

Arguments that there are theoretical limits to arbitrage have been proposed by many scholars. Shleifer (2000) states that real life arbitrage is risky. He argues that close substitutes for securities in many instances do not exist and arbitrageur has no riskless hedge. The same holds if short selling is not feasible as it is the case in Estonian stock market (although short selling is legal, there are no standardized mechanisms through which to perform it so in practise it rarely happens). Arbitrageur can only sell or buy the affected stock and hope that there are no surprises. Arbitrage is no longer even close to being riskless. If arbitrageur is risk averse, she will lose interest in such participation. Shleifer (2000) further argues that even if substitutes exist, they are usually not perfect. Therefore, arbitrageur bears some idiosyncratic risk that news will be surprisingly good for the security she is short and vice versa for the security she is long. Such trading is called 'risk arbitrage' and it is built on statistical likelihood rather than on unconditional profit. De Long, Shleifer, Summers, Waldmann (1990) finds another risk – 'noise trader risk'. According to them, arbitrageur faces risk that the price divergence can get much worse before eventually converging to the fundamental value. So arbitrageur might be unable to maintain his position through initial losses and might need to liquidate it.

Scholars found many anomalies that are not consistent with Fama's third proposition of the EMH. Extreme losers performing better than extreme winners, stock price momentum explaining returns, January effect, small firm effect, B/M effect, price movements to non-information, and etc. However, most of them were built on weak theoretical foundations and therefore were open to critique. Improper risk adjustment, data mining, sample selection biases, trading costs, and taxes were among the top objections to such literature.

Rather than testing the channel of limits of arbitrage or searching for anomalies, it is more meaningful to detect a direct link between irrational investor behaviour and security prices. Very few such researches have yet been conducted. A recent attempt was undertaken by Goetzmann and Massa (2008). Authors base their work on the theoretical implications of Grinblatt and Han (2005) that have created a model of equilibrium prices under disposition effect. According to Grinblatt and Han (2005), because of disposition prone investors, a stock that has good news has excess selling pressure compared to the stock that has bad news. Such perturbation generates price under-reaction to public information. Stock price diverges from its fundamental value. Because of investor heterogeneity, trades that represent the disposition

effect occur and reference points start to change. Price in the next trading period reverts towards fundamentals. Their model is unique as it states that lagged capital gains or losses are enough to forecast stock returns. So, presence of investors that exhibit the disposition effect decreases price fluctuations. The higher fraction of disposition prone investors there are in the market, the less responsive stock prices are to shocks in fundamentals.

Goetzmann and Massa (2008) perform regression analysis and constantly find negative statistically and economically significant relationship between disposition proxy and stock returns, volatility, turnover, and volume. This confirms that those stocks that have more disposition prone investors as shareholders are less sensitive to fundamental shocks. Additionally, authors find that disposition effect is not just stock specific but also aggregates at the market level.

Statman, Thorley, and Vorkink (2006) examine stock market reaction to overconfidence. They rest on theoretical implications of Odean (1998b) and Gervais and Odean (2001) that develop a multi period model where overconfidence increases as investors attribute high returns to their skills rather than to random walk of security prices. These models conclude that higher market returns lead to higher subsequent volume. Statman, Thorley, and Vorkink (2006) test this and find strong relation which confirms theoretical predictions – higher market returns predict higher turnover. Findings are also economically significant as market return of 7% compared to -5% in a given month gives additional month's turnover over the following 6 months. Authors also find that stock returns can be predicted using past trading volume. Results are consistent with Daniel, Hirshleifer, and Subrahmanyam (1998). Thus if investor overconfidence increases turnover, and trading volume predicts security returns, overconfident investors indeed have a price impact.

This is not the only evidence on the market impact of investor decisions. Warther (1995) examines relation between aggregate security returns and fund flows. He finds some evidence that fund flows predict subsequent returns. Edelen and Warner (2001) examine the link between returns and aggregate flow into the U.S.A equity funds and find that daily relation is positive and significant. Goetzmann and Massa (2003) assess the relation between index fund flows and market returns. They find a strong contemporaneous correlation.

III. Methodology

Data

Data for this study were provided by Tālis Putniņš, who obtained the dataset from Estonian Central Securities Depository. There are more than 40,000 accounts with trading information from January, 2004 to October, 2010. The data consist of four major parts. First part of the data describes personal characteristics of investors. It indicates account number, gender, foreign, date of birth, and investor type variables. Investor's type takes four values: individual, fund, government, and institution. As the focus of this paper is individual investors, we filter out other groups. Second part of the data describes portfolio positions of investors at the end of every trading day in our sample. It shows every investor's holdings in every stock expressed in EUR. Third and the largest part of the data consist of every trade that took place during the sample period in Estonian stock market. Account number, stock, price, quantity, trade direction (buy or sell), and settlement date are shown. There are over 990,000 records. Fourth part of the data consists of files with daily returns of every stock in Estonian stock market from NASDAQ OMX Baltic. Stock returns are adjusted for dividends and stock splits.

We calculate trading costs firstly by calculating realized spread. It is equal to:

$$2D(P - M)/M$$

D is direction of the trade (takes value of -1 for a sell and 1 for a buy), P is the trade price and M is the day's closing midquote. For brokerage costs, we take the average of cost charged by three most popular Estonian brokerage firms. They are equal to 0.17% of the trade size, but not lower than 3.2 EUR. Sum of these measures shows the cost of an average roundtrip trade.

Methods

The methods we use correspond to the three steps of analysis we make: examine behavioural biases of the disposition effect and overconfidence, measure correlation of investors' trading, and quantify the impact of behaviourally biased investors on the stock market. In order to test whether investors exhibit the disposition effect, we employ methodology by Odean (1998a). When testing for investor overconfidence we use Odean (1999) method. To test the correlation of investors' trading we employ some of the methods proposed by Barber, Odean, and Zhu (2009). To check the disposition prone investors' impact on prices we use a method

proposed by Goetzmann and Massa (2008). Finally, in order to test stock market reaction to overconfidence, we employ Statman, Thorley, and Vorkink (2006) methodology.

Disposition effect

The disposition effect is measured by checking the frequencies with which investors sell losers and winners compared to their possibilities to sell each. Consistent with Odean (1998a), we construct portfolios for each account on each day for which the purchase price and date are available. Aside from those stocks that are purchased before January 1, 2004, we have data on prices and dates of trade for each account. Our rather unique dataset provides us with the possibility to research each trade undertaken in the Estonian stock market. Odean (1998a) does not have such possibility. In other words, we have the whole population of investors, while Odean (1998a) only has a subset of them. This helps to avoid possible representation bias. Likewise Odean (1998a) we do not possess the entire universe of stocks an investor has in her portfolio. We only have the data for the trades after the start of 2004. Odean (1998a) points out that this should not be a problem as constructed portfolios are highly unlikely to be biased towards stocks with different magnitude of disposition effect.

For each day when a sale takes place in a portfolio with at least two stocks (so that investor is not completely liquidating his portfolio) the selling price of each stock is compared to the average purchase price (reference point). Average purchase price is the average euro amount paid per one share in multiple transactions to obtain a number of shares held at the date of interest. The price is weighted by the number of shares bought in each transaction. There are number of proxies for reference point including the last purchase price, the highest purchase price, etc. Odean (1998a) uses the average price as the base case. He also employs other proxies but this does not yield any significant differences. Therefore, based on the evidence that the choice of the reference point should not alter results we use the average purchase price. Purchase and sale prices are adjusted for commissions, to capture their effect on capital gains and losses. This is important when contrasting the disposition effect with tax-motivated selling (Odean, 1998a). By comparing the sale price with the reference point (average price) we identify whether the stock was sold for a gain or for a loss. Stocks that are not sold and are in the portfolio at the beginning of a particular day when a sale takes place, are counted as a paper, or unrealised, gain, loss or neither. If both day's high and low prices for a security are higher than its average purchase price, the unsold stock is counted as a paper gain; if both of these prices are lower than the reference point stock is counted as a paper loss; while in

other cases it is considered as neither a gain nor a loss. Days with no sales are excluded. The final step before testing the disposition effect is to construct two ratios:

PGR (Proportion of Gains Realized) = Realized Gains / (Realized Gains + Paper Gains)

PLR (Proportion of Losses Realized) = Realized Losses / (Realized Losses + Paper Losses)

Each realized or paper gain (loss) is treated as an independent observation and aggregated across investors. Such approach requires assumption of independence both at account and transaction level. After aggregation, the ratios are compared to see whether there is statistical and economic significance in the difference. PGR ratio being higher than PLR ratio implies existence of the disposition effect. As an alternative, following Odean (1998a), we also measure the disposition effect by first calculating the difference between PGR and PLR for each investor, subsequently aggregating the measures across the accounts, and finally comparing the measures to test the presence of disposition effect. In this case we do not need to assume independence of each observation. We only assume that ratios in one account are independent of those in other accounts. For robustness we also calculate the PGR and PLR measures on number of shares traded and euro value of shares traded basis instead of number of trades. Following Odean (1998a), we also make analysis on monthly basis to investigate, whether the disposition effect is reduced by tax-motivated selling getting closer to the year-end.

Odean (1998a) method is not the only one for testing disposition effect and scholars have pointed some limitations of it. Grinblatt and Keloharju (2001) use logit regression specification to estimate the decision to sell or hold a stock. They state that Odean (1998a) is not able to distinguish the reasons for the observed disposition effect – whether it is due to capital gains (losses) or investors correctly or incorrectly believing that contrarian trading strategies will be profitable. Dhar and Zhu (2006) further argue that Odean does not check for the differences in the disposition effect across individuals and possible disposition effect explanations based on investor characteristics. Feng and Seasholes (2005) also note that the disposition effect might be related to the demographic variables of individual investors, which is not tested by Odean (1998a). Moreover, they argue that inferences drawn using Odean (1998a) method can be incorrect if capital gains or losses vary over time – for example, stock experiences a sudden gain that is reverted only after a long time period.

Albeit there are drawbacks when using the method for identifying the reasons of the disposition effect, method is perfectly usable for the purpose of documenting the disposition

effect on the investor base as a whole. This method has strong logic, long withstanding foundations, and has been widely used in academia. Barberis and Wei (2009), Locke and Mann (2005), Strobl (2003) and Frazzini (2006), to name a few, use Odean's (1998a) or a comparable method in their papers.

Overconfidence

Overconfidence is measured by comparing investor purchases' returns to sales' returns (Odean, 1999). We take return horizons of 100 days (5 months) and 20 days (one month). 100 days is the average stock holding period in our sample while 20 day is the time period in which investors on average turn over their portfolio in our dataset. In order to calculate average returns for securities bought/sold in investor accounts over time periods T (20, 100 days) subsequent the purchase/sale, we mark each transaction with index i = 1 to N. Each transaction has a security j, and a date, t. The average return for securities bought/sold over T trading days after the purchase/sale is equal to:

$$R_T = \frac{\sum_{\mathrm{i}=1}^{\mathrm{N}}[\ln\left(\frac{M_{j_i,t_i+T}}{M_{j_i,t_i}}\right) - \ln\left(\frac{I_{t_i+T}}{I_{t_i}}\right)]}{\mathrm{N}}$$

M is the midquote and I is the market index. Note that we adjust returns by market index. This is done because as we are interested in 'real' performance of investors. We do not want the results to be affected by rising or falling market. We also use midquote so as not to incorporate bid-ask spread into returns and avoid microstructure noise. After we calculate returns for every investor account using the aforementioned method, we average the purchase/sale returns over all investors' accounts. This gives us the average purchase/sale returns for individual investors in the Estonian stock market. If the sold securities outperform the purchased securities after accounting for transaction costs investors are overconfident in their precision of information. If this is true even before accounting for transaction costs investors are also overconfident in their ability to pick stocks.

There are some pitfalls of this method as noted by Odean (1999). Many stocks are sold or bought on more than one day and could even be bought or sold on the same date by different investors. The returns of some stocks are not independent because the periods overlap for different investors. Because of the violation of independence condition conventional statistical tests are not applicable. However, there is a solution to this problem. Following

methodology by Brock, Lakonishok, and LeBaron (1992) and Ikenberry, Lakonishok, and Vermaelen (1995), Odean (1999) uses bootstrapping for statistical significance tests. Following his suggestion we also perform statistical significance tests by bootstrapping empirical distribution for differences in returns to bought and sold stocks. Another pitfall of the methodology by Odean (1999) is spotted by Barber and Odean (2000). They argue that Odean (1999) method makes it impossible to analyze aggregate performance of all stocks held by individuals and thus he is unable to draw conclusions of how well individual investors perform on aggregate. As the purpose of our study is to test whether investors in Estonia suffer from overconfidence bias, it is enough to check whether investors trade excessively. This argument is also noted by Barber and Odean (2000). Same or similar method is replicated, among many others, by Annaertm Heyman, Vanmaele, and Van Osselaer (2008), Linnainmaa (2010), Seru, Shumway, and Stoffman (2010).

Correlation of investors' trading

In accordance to Barber, Odean, and Zhu (2009) we randomly divide our sample of investor accounts into two groups. In each month, we calculate the buying intensity, which is simply the ratio of buys to all trades, for every stock for the two groups. We then calculate the correlation of the buying intensity between the stocks of the two groups in each month. This gives us 82 months' time-series of correlations. We then average the correlations over time. If investors' trading was not systematic, we would expect the mean correlation between the two groups to be equal to zero. We perform statistical test based on standard deviation of correlation time-series.

We also test the persistence of buying intensity's correlation over time. We do this again by calculating buying intensity each month across stocks for the two groups, and then calculating the correlation of buying intensity each month between the two groups. This yields the same 82 months' time-series as in the method above. We then calculate mean correlations for lag lengths (L) from one month to two years. In particular, we check if correlation of buying intensity in month t and month $t+L$ is zero for group one at both horizons, group two at both horizons, group one in month t and group two in month $t+L$, and group two in month t and group one in month $t+L$.

We follow Barber, Odean, and Zhu (2009) and calculate correlation for disposition prone investors. Using first half of the sample (3 years) we identify disposition prone investors according to Odean(1998a) and calculate correlation among those investors that have PGR

larger than PLR using the other half of the sample. By identifying disposition investors out of sample, we avoid the problem of identifying relationship between the disposition effect spuriously. We do the same for overconfident investors that are defined as those that have negative 100 days buy minus sell returns before accounting for transaction costs in the first half of our sample.

Disposition impact on prices

First of all, following Goetzmann and Massa (2008) we construct the disposition proxy. This variable measures the proportion of trades originated by disposition prone investors. We define disposition prone investors using out of sample method. This is done by identifying disposition prone investors in one month and then tracking their behaviour in the following month. Disposition investors are identified using the same Odean's (1998a) methodology we use to measure the disposition effect. We calculate PGR and PLR variables and define disposition prone investor as one, whose PGR is higher than PLR. In the following month, each day, we calculate the net trades originated by disposition prone and the other investors, and construct the disposition proxy. It is calculated for each stock and is equal to the net trades of the disposition prone investors minus the net trades of the rest of the market, standardized by total trades. The higher the disposition proxy is, the bigger proportion of disposition prone investors there are among shareholders. According to the theory, the higher fraction of disposition prone investors there are in the market, the less responsive stock price is to shocks in fundamentals. Thus, we anticipate the disposition proxy to be negatively correlated with stock volatility, returns, turnover, and volume.

Replicating Goetzmann and Massa (2008) approach we investigate the impact of disposition effect on stock volatility, return, volume and turnover using the following regression functional form:

$$Z_{it} = \alpha + \beta W_{it} + \gamma C_{it} + \varepsilon_{it}$$

All variables are in daily frequency. Z_{it} is dependant variable (stock volatility, stock returns, stock volume, and stock turnover), W_{it} is the disposition proxy, and C_{it} is a set of control variables. Goetzmann and Massa (2008) use a broad set of control variables: market returns, HML, SMB, riskless rate, company size, market volume, stock price, stock return, stock volume, and stock volatility. We use the same set of control variables, except for HML and SMB. We find this specification virtually the same as authors themselves do not focus on control variables. There is no real reason to believe that our disposition proxy is correlated

with HML or SMB. We use two specifications depending on whether stock price is included in the set of control variables or not. Goetzmann and Massa (2008) note the problem of reverse causality using returns, volume, and turnover as dependent variables. Authors find that volatility should not suffer from reverse causality as theoretically disposition prone investors should not be more willing to sell when volatility is high and buy when volatility is low.

Following Goetzmann and Massa (2008) we use range based measure of volatility. It is measured as log range between the highest price of the day minus the lowest price of the day. Stock returns are simply the daily change in closing prices. Stock turnover is measured as log number of shares traded in a particular day divided by the number of shares outstanding. As we were unable to acquire the number of shares outstanding at daily frequency, we use the end of the period measure as a proxy. Stock volume is simply log number of shares traded in a particular day times closing stock price. We measure market returns as the daily change in the market index. Company size is measured as the end of the day market capitalization. Overall market volume is simply the log number of shares traded in the Estonian stock market each day. Daily 6 months TALIBOR is taken as a proxy for riskless rate.

Stock market reaction to overconfidence

Following Statman, Thorley, and Vorkink (2006) we first estimate the relationship for weekly market turnover and weekly market returns and do the same for every stock in the market separately. For the market-wide level analysis we use the following vector auto regression (VAR) specification:

$$Y_t = \propto + \sum_{i=1}^{I} A_i Y_{t-i} + \sum_{j=0}^{J} B_j X_{t-i} + e_t$$

Y is a vector of endogenous variables and X is a vector of exogenous or control variables. Endogenous variables used in the market level analysis are the logarithm of overall market volume (comparable to Statman, Thorley, and Vorkink (2006) measure of turnover) and the weekly return on the OMX Tallinn index. Consistently with Statman, Thorley, and Vorkink (2006) we also include these exogenous variables: weekly market volatility estimate, as specified in the study by French, Schwert, and Stambaugh (1987)[1], and weekly returns dispersion, measured as weekly cross-sectional standard deviation of stock returns.

[1] $\sigma = \sqrt{\sum_{t=1}^{T} r_\tau^2 + 2\sum_{t=1}^{T} r_\tau r_{\tau-1}}$, where r_t is return on the day τ and T is the number of trading days in a week

According to models by Odean (1998b) and Gervais and Odean (2001) we should expect positive coefficients on lagged returns as greater overconfidence should induce more trading and increase overall market volume.

The observed increase in volume due to positive returns would be consistent not only with overconfidence, but also with the disposition effect as investors enjoy realizing gains due to rising security prices. This is due to the fact that disposition investors are acting to the changes in the returns of a particular stock. When stock returns are rising/falling disposition prone investors are more likely to sell/keep the stock. This behaviour aggregates to the market level. Stock level analysis help to disentangle the effect of overconfidence. Market returns cannot influence decisions of the disposition prone investors to keep or sell a particular stock. For such analysis we adjust the VAR to be trivariate and employ logarithm of stock volume, market returns and security returns as endogenous variables. Stock volatility, measured in the same way as market volatility, is used as an exogenous control variable. If overconfidence plays a role in affecting volume, we should expect a positive and significant relationship between lagged market returns and stock trading volume. As there is no established definition of the length of the relationship between turnover and returns, we use Schwartz Information Criteria (SIC) to choose the lag lengths in vector auto regressions. This gives us 4 lags. Moreover, for robustness purposes we continue to use the same lag length (10) as Statman, Thorley, and Vorkink (2006). We use 2 lags of exogenous variables.

In addition to the market level VARs we use the associated impulse response functions (IRFs). This allows us to identify the relationship of the endogenous variables over time (Hamilton 1994). By using IRFs we are able to trace the effect through the dynamic structure of vector auto regression. It shows how an exogenous shock in one residual of a magnitude of one standard deviation affects the endogenous variables. To correct for possible risk of contemporaneous correlation in residuals, instead of simple IRFs we employ the orthogonalized impulse response functions (OIRFs).

Statman, Thorley, and Vorkink (2006) use 40 years of data which gives them 480 months of time series. We have less than 7 years or 82 months. For this reason, we perform analysis on weekly basis and have 328 periods of the time series. While daily frequency might be not appropriate in such study as people mentally process information about increasing market returns and become overconfident slower than that, weakly returns should not have such problem.

The methodology by Statman, Thorley, and Vorkink (2006) is further used in studies by Zaiane and Abaoub (2009), Chuang and Lee (2006), and Glaser and Weber (2007). No considerable drawbacks were spotted.

IV. Results

We present results according to the three steps. We first look at the results of the disposition effect and overconfidence. We do it separately as it is the most significant step of our analysis. Then we present evidence of systematic trading among the individual investors. Finally, we look at the results of the disposition prone and overconfident investors' impact on stock prices.

Trading patterns

Disposition effect

We find that given the opportunity to sell a stock investors in the Estonian stock market are less willing to get rid of the stocks that have lost value as compared to the stocks that have gained value. Final dataset contains 2880 individual investors for whom we are able to calculate PGR and PLR measures. Results are presented in Table 1. Panel A shows that proportion of gains realized is equal to 0.45 while only one third (0.33) of all losses are realized. The difference between PGR and PLR proportions is equal to 0.12 and provides strong evidence for the disposition effect. The hypothesis that PGR is higher than PLR is rejected with t-statistic of 39. The numerical value of the disposition effect (0.12) in Estonian dataset is more than twice as high as in the U.S. dataset, where PGR – PLR is equal to 0.05. One explanation for such difference could be that Estonia being emerging market consists of less sophisticated investors. Studies by Feng and Seasholes (2005), Dhar and Zhu (2006), and Seru, Shumway, and Stoffman (2010) suggest that disposition effect can be reduced by investors learning by trading. While U.S. investors have been trading stocks for a couple of centuries, Estonian stock market counts only its second decade. Although investors in Estonia are more prone to the disposition effect, both PGR and PLR are around 3.5 times higher in Estonia than in the U.S. (0.15 and 0.10 respectively).

However, all the difference disappears when instead of assuming independence both at account and transaction level we only assume it at account level (Table 1, Panel B). Mean PGR and PLR are 0.59 and 0.43 respectively for the Estonian data compared to 0.57 and 0.36 for the U.S. data. Numbers imply that the disposition is higher for the U.S. investors (0.21, t-statistic 19) as compared to Estonia's (0.16, t-statistic 17).

We always calculate the realized and paper gains (losses) on stock basis, measuring the actual and potential trades. Thus, any trade size counts equally. To check the robustness of our findings we also calculate the PGR and PLR measures in terms of actual number of shares traded and potential number of shares traded (Table 1, Panel C and D). Findings remain practically the same, as the average PGR and PLR are 0.56 and 0.40 implying a significant difference of 0.16 (t-statistic 16). We also tackle another possible issue. If investors would be more prone to realize small gains than large losses, it might be that proportions of gain (loss) values realized are actually smaller than reported on trade basis or on number of share basis. Calculating PGR and PLR on euro value basis yields a virtually unchanged difference of PGR-PLR (0.17, t-statistic 14). We conclude that the disposition effect is indeed present in the Estonian stock market, is as visible as in the U.S. stock market, and is robust to various methods of calculation.

Panel A: Assuming independence both at account and transaction level		**Panel E: Prior and after the crisis (01 2004 - 02 2007 and 08 2009 - 10**	
Proportion of Gains Realized	**0.45**	**Proportion of Gains Realized**	**0.42**
Proportion of Losses Realized	**0.33**	**Proportion of Losses Realized**	**0.30**
PGR-PLR	**0.12**	**PGR-PLR**	**0.12**
(t-statistic)	(39)	(t-statistic)	(28)
Panel B: Assuming independence at account level		**Panel F: The crisis period (03 2007 - 07 2009)**	
Proportion of Gains Realized	**0.59**	**Proportion of Gains Realized**	**0.54**
Proportion of Losses Realized	**0.43**	**Proportion of Losses Realized**	**0.36**
PGR-PLR	**0.16**	**PGR-PLR**	**0.18**
(t-statistic)	(17)	(t-statistic)	(34)
Panel C: Number of shares traded instead of a trade		**Panel G: December**	
Proportion of Gains Realized	**0.56**	**Proportion of Gains Realized**	**0.44**
Proportion of Losses Realized	**0.40**	**Proportion of Losses Realized**	**0.35**
PGR-PLR	**0.16**	**PGR-PLR**	**0.09**
(t-statistic)	(16)	(t-statistic)	(7)
Panel D: Euro value of shares traded instead of a trade		**Panel H: January - November**	
Proportion of Gains Realized	**0.60**	**Proportion of Gains Realized**	**0.45**
Proportion of Losses Realized	**0.43**	**Proportion of Losses Realized**	**0.33**
PGR-PLR	**0.17**	**PGR-PLR**	**0.12**
(t-statistic)	(14)	(t-statistic)	(39)

Table 1.Disposition effect in the Estonian stock market. Table shows the propensity to realise gains and propensity to realize losses. PGR-PLR measures the disposition effect. Proportion of gains (losses) realized is measured as total number of gains (losses) realized divided by number of realized gains (losses) and paper gains (losses).

One could argue that our results are affected by the global financial crisis, which struck the Estonian stock market from January, 2007 to July, 2009. Crisis marks the time period from the highest value of OMX Tallinn (market index) through the collapse until the market picked up the positive trend in August of 2009. When we exclude this period the disposition measure still stays around 0.12 (Table 1, Panel E). The disposition measure is slightly higher for the

crisis period (0.18) (Table 1, Panel F). This is intuitive as during the times of crisis people tend to realize any possible gains faster, but hold on to their losing stocks with a hope of market bouncing back soon. Such explanation is documented empirically by Wang (2010) and Szyszka (2010). Wang (2010) empirically finds that the difference of net flow elasticity of positive returns before and after the crisis is significant and individual traders experiencing the same level of positive returns are more likely to realize them during the time of the crisis.

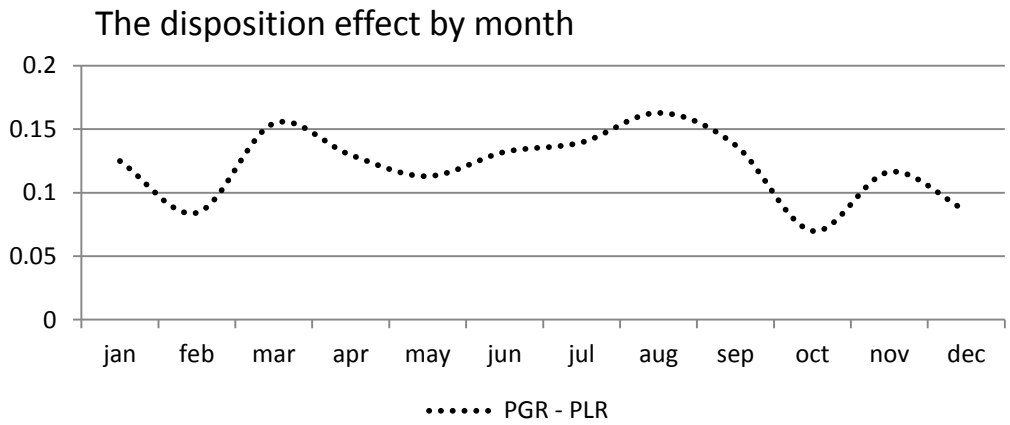


Figure 1. Monthly disposition effect. This figure presents PGR-PLR measure calculated from realized and paper gains (losses) each month in the sample period.

Overconfidence

When we calculate buy and sell returns for any individual investor who made at least one buy and one sell during the period from January, 2004 to October, 2010, we are left with 7566 individual investors. There are 84,674 buys and 75,758 sells during the period. Odean (1999) has more accounts (10,000), but less trades (49,948 buys and 47,535 sells) in the U.S. data. Consistently with Odean (1999) we get that the securities bought underperform the securities sold even before accounting for transaction costs. This means that investors are not only paying transaction costs, which are equal to 2.2% on average, but also lose money by trading. Results are presented in Table 2. Panel A shows that over 100 days' horizon securities investors buy underperform the ones they sell by 0.54% (t-statistic -2.5). Buy minus sell over 20 days' horizon underperforms by 0.36% (t-statistic -3.5). Odean (1999) finds a stronger effect in the U.S. stock market. Purchases underperform sales by 1.36% over 84 days' horizon.

We find that 3,468 or 46% of investors have on average 100 days' buy minus sell returns lower than zero, or in other words are overconfident in their ability to pick stocks. Proportion of such investors using 20 days' horizon is similar, equal to 50% or 3,813. For robustness check we have also identified investors that are overconfident according to both horizons. Number confirms the robustness of the results as 30% of investors are overconfident at both horizons, 100 and 20 days'.

Buy minus sell returns after accounting for transaction costs are the following: -2.88% (t-statistic -11.1) for 100 days' horizon, and -2.56% (t-statistic -15.6) for 20 days' horizon. We have also identified the number of investors that are overconfident only in precision of their information. This means that their buy minus sell returns before accounting for transaction costs are equal to or more than zero, but are negative after transaction costs. There are 192 or 5% of such investors if we take 100 days' returns, and 742 or 10% of such investors when we take 20 days returns. So, in aggregate there are 51% of overconfident investors (both in ability to interpret information and in precision of information) according to 100 days' horizon, and 60 %, when using 20 days' horizon.

To check for robustness of the results we partition investors into two groups: first group consists of 10% of investors, who trade the most measured by total number of trades, and second group consists of the rest 90% of investors. Results are presented in Table 2, Panel B and C. The first group consists of 528 individual investors and second of 6,170. We find that active investors have slightly negative 100 day returns equal to -0.05%; however they are statistically insignificant from 0 (t-statistic -0.1). Interestingly, we even get slightly positive 20 days' returns equal to 0.37% (t-statistic 2). After accounting for transaction costs both numbers are negative and statistically significant at 10% (-0.75%, t-statistic -1.7, and -0.26%, t-statistic -1.44 respectively). Less active investors perform worse: 100 days' returns are equal to -0.58% and 20 days' to -0.44%. After transaction costs numbers are -3.5% and -4.2% respectively. All numbers are statistically significant. Although Odean (1999) gets negative numbers for both groups, he observed the same tendency of higher buy minus sell returns for more active investors. He explains that it might be because more active traders are more sophisticated so better at security picking, or because they hold securities for shorter horizons so 100/20 days' period following purchase overlaps with part of the 100/20 days' period after sale.

Panel A: All transactions		
Number of investors	*6,698*	*7,517*
	100 trading days	**20 trading days**
Purchases	**-3.27%**	**-0.82%**
Sales	**-2.73%**	**-0.46%**
Difference	**-0.54%**	**-0.36%**
(t-tatistic)	(-2.49)	(-3.50)
Difference after transaction costs	**-2.88%**	**-2.56%**
(t-statistic)	(-11.14)	(-15.63)

Panel B: 10% of investors that trade the most		
Number of investors	*528*	*773*
	100 trading days	**20 trading days**
Purchases	**-3.84%**	**-0.38%**
Sales	**-3.79%**	**-0.75%**
Difference	**-0.05%**	**0.37%**
(t-tatistic)	(-0.12)	(2.03)
Difference after transaction costs	**-0.75%**	**-0.26%**
(t-statistic)	(-1.70)	(-1.44)

Panel C: 90% of investors that trade the least		
Number of investors	*6170*	*6744*
	100 trading days	**20 trading days**
Purchases	**-3.22%**	**-0.87%**
Sales	**-2.63%**	**-0.42%**
Difference	**-0.58%**	**-0.44%**
(t-tatistic)	(-2.53)	(-3.90)
Difference after transaction costs	**-3.06%**	**-2.83%**
(t-statistic)	(-10.99)	(-15.79)

Panel D: Prior and after the crisis (01 2004 - 02 2007 and 08 2009 - 10	
Number of investors	*2617*
	100 trading days
Purchases	**0.69%**
Sales	**2.08%**
Difference	**-1.39%**
(t-tatistic)	(-3.44)
Difference after transaction costs	**-2.18%**
(t-statistic)	(-5.75)

Panel E: The crisis period (03 2007 - 07 2009)	
Number of investors	*6036*
	100 trading days
Purchases	**-5.17%**
Sales	**-4.82%**
Difference	**-0.35%**
(t-tatistic)	(-1.52)
Difference after transaction costs	**-1.42%**
(t-statistic)	(-5.80)

Table 2. Average returns following purchases and sales. Table shows the average buy and sell returns after each transaction for individual investors in Estonian stock market from January, 2004 to October, 2010. Returns are adjusted by market index. Standard errors are calculated by bootstrapping empirical distribution for the differences in returns.

We also calculate buy minus sell returns for two partitions of our sample (Table 2, Panel D and E). First partition is the time period from January, 2004 to February, 2007 and from August, 2009 to October, 2010. This period, identified in the same manner as in the disposition effect section, captures the time when there was no crisis. Second partition is the time period from March, 2007 to July, 2009 and captures the global financial crisis. By doing such partitioning we accomplish two goals. First, we perform a robustness check by dividing our sample in two halves and checking, whether overconfidence is not just a single occurrence that happened sometime by chance. Second, we also test whether the evidence of overconfidence could be driven by the crisis period. We find that overconfidence is evident in both periods. Interestingly, investors exhibit less overconfidence during the global financial crisis. Buy minus sell returns over 100 days' horizon before accounting for transaction costs are -0.35% (t-statistic -1.52), while it is -1.39% (t-statistic -3.44) for non-crisis period[2]. It

[2] Note that we can compare investors' performance during crisis and non-crisis periods as returns are market adjusted

might be that investors are less overconfident in their ability to interpret information when the market goes down as they do not earn positive returns that they could attribute to their investment ability. This is supported by the fact that the number of overconfident investors is equal for the two periods (51%). Thus crisis reduces only the magnitude of the overconfidence, while the number of investors suffering from this bias stays at the same level.

Likewise Odean (1999), after performing analysis and robustness checks, we conclude that individual investors in Estonia are indeed overconfident both in their ability to interpret information, and in their precision of information signals. However, the level of overconfidence is lower than in the U.S.

Systematic trading

We find that individual investors' buying decisions are highly correlated. Results are presented in Table 3. Panel A shows that the correlation of buying intensity across stocks among two randomly assigned groups of investors is equal to 44% and statistically significant (t-statistic 10). Note that the result is the same to what Jackson (2003) records in Australia. He found that correlation among the 9 internet brokerage clients is equal to 44%. Barber, Odean, and Zhu (2009) find the correlation to be equal to 73% for discount brokerage clients in the U.S. Although authors note that the correlation measure declines when there are less accounts in both of the two random groups it could not be the reason why we witness lower correlation. Our sample size is comparable to Barber, Odean, and Zhu (2009) as we likewise have around 10,000 accounts in each of the random groups. This implies that investors in Estonia are less prone to systematic behaviour than those in the U.S. This result could be driven by the fact that there are only 15 stocks in the Estonian stock market and therefore it is far less complicated to research and decide on which stocks to trade. So the need to follow others is not so significant. On the other hand, Estonian stock market is apparently less liquid than the one in the U.S. so people's choice might be more limited. However, study of the relationship between the number of stocks on offer and the level of correlation is out of the scope of this research.

We further check whether the correlation is only contemporaneous or persists over time. Table 4 presents the time series correlations of two randomly assigned investor groups. We find that systematic trading is highly persistent. Buying intensity of one group in the current period can explain considerable fraction of buying decisions of the other group as far as ten

months in the future and sometimes even more. Correlations diminish over time, but even around ten months in the horizon, correlation is 10-20 %. Consistent with the results that the contemporaneous correlation is lower in Estonia, we find that the positive correlation persists for shorter time span than in the study by Barber, Odean, and Zhu (2009). They find consistently positive correlation for up to two years.

Panel A: All investors		
Correlation	**43.65%**	
(t-statistic)	(14.33)	
Panel B: Disposition prone investors versus the rest		
	Disposition investors	Other
Correlation	**17.10%**	**17.50%**
(t-statistic)	(3.97)	(4.01)
Panel C: Overconfident investors versus the rest according to 100 days returns		
	Overconfident investors	Other
Correlation	**18.09%**	**11.84%**
(t-statistic)	(3.88)	(2.51)
Panel D: Overconfident investors versus the rest according to 20 days returns		
	Overconfident investors	Other
Correlation	**25.72%**	**13.64%**
(t-statistic)	(6.18)	(3.17)

Table 3.Correlation of buying intensity among investors. Table presents the buying intensity's correlation among two randomly assigned investor groups.

Having proven that systematic behaviour in the Estonian stock market is evident we now turn to check, whether investors suffering from behavioural biases of disposition effect and overconfidence could be the driving force that coordinates traders' actions in Estonia. We address these biases one by one.

If disposition prone investors would drive systematic trading we would see more coordinated trading among the investors that suffer from disposition effect as compared to non-disposition traders. Table 3, Panel B shows that there is hardly any difference between the correlation of two randomly assigned investor groups in the subset of disposition prone investors versus non-disposition ones. Correlation for disposition investors is 17.1% (t-statistic 3.97) while it is 17.5% (t-statistic 4.01) for non-disposition investors. Therefore, we conclude that systematic trading is equally evident for both those, who suffer from disposition effect, and those, who do not. Disposition prone investors do not induce more coordinated trading.

Horizon (L)	Group1 with Group 2	Group2 with Group 1	Group 1 with Group1
0	55.84%	55.84%	100.00%
1	47.59%	42.16%	51.21%
2	24.39%	32.42%	39.63%
3	25.71%	41.45%	29.58%
4	28.37%	39.63%	41.31%
5	36.00%	28.23%	34.63%
6	21.57%	25.19%	32.93%
7	24.97%	34.81%	42.66%
8	16.50%	52.10%	40.67%
9	12.89%	21.14%	35.34%
10	6.23%	13.89%	20.54%
11	8.44%	12.84%	20.47%
12	-11.06%	10.61%	-3.73%
13	-8.25%	8.85%	-3.17%
14	-0.80%	10.72%	13.76%
15	3.01%	20.44%	24.42%
16	-4.30%	8.51%	19.37%
17	-22.89%	7.85%	-4.40%
18	-10.25%	5.50%	9.96%
19	-5.55%	10.27%	5.33%
20	-18.55%	2.58%	2.26%
21	-22.26%	-6.33%	-14.59%
22	-21.88%	0.99%	-0.64%
23	-14.52%	-4.65%	-4.63%
24	-7.99%	-0.57%	3.49%

Table 4. Contemporaneous and times series correlations. Table presents the persistence of buying intensity's correlation among the randomly assigned investor groups in month *t* and in month *t+L*.

Contrary to the findings of correlation among disposition investors, traders suffering from overconfidence seem to be a factor associated with more coordinated trading in the Estonian stock market. In Table 3, Panel C and D we see that while the correlation coefficient for two randomly assigned groups of overconfident investors, defined as those whose 100 day buy minus sell returns are negative before transaction costs, is 18.1% and statistically significant (t-statistic 3.88), the level of correlation for those investors that are not overconfident is only 11.8% (t-statistic 2.51). Even stronger tendency can be spotted with 20 days returns. Correlation for overconfident investors is almost two times higher than for the rest of the sample. We conclude that investors possessing overconfidence bias are partly responsible for the buying intensity's correlation among the traders in the Estonian stock market.

One can instantly point out that the figures in the last paragraphs are much lower than those found for the whole sample of investors. However, the later calculations were done with much smaller subsets of the database due to the fact that non-zero PGR and PLR denominators are available for only 2880 accounts, which is barely 15 % of the whole sample. Buy minus sell returns could only be calculated for around 30% of the sample. This indicates that only a small proportion of investors in Estonia stock market are active traders, who also hold at least two stocks at any day when they sell a security. As noted before,

Barber, Odean, and Zhu (2009) state that the strength of the common component of trading declines in relation to the idiosyncratic component as the number of investors in the sample decreases. Our dataset supports such explanation. If the sample is randomly divided by half, the correlation coefficient of the disposition prone investors' stock buying intensity further diminishes to 5%. Another possible explanation might be that investors, who comprise the subsets of the disposition prone and overconfident investors, are those, who trade more often, hold more stocks, and thus are classified as more sophisticated investors. In such case they might be less susceptible to systematic trading.

All in all, we find that investor trading in the Estonian stock market is highly correlated and persistent. Disposition prone investors trade systematically, but their buying intensity is equally as correlated as of non-disposition investors. Overconfident investors' trading is more correlated than non-overconfident investors' and is partly responsible for the systematic trading we witness in the market.

Stock market impact

We separately test the impact of the disposition effect and overconfidence on the Estonian stock market. We start by examining the disposition effect. We expect that when the number of disposition prone investors among the shareholders of a stock increases we should observe lower returns. We find such relationship in both specifications, with and without inclusion of stock price. The results of the disposition effect regressions are summarized in the Appendix 1, Table 1. The coefficient estimate of the disposition proxy is negative (-0.4) and statistically significant (t-statistic 11). The coefficient is also significant in economic sense. Compared to the base case (the net trades by disposition prone investors equal net trades of remaining investors), when there are no disposition traders among the buyers the average daily stock returns should be higher by 0.4% or 8.7% per month.

Contrary to the findings of the first specification, other regressions show less statistically significant results. Disposition proxy does not have a strong association with stock volatility, volume or turnover. The hypothesis that the coefficient on the disposition proxy is equal to zero cannot be rejected at conventional levels of significance. Nevertheless, in line with the predictions by the model of Grinblatt and Han (2005) as well as empirical results of Goetzmann and Massa (2008) we find negative relationship between the disposition proxy and volume, turnover, and volatility. The fact that Goetzman and Massa (2008) were able to achieve much higher levels of statistical significance could be attributed to more than 10

times larger number of observations in their sample (149,000). The statistical significance in studies with exceptionally high number of observations is criticized in academia. McCloskey and Ziliak (2008) refer to a study with around 80,000 observations and state that "with such sample sizes a variable that is economically unimportant will show up as statistically significant, through the share force of large N". All in all, we conclude that there is some evidence of disposition prone investors impacting stock prices.

Having identified and quantified disposition effect's impact on stock prices, we now turn to test whether overconfidence has any impact on the Estonian stock market. If we find positive effect on volume from lagged returns, this would imply that overconfidence induces more trading. Moreover, evidence that stock returns can be predicted using past trading volume would put the ultimate connection from overconfidence to stock returns.

The results from market level VARs with 4 and 10 lags are presented in Appendix 2, Panel A and Panel B respectively. Both specifications of market level analysis provide mixed evidence about the returns impact on volume. First and fourth lags of market returns are consistently negative when using lag length of 4 and 10 weeks, while second and third lags are consistently positive. Hardly any of the coefficients on lagged returns are significant at least at 10% level. The same holds for the predictive power of market volume on market returns. Coefficients on lagged volume are insignificant and with varying signs.

Since the coefficients recorded in VAR do not capture the full effect of the exogenous impulse from one variable to another, we employ the orthogonalized impulse response functions (OIRFs) to trace down the impact. OIRFs results are presented in Appendix 3 and Appendix 4. Analysis of OIRFs confirms the results of the associated VARs. Neither lagged market returns have a statistically significant impact on market volume, nor vice versa (see Appendix 3, Panel B and C for details). The largest t-statistic for the response in market volume from impulse in market return is achieved for the third lag (1.52). However, it is still not enough to reject the hypothesis of no relationship at conventional levels of significance. Nevertheless, the coefficient estimate (magnitude of response) is in line with the expectation that higher returns should make investors overconfident and drive higher levels of trading volume in subsequent periods. The coefficient is positive and shows that a one standard deviation shock in market return should raise the level of volume by 7.5 % in the third subsequent week, conditional on no contemporaneous shift in market volume. The cumulative impact over a month (4 weeks) is equal to 9.3% and is similar to the findings of Statman, Thorley, and Vorkink (2006). Using monthly data they find a statistically significant

market turnover increase of 8.6% one month after one standard deviation shock in market returns. However, direct comparison of these results can be misleading. The economic significance is lower for the Estonian stock market, since standard deviation of returns is 10 times the mean value, compared to 4 times in the U.S. dataset.

We now turn to investigate, whether market returns can be predicted using past trading volume by employing OIRFs. We trace the impact of one standard deviation shock in market volume on subsequent market returns. Consistent with the results of Statman, Thorley, and Vorkink (2006) we do not find a strongly significant effect (see Appendix 3, Panel C). We check the robustness of our findings from OIRF analysis using the lag length of 10 periods in line with Statman, Thorley, and Vorkink (2006). We do not observe any material change in the relationships and their significance (OIRFs are reported in Appendix 4, Panels A through D).

We also test if the relationships between return and volume hold on the stock level. If we found that even after controlling for stock returns there is a positive relation between market returns and stock volume, it would contribute to the evidence that positive returns make investors overconfident about their investment abilities and induce them to trade more actively. This would increase the stock volume independent of the disposition effect as noted in the methodology. The evidence of overconfidence impact is mixed. For 9 out of 14 stocks in the VAR where dependent variable is stock volume, the coefficient on the first lag of market returns is positive. It is statistically significant at 5% in 3 of the 9 stocks with a positive coefficient (see Appendix 2, Panel C). Similar relationships can be noticed with second and third lag. However, consistently with the findings in market level analysis, the impact of market returns on stock volume decline very fast and 13 out of 14 stocks have negative coefficients on market return in the fourth period. The results are also statistically insignificant for 12 out of 13 of these stocks.

We found mixed evidence of returns association with subsequent trading volume both at market and stock level. We found a statistically significant short time evidence of market returns effect on market volume. This would imply that overconfident investor behaviour affects the Estonian stock market. However, as longer effect is not statistically significant, we cannot make any strong inferences. What is more, we found no evidence of return predictability using volume. We believe that further studies using alternative proxies to account for and quantify overconfidence might yield interesting insights and might achieve clearer results.

To summarize, we have shown that the disposition effect has an impact on stock prices. However, when testing for overconfidence effect on the Estonian stock market, almost no statistically significant relationships were documented. No clear cut conclusions can be drawn on that.

V. Discussion

After the explicit analysis, we now turn to the discussion of our findings. There are two major observations that lead to the implications we draw: first, there is a strong evidence of investors suffering from behavioural biases of the disposition effect and overconfidence; second, there is aggregated evidence of all three steps of our analysis that challenge the underlying propositions of the EMH. We here present the three implications one by one: we start by implying that investor sophistication in Estonia could be improved, continue with discussion about the need to improve the tools of arbitrage, and eventually question the three foundations of the EMH.

Investors in Estonia suffer from behavioural biases of the disposition effect and overconfidence. This yields a reduction in their final wealth. Investors would be better off, if they would not hold on to their losing stocks too long and would not sell their winning stocks too soon, and if they would not trade so much. Such goal could be achieved by increasing investor sophistication. Investor literacy could be improved by educating the youth. Such approach is undertaken in many developed countries. For example, in the U.S. there is an organization that aims at improving financial literacy of pre-kindergarten to college age people (Jump$tart, 2011). The organization provides resources, standards and various supports for the financial education. Future investors are raised in the environment, where the basic financial knowledge is well spread. Initiative to improve investor sophistication in Estonia could start with small steps. Government could include financial courses into the school curriculum. Such courses are of course costly, but could offer a solid return on investment. If less investors were behaviourally biased, market would have higher informational efficiency and prices would better correspond to the fundamentals. This would ultimately lead to a better resource allocation.

Of course, we must consider the argument that noise trading facilitates trade and is essential for a stock market to function. Noise traders are investors that are “subject to systematic biases” (Shleifer and Summers, 1990). According to the rational expectations equilibrium models that analyze price formation, noise trading is an essential part of the process.

Diversion in the opinion about security value induces investors to take both sides in a trade and impound new information into price. Black (1986) states that noise allow markets to function and prevent from market failure. Berkman and Koch (2008) empirically test the association of noise trader proxy and various market quality measures. Authors find that in line with Kyle (1985) model, noise trading is positively associated with volume and depth. They also find that noise trading narrows bid-ask spread. Although generally scholars agree that some level of noise is needed for the markets to function and too much is harmful to the quality of the markets, the optimal level is yet unclear. The proportion of the disposition prone and overconfident investors in the Estonian stock market that we document (more than 60% and more than 50% respectively) is simply too high to be treated as "some noise". Although investors' education would increase their sophistication and decrease noise trading, the market failure from too little trading is highly unlikely.

A very important mechanism that facilitates market quality is arbitrage. There always are sophisticated investors that profit from misvaluations in the stock market. Competition between them drives their profits down and further improves informational efficiency. However, as noted by Shleifer (2000), there are number of barriers that arbitrageurs face. We find some evidence that disposition prone investors have some impact on prices, which confirms that arbitrageurs are unable to fully eliminate price impact. For these reasons we think that there are grounds for improving the means of arbitrage. For example, it is very difficult and practically impossible to short sell stocks in the Estonian stock market. To improve the means of short selling a platform for easier stock borrowing could be created. Of course, this is only an example and a potential threat of increased market manipulation should also be carefully analyzed.

We find evidence that investors in Estonian stock market suffer from the disposition effect and overconfidence, trade systematically, and behaviourally biased investors have some impact on stock prices. This three step evidence corresponds to the underlying propositions of the EMH. First, Fama (1970) assume that investors are rational utility maximizing individuals. We show that this is very unlikely to be true. Investors are prone to the behaviour that is decreasing their wealth in the Estonian stock market. The findings withstand various robustness checks and contribute to the behavioural finance literature. It shows that long-overlooked patterns in decision making found in psychology and sociology help to understand financial markets. Second, Fama (1970) argues that even if some investors are irrational, their trades are random and cancel each other out. Thus, market prevails

informationally efficient. Contrary to this proposition, we find that investors' trading in the Estonian stock market is correlated and persistent. It implies that investors trade in the same direction at a particular point in time. This could be driven by similar trading strategies or patterns. This is supported by our finding that disposition prone and overconfident investors trade systematically. Overconfident investors can even be treated as a force that drives systematic trading. Third, Fama (1970) insists that even if a group of irrational investors trade systematically, there are rational arbitrageurs, who eliminate the price impact and informational efficiency prevails. However, we find some empirical evidence that disposition prone investors have an impact on prices. Note that we do not claim that arbitrage is ineffective; rather, we say that arbitrageurs face barriers and do not eliminate the full price impact. We have grounds to believe that even the third argument of the EMH is shaky. This is further supported by the strong theoretical arguments of the limits of arbitrage (Shleifer, 2000).

The three underlying mechanisms of the EMH are economically very important. Think of what happens if none of them holds. Irrational investors trade systematically and affect security prices. The information that is impounded into prices is incorrect. Thus, the price of a security does not correspond to its fundamental value. This effect is very important in several ways. First, investment is distorted. Investors do not know the true value of the companies they are investing. Some firms have excessive investment inflows and others suffer from shortage. Resources are not allocated to their most efficient uses. Second, smart investors can systematically beat the market. If they successfully identify the pattern of misvaluation, abnormal profits are possible. Active fund management suddenly makes sense. Holding market portfolio, diversifying and constantly rebalancing is unnecessary. Third, there is a point in timing investment as market conditions change. It is plausible that misvaluation increases or decreases as time passes. Fourth, Capital Asset Pricing Model (CAPM) is not fully accurate as long as it does not incorporate behavioural measures. Fifth, price reaction to new information is not necessarily fast and accurate.

VI. Conclusions

The aim of this paper was to perform a three step analysis according to the three underlying mechanisms of the EMH in the Estonian stock market. First step was to identify whether investors behave irrationally. By measuring the disposition effect and overconfidence we have shown that investors are behaviourally biased. They are more willing to realize gains as compared to losses. Furthermore, investors are overconfident and trade too much. Such

investors' behaviour decreases their final wealth and expected utility. We took the second step to test if investors trade systematically. We found that investors' trading is indeed highly correlated and persistent. We also documented that disposition prone and overconfident investors trade systematically and that overconfident investors induce more correlated trading. All this evidence supports the fact that irrational choices of investors to buy or sell a stock are not random and do not cancel out as predicted by the EMH. Finally, we have undertaken the third step in order to analyze, whether investors suffering from behavioural biases of disposition effect and overconfidence have an impact on stock prices. We found some evidence that disposition prone investors have an impact on prices, while we could not draw any conclusions about overconfidence.

Taking everything together, we see three main implications. First, as investors in the Estonian stock market act irrationally we believe there are grounds for improvement. Existing or future investors could be educated about the rational financial behaviour. Second, relying on our analysis and evidence from other studies we imply that limits to arbitrage is an issue to be considered. Better means of arbitrage could improve the quality of the financial markets. Third, the above evidence questions the three underlying mechanisms of the EMH. If markets are not fully informationally efficient, then prices do not correspond to fundamentals and investment is distorted.

We present possible directions for further studies. A research could investigate the disposition effect and overconfidence in the Estonian stock market at the investor level. The relationship between these biases and investor characteristics such as age, gender, home or foreign would provide useful insights for policy decisions. Whether investors in Estonian stock market are aware of tax-motivated selling is another attractive phenomenon to research. While tax-motivated selling is widely documented in other countries, we found very little evidence in Estonia. A study about the relationship between the number of stocks on offer and correlation of investors trading would tackle the issues of a small set of stocks on the market. Finally, a research that undertakes the three step analysis according to the EMH in another market using a single dataset would contribute to the evidence found.

References

Alpert, M., Raiffa, H., (1982). A Progress Report on the Training of Probability Assessors. *Judgement Under Uncertainty: Heuristics and Biases*, by Kahneman, Slovic, and Tversky, Cambridge University Press, Cambridge and New York.

Annaert, J, Heyman, D., Vanmaele, M, and Van Osselaer, S., (2008). Disposition Bias and Overconfidence in Institutional Trades. Retrieved December 5, from http://www.fma.org/Prague/Papers/Paper_disposition_bias_and_overconfidence_in_institutional_trades.pdf

Baltussen, G., (2009). Behavioral Finance: an Introduction. SSRN Working Paper. Retrieved March 2, 2011, from http://papers.ssrn.com/sol3/papers.cfm?abstract_id=1488110

Barber, B. M., and Odean, T., (2000). Trading is Hazardous to your Wealth: The Common Stock Investment Performance of Individual investors. *Journal of Finance*, 22, 19-36.

Barber, B. M., and Odean, T., (2001). Boys Will Be Boys: Gender, Overconfidence, and Common Stock Investment. *Quarterly Journal of Economics*, 116(1), 261-292.

Barber, B. M., and Odean, T., (2002). Online Investors: Do the Slow Die First? *Review of Financial Studies*, 15, 455-487.

Barber, B. M., and Odean, T., (2005). Individual Investors, in R. Thaler *Advances in behavioural finance:* Volume II, Princeton University Press, Princeton.

Barber, B. M., Odean, T., and Zhu, N., (2009). Systematic Noise. *Journal of Financial Markets*, 12, 547-569.

Barberis, N. and Wei, X. (2009). What Drives the Disposition Effect? An Analysis of a Long-standing Preference-based Explanation. *Journal of Finance*, 64, 751-784.

Berkman, H., and Koch, P. D., (2008). Noise Trading and the Price Formation Process. *Journal of Empirical Finance*, 15(2), 232-250.

Biais, B., Hilton, D., and Mazurier, K., (2005). Judgemental Overconfidence, Self-Monitoring, and Trading Performance in an Experimental Financial Market, *Review of Economic Studies*, 72(2), 287-312.

Black, F., (1986). Noise. *Journal of Finance*, 41 (3), 529-543.

Blume, M., E., and Friend, I., (1975). The Asset Structure of Individual Portfolios and Some Implications for Utility Functions. *Journal of Finance* 30, 585-603.

Brock, W., Lakonishok, J, and Lebaron, B., (1992). Simple Technical Trading Rules and the Stochastic Properties of Stock Returns. *Journal of Finance*, 47(5), 1731-1764.

Chen, G., Kim, K. A., Nofsinger, J. R., and Rui, O. M., (2007). Trading Performance, Disposition Effect, Overconfidence, Representativeness Bias, and Experience of Emerging Market Investors. *Journal of Behavioral Decision Making*, 20, 425-451.

Chuang, W., and Lee, B., (2006). An Empirical Evaluation of the Overconfidence Hypothesis. *Journal of Banking and Finance*, 30(9), 2489-2515.

Constatinides, G. M., (1984). Optimal Stock Trading with Personal Taxes: Implications for Prices and the Abnormal January Returns. *Journal of Financial Economics*, 13(1), 65-89.

Daeves, R., Luders, E., and Luo, G. Y., (2009). An Experimental Test of the Impact of Overconfidence and Gender on Trading Activity. *Review of Finance*, 13(3), 555-575.

Daniel, K., Hirshleifer, D., and Subrahmanyam, A., (1998). Investor Psychology and Security Market Under- and Over-reactions. *Journal of Finance*, 42, 557-581.

DeLong, J. B., Shleifer, A., Summers, L. H., and Waldmann, R. J., (1990). Noise Trader Risk in Financial Markets. *Journal of Political Economy*, 98(4), 703-738.

Dhar, R. and Zhu, N. (2006) Up Close and Personal: An Individual Level Analysis of the Disposition Effect. *Management Science*, 52(5), 726-790.

Dorn, D., Huberman, G., and Sengmueller, P., (2008). Correlated Trading and Returns. *Journal of Finance*, 63, 885-920.

Edelen, R. M., and Warner, J. B., (2001). Aggregate Price Effects of Institutional Trading: A Study of Mutual Fund Flow and Market Returns. *Journal of Financial Economics*, 59(2), 195-220.

Fama, E., (1965). The Behavior of Stock-Market Prices. *The Journal of Business*, 38(1), 34-105.

Fama, E., (1970). Efficient Capital markets: A Rewiev of Theory and Empirical Work. *Journal of Finance*, 25(2), 383-417.

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

Fernandes, J. L. B., Pena, J. I., and Tabak, B. M., (2008). How Do Prior Outcomes Affect Risk Taking Behavior? A Cross-Country Experimental Analysis. SSRN Working Paper. Retrieved February 12, 2011, from http://papers.ssrn.com/sol3/papers.cfm?abstract_id=905205

Fischhoff, B., Slovic, P., and Lictenstein, S., (1977). Knowing with Certainty: The Appropriateness of Extreme Confidence. *Journal of Experimental Psychology*, III, 552-564.

Frank, J. D., (1935). Some Psychological Determinants of the Level of Aspiration. *American Journal of Psychology*, 47(2), 285-293.

Frazzini, A. (2006). The Disposition Effect and Underreaction to News. *Journal of Finance*, 61(4), 2017-2046.

French, K. R., Schwert, G. W., and Stambaugh, R. E., (1987). Expected Stock Returns and Volatility. *Journal of Financial Economics*, 19, 3-29.

Friedman, M., (1953). Essays in Positive Economics. University of Chicago Press, Chicago.

Gervais S., and Odean, T., (2001). Learning to be Overconfident. *Review of Financial Studies*, 14(1), 1-27.

Glaser, M., and Weber, M., (2007). Overconfidence and Trading Volume. *The Geneva Risk and Insurance Review*, 32, 1-36.

Goetzmann , W. N., and Massa, M., (2003). Index Flows and Stock Market Growth. *The Journal of Business*, 76(1), 1-28.

Goetzmann, W. N., and Kumar, A., (2008). Equity Portfolio Diversification. *Review of Finance*, 12, 433-463.

Goetzmann, W. N., and Massa, M., (2008). Disposition Matters: Volume, Volatility, and Price Impact of a Behavioral Bias. *Journal of Portfolio Management*, 34(2), 103-125.

Griffin, J. M., Harris, J. H., and Topaloglu, S., (2003). The Dynamics of Institutional and Individual Trading. *Journal of Finance*, 58, 2285-2320.

Grinblatt M., and Han, B., (2005). Prospect Theory, mental Accounting, and Momentum. *Journal of Financial Economics*, 78, 311-339.

Grinblatt, M. and Keloharju, M., (2001). What Makes Investor Trade? *Journal of Finance* 56(2), 589-616.

Grinblatt, M., and Keloharju, M., (2000).The Investment Behavior and Performance of Various Investor Types: A Study of Finland's Unique Data Set. *Journal of Financial Economics*, 55, 43-67.

Grinblatt, M., and Keloharju, M., (2009). Sensation Seeking, Overconfidence, and Trading Activity. *Journal of Finance*, 64, 549-578.

Grossman, S. J., and Stiglitz, J. E., (1980). On the Impossibility of Informationally Efficient Markets. *American Economic Review*, 70, 393-408.

Hamilton, J., (1994). Time Series Analysis. Princeton University Press, Princeton.

Harris, M., and Raviv, A., (1993). Differences of Opinion Make a Horse Race. *Review of Financial Studies*, 6, 473-506.

Hirshleifer, D. A., Myers, L. A., and Teoh, S. H., (2008). Do Individual Investors Cause Post-earnings Announcement Drift? Direct Evidence from Personal Trades. *The Accounting Review*, 83, 1521-1550.

Hsu, Y., and Shiu, C., (2010). The Overconfidence of Investors in the Primary Market. *Pacific-Basin Finance Journal*, 18, 217-239.

Ikenberry, D. L.; Lakonishok, J. and Vermaelen, T. (1995). Market Underreaction to Open Market Share Repurchases. *Journal of Financial Economics*, 39(2-3), 181-208.

Jackson, A., (2003). The Aggregate Behaviour of Individual Investors. SSRN Working paper. Retrieved January 15, 2010, from http://papers.ssrn.com/sol3/papers.cfm?abstract_id=536942

Jump$tart, (2011). Wellcome to the Jump$tart Coalition for Personal Financial Literacy. Retrieved March 20, from http://www.jumpstart.org/

Kahneman, D. and Tversky, A., (1973). On the Psychology of Prediction. *Psychological Review*, 80(4), 237-251.

Kahneman, D. and Tversky, A., (1979). Prospect Theory: An Analysis of Decision Making Under Risk. *Econometrica*, 47(2), 263-291.

Kaniel, R., Saar, G., and Titman, S., (2008). Individual Investor Trading and Stock Returns. *Journal of Finance,* 63, 273-310.

Kumar, A., (2009). Dynamic Style Preferences of Individual Investors and Stock Returns. *Journal of Financial and Quantitative Analysis*, 44(3), 607-640.

Kumar, A., and Lee, C., (2006). Retail Investor Sentiment and Return Comovements. *Journal of Finance*, 61, 2451-2486.

Kyle, A. S., (1985). Continious Auctions and Insider Trading. *Econometrica*, 50, 863-894.

Linnainmaa, J. T., (2010). Do limit Orders Alter Inferences about investor Performance and Behavior? *Journal of Finance,* 65(4), 1473-1506.

Locke, P. R., Mann, S. C. (2005). Professional Trader Discipline and Trade Disposition. *Journal of Financial Economics*, 76(2), 401-444.

NASDAQ OMX Baltic, (2010). History. Retrieved November 17, 2010, from http://www.nasdaqomxbaltic.com/en/exchange-information/about-us/nasdaq-omx/nasdaq-omx-tallinn-3/history

Odean, T., (1998a). Are Investors Reluctant to Realize Their Losses? *Journal of Finance* 53(5), 1775-1798.

Odean, T., (1998b). Volume, Volatility, Price, and Profit When All Traders Are Above Average. *Journal of Finance,* 53(6), 1887-1934.

Odean, T., (1999). Do Investors Trade Too Much? *The American Economic Review,* 89(5), 1279-1298.

Oehler, A., Heilmann, K. R., Volker, L., and Oberlande, M., (2002). Dying Out Or Dying Hard? Disposition Investors in Stock Markets. SSRN Working Paper. Retrieved February 12, from http://papers.ssrn.com/sol3/papers.cfm?abstract_id=314139

Polkovnichenko, V., (2005). Household portfolio Diversification: A Case for Rank-Dependent Preferences. *Review of Financial Studies*, 18, 1476-1502.

Seru, A., Shumway, T. and Stoffman, N. (2010). Learning by Trading. *Review of Financial Studies*, 23(2), 705-739.

Shefrin, H. and Statman, M., (1985). The Disposition to Sell Winners Too Early and Ride Losers Too Long: Theory and Evidence. *Journal of Finance*, 40(3), 777-790.

Shleifer, A., (2000). Inefficient Markets. An Introduction to Behavioral Finance. Oxford University Press, Oxford and New York.

Shleifer, A., and Summers, L. H., (1990). The Noise Trader Approach to Finance. *The Journal of Economic Perspectives*, 4(2), 19-33.

Statman, M., Thorley, S., and Vorkink, K., (2006). Investor Overconfidence and Trading Volume. *Review of Financial Studies*, 19(4), 1531-1565.

Strobl, G. (2003). Information Asymmetry, Price Momentum, and the Disposition Effect. University of Pennsylvania Working Paper.

Szyszka, A., (2010). Behavioral Anatomy of the Financial Crisis. *Journal of Centrum Cathedra*, 3(2), 121-135.

Talpsepp, T., (2010). Does Gender and Age Affect Investor Performance and the Disposition Effect. *Research in Economics and Business: Central and Eastern Europe*, 2(1), 76-93.

Varian, H. R., (1989). Differences of Opinion in Financial Markets. *Judgement Under Uncertainty: Heuristics and Biases*, by Kahneman, Slovic, and Tversky, Cambridge University Press, Cambridge and New York.

Von Neumann, J., and Morgenstern, O., (1944). Theory of Games and Economic Behavior. Princeton University Press, Princeton.

Wang, N., (2010). Individual Investors and the Financial Crisis. SSRN Working paper. Retrieved February 2, 2011 from http://papers.ssrn.com/sol3/papers.cfm?abstract_id=1567943

Warther, V. A., (1995). Aggregate Mutual Fund Flows and Security Returns. *Journal of Financial Economics*, 39(2-3), 209-235.

Weber, M., and Camerer, C. F., (1998). The Disposition Effect in Securities Trading: An Experimental Analysis, *Journal of Economic Behavior & Organization*, 33(2), 167-184.

Weber, M., and Zuchel, H., (2001). How Do Prior Outcomes Affect Risky Choice? Further Evidence on the House-Money Effect and Escalation of Commitment, University

of Mannheim Working Paper. Retrieved February 10, 2011 from http://www.sfb504.uni-mannheim.de/~gewws/papers/Weber_paper.pdf

Zaiane, S., and Abaoub, E., (2009). Investor Overconfidence And Trading Volume: The Case Of An Emergent Market. *International Review of Business Research Papers*, 5(2), 213-222.

Ziliak, S. T., and McCloskey, D. N., (2008). The Cult of Statistical Significance: How the Standard Error Costs us Jobs, Justice, and Lives. University of Michigan Press, Michigan.

Appendices

Appendix 1

	Specification I	Specification II
Return		
Disp. Proxy	**-0.405**	**-0.404**
(t-statistic)	(-11.57)	(-11.56)
Controls	Yes	Yes
Stock price included as control	Yes	No
Adjusted R^2	0.23	0.23
N		
Turnover		
Disp. Proxy	**-0.020**	**-0.019**
(t-statistic)	(-1.68)	(-1.52)
Controls	Yes	Yes
Stock price included as control	Yes	No
Adjusted R^2	0.61	0.57
N	10507	10507
Volume		
Disp. Proxy	**-0.003**	**-0.003**
(t-statistic)	(-0.16)	(-0.15)
Controls	Yes	Yes
Stock price included as control	Yes	No
Adjusted R^2	0.40	0.40
N	10507	10507
Volatility		
Disp. Proxy	**-0.005**	**-0.005**
(t-statistic)	(-0.39)	(-0.39)
Controls	Yes	Yes
Stock price included as control	Yes	No
Adjusted R^2	0.10	0.07
N	10507	10507

Table 1. Disposition effect on the stock market. This table summarizes the regression analysis used to estimate the relationship of the representation of disposition investors (Disp. Proxy as a variable of interest) and stock characteristics (dependent variables): return, turnover, volume, and volatility. The broadest set of control variables used in the regression contains: market returns, overall market volume, stock price, stock return, stock volume, stock volatility, riskless rate, and company size.

Appendix 2

Panel A: Market level VAR with 4 lags of endogenous variables

Dep var: Market volume		L=1	L=2	L=3	L=4
MKTvol(t-L)	**Coefficient**	**0.5409**	**0.0701**	**0.0581**	**0.2796**
	(t-statistic)	(9.8)	(1.12)	(0.93)	(5.2)
MKTret(t-L)	**Coefficient**	**-0.5976**	**1.6059**	**1.6019**	**-2.0323**
	(t-statistic)	(-0.48)	(1.26)	(1.25)	(-1.65)
Dep var: Market returns					
MKTvol(t-L)	**Coefficient**	**-0.0004**	**-0.0006**	**-0.0016**	**0.0008**
	(t-statistic)	(-0.16)	(-0.21)	(-0.56)	(0.34)
MKTret(t-L)	**Coefficient**	**0.1884**	**0.2110**	**0.0125**	**-0.0828**
	(t-statistic)	(3.28)	(3.61)	(0.21)	(-1.47)

Panel B: Market level VAR with 10 lags of endogenous variables

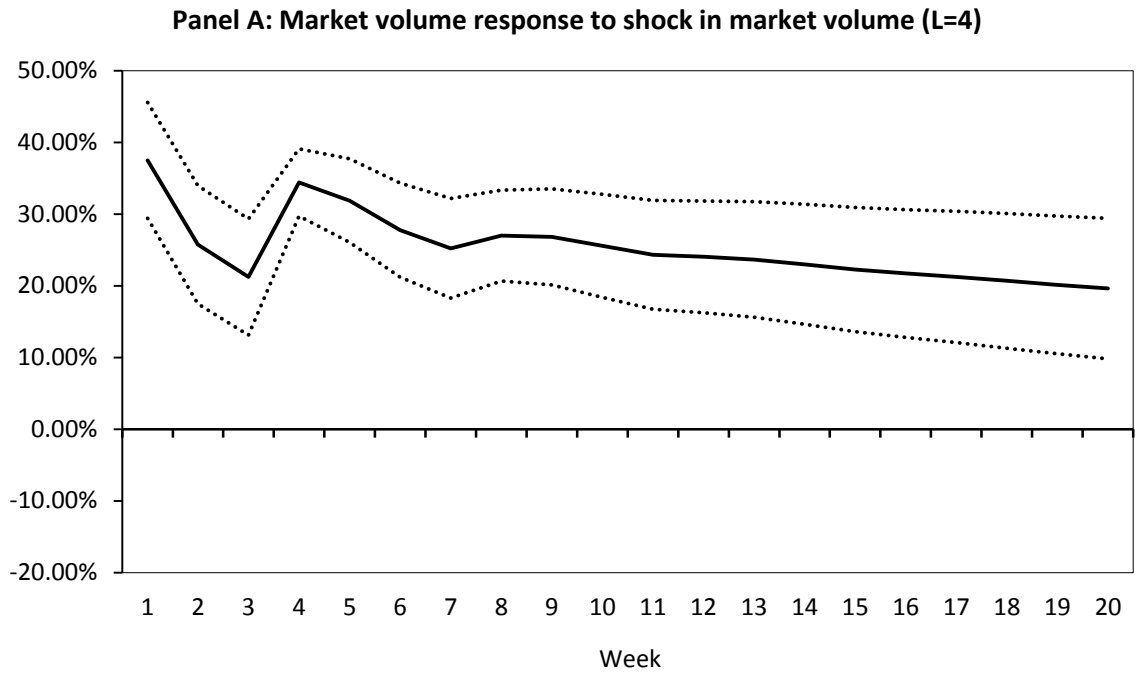
Dep var: Market volume		L=1	L=2	L=3	L=4	L=5	L=6	L=7	L=8	L=9	L=10
MKTvol(t-L)	**Coefficient**	**0.4940**	**0.0096**	**0.0230**	**0.1849**	**0.0379**	**0.0892**	**-0.0089**	**0.1667**	**-0.1101**	**0.0797**
	(t-statistic)	(8.52)	(0.15)	(0.37)	(2.95)	(0.59)	(1.36)	(-0.14)	(2.56)	(-1.7)	(1.37)
MKTret(t-L)	**Coefficient**	**-0.2111**	**1.7032**	**2.0569**	**-1.4325**	**-0.3769**	**1.4446**	**-0.7782**	**1.5231**	**-0.6041**	**0.7913**
	(t-statistic)	(-0.17)	(1.36)	(1.6)	(-1.14)	(-0.3)	(1.13)	(-0.61)	(1.16)	(-0.48)	(0.63)
Dep var: Market returns											
MKTvol(t-L)	**Coefficient**	**0.0004**	**0.0001**	**-0.0020**	**0.0020**	**-0.0015**	**-0.0022**	**-0.0012**	**0.0038**	**0.0008**	**-0.0022**
	(t-statistic)	(0.14)	(0.05)	(-0.67)	(0.69)	(-0.51)	(-0.71)	(-0.4)	(1.24)	(0.28)	(-0.79)
MKTret(t-L)	**Coefficient**	**0.2064**	**0.2288**	**-0.0309**	**-0.1028**	**0.0766**	**0.0419**	**-0.0855**	**0.0654**	**0.1043**	**-0.1328**
	(t-statistic)	(3.55)	(3.86)	(-0.51)	(-1.73)	(1.28)	(0.69)	(-1.41)	(1.06)	(1.75)	(-2.24)

Panel C: Stock level VAR with 4 lags of endogenous variables (other coefficients suppresed for better readability)

Dep var: Stock volume		Stock 1	Stock 2	Stock 3	Stock 4	Stock 5	Stock 6	Stock 7	Stock 8	Stock 9	Stock 10	Stock 11	Stock 12	Stock 13	Stock 14
MKTret(t-1)	**Coefficient**	**-2.9767**	**-0.9467**	**3.0469**	**1.0675**	**3.5741**	**3.7928**	**4.8043**	**-0.1458**	**-1.5184**	**3.4220**	**5.6452**	**2.9812**	**2.4164**	**-6.3577**
	(t-statistic)	(-1.13)	(-0.35)	(1.55)	(0.47)	(2.02)	(1.46)	(2.35)	(-0.05)	(-0.58)	(1.16)	(2.67)	(0.94)	(0.94)	(-0.41)
MKTret(t-2)	**Coefficient**	**-0.4335**	**0.1657**	**-0.3020**	**1.6249**	**-0.1548**	**4.6868**	**4.5384**	**6.9121**	**2.8515**	**1.1172**	**1.6879**	**0.1248**	**-2.2587**	**11.2700**
	(t-statistic)	(-0.16)	(0.06)	(-0.15)	(0.7)	(-0.08)	(1.82)	(2.2)	(2.57)	(1.08)	(0.36)	(0.76)	(0.04)	(-0.84)	(0.74)
MKTvol(t-3)	**Coefficient**	**1.3905**	**4.3984**	**1.9488**	**1.9281**	**-3.6683**	**1.1995**	**-1.4787**	**4.8017**	**3.2279**	**-1.0224**	**2.3845**	**1.8915**	**-1.0978**	**-7.4642**
	(t-statistic)	(0.53)	(1.66)	(0.98)	(0.85)	(-2.04)	(0.45)	(-0.72)	(1.77)	(1.14)	(-0.33)	(1.14)	(0.62)	(-0.46)	(-0.89)
MKTret(t-4)	**Coefficient**	**-4.2195**	**-4.6087**	**-0.5203**	**1.8709**	**-1.5198**	**0.0008**	**-6.1849**	**-0.3344**	**-0.3638**	**-2.3573**	**-0.6934**	**0.7604**	**-1.4308**	**5.3627**
	(t-statistic)	(-1.59)	(-1.7)	(-0.26)	(0.84)	(-0.85)	(0)	(-2.99)	(-0.12)	(-0.14)	(-0.81)	(-0.32)	(0.27)	(-0.57)	(0.63)

Table 1. Vector auto regressions of returns and volume. (Panel A) presents the market level VAR with market volume and market returns as endogenous variables with lag length of 4. Exogenous variables used in this specification are market volatility and cross sectional dispersion with lag length of 2. (Panel B) is essentially the same estimation as (Panel B) but uses 10 lags for endogenous variables. (Panel C) presents the suppressed form of stock level VAR. For simplicity only the stock volume dependent variable regression and coefficients with t-statistics on market return lags are reported, as these coefficients are of the primary interest. In this model stock returns are also used as endogenous variable and stock volatility as and exogenous variable with lag length of 2. Lag length of endogenous variables is 4. Specifications also include month of the year dummies for potential calendar effects.

Appendix 3



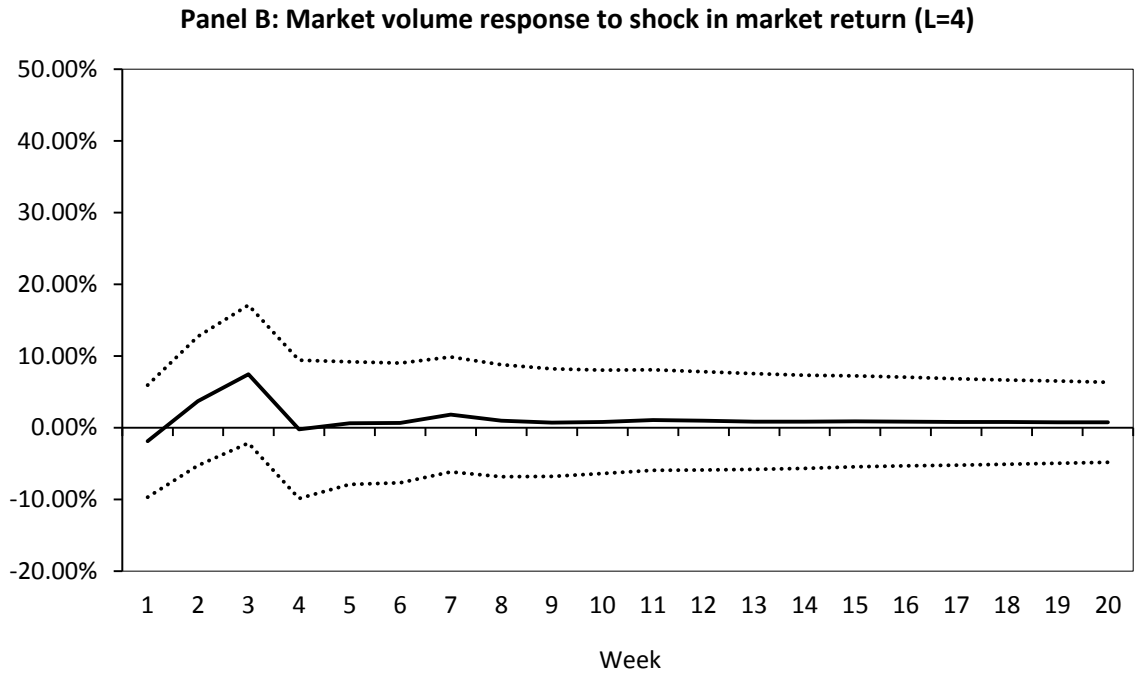
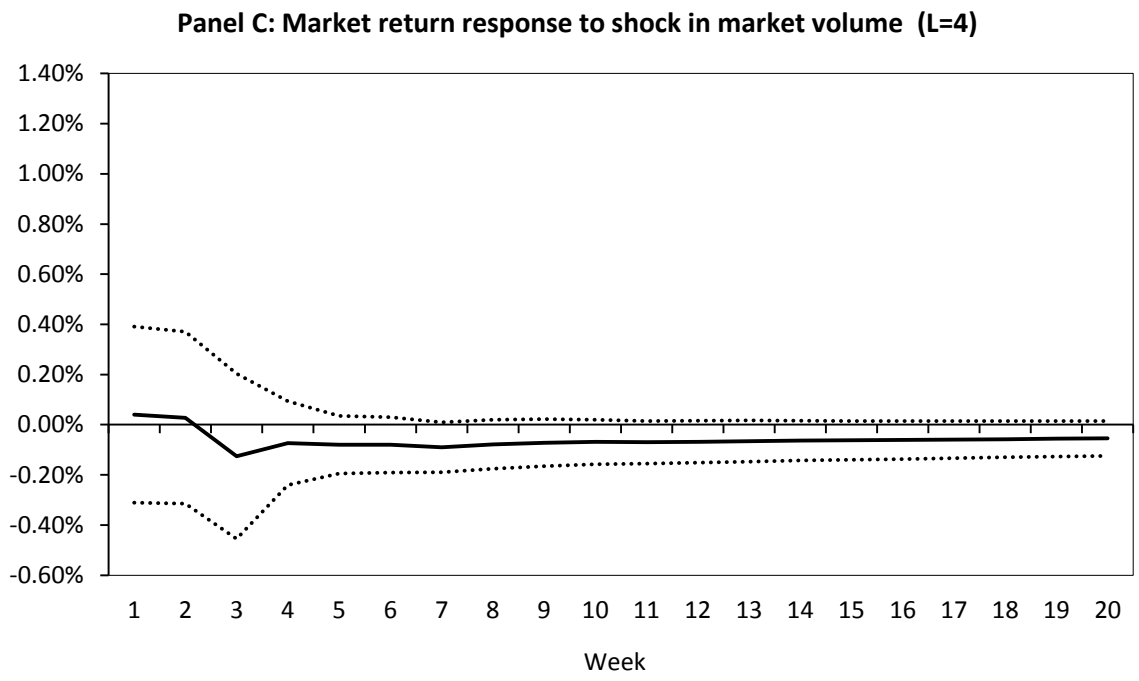


Figure 1. Market level orthogonalized impulse response functions corresponding to VAR with lag length for endogenous variables of 4. Cholesky ordering of the endogenous variables: 1. market volume, 2. market return. All panels include 95% confidence bands for the response coefficients. **(**Panel A) presents the subsequent market volume response to a one standard deviation shock in market volume. (Panel B) shows the market volume response to a shock in market return, conditional on no change in market volume contemporaneously. (Panel C) presents the market return response to a shock in market return. (Panel D) shows the response of market return to a shock in market volume, conditional on no change in market volume contemporaneously.



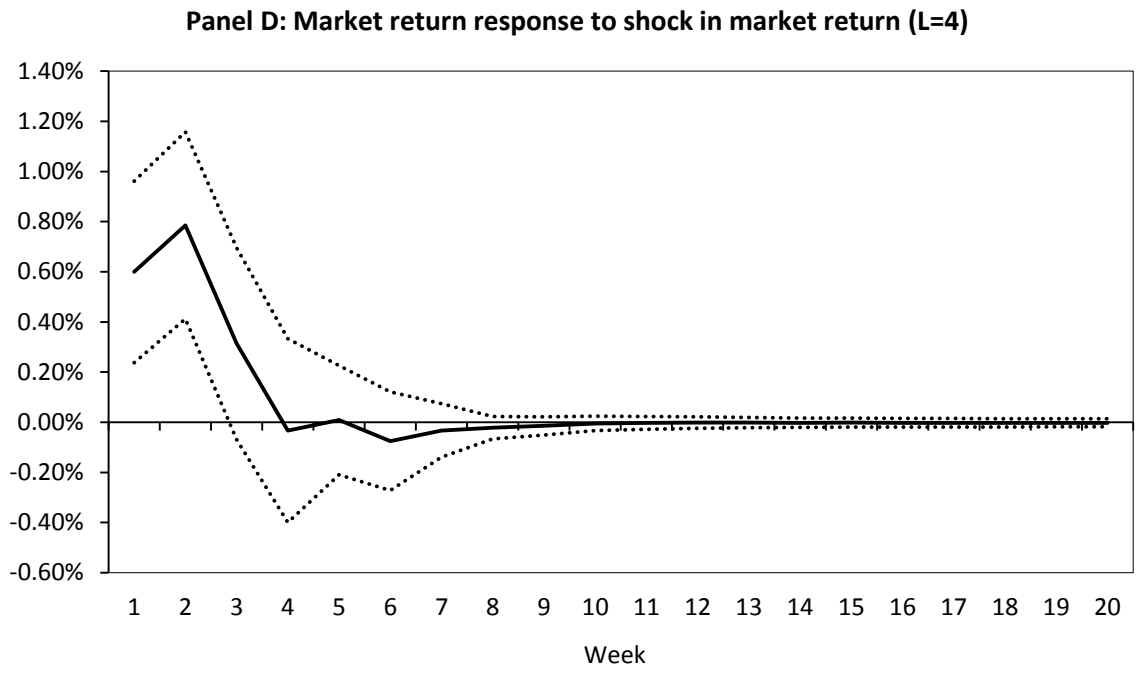
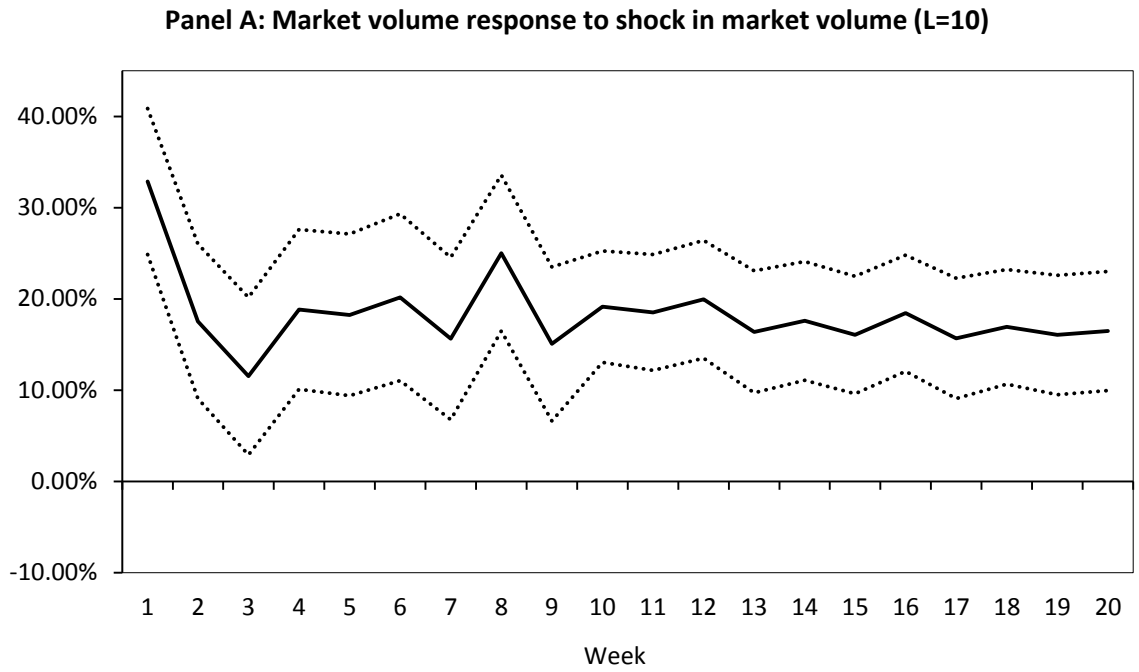


Figure 1. Continued.

Appendix 4



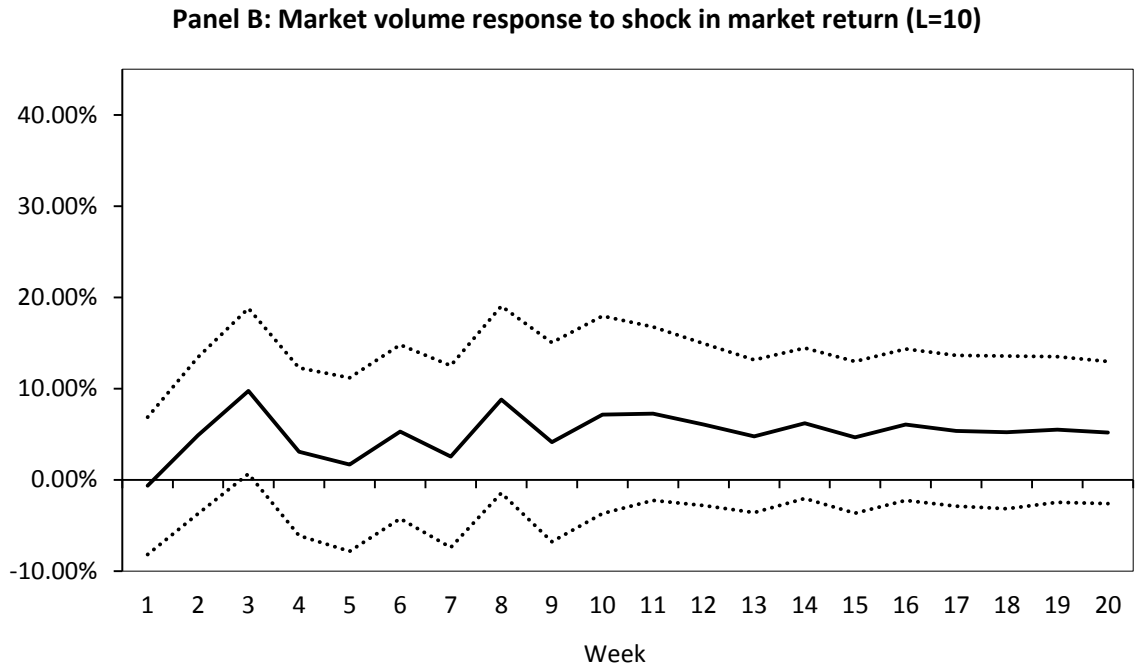
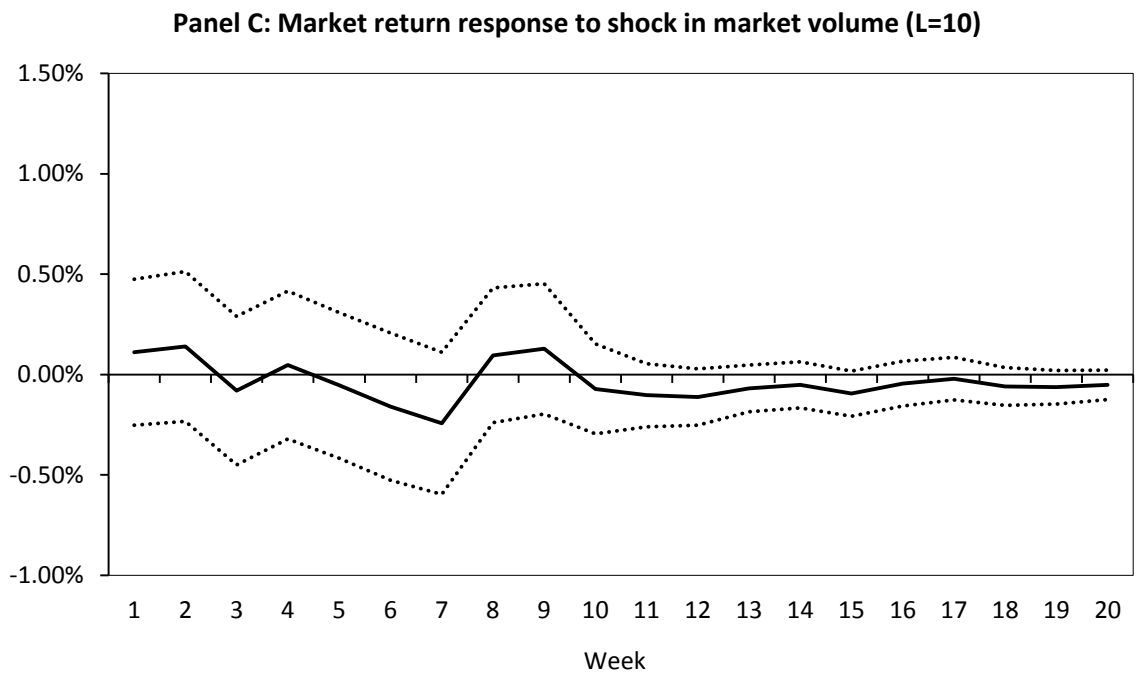


Figure 1. Market level orthogonalized impulse response functions corresponding to VAR with lag length for endogenous variables of 10. Cholesky ordering of the endogenous variables: 1. market volume, 2. market return. All panels include 95% confidence bands for the response coefficients. **(**Panel A) presents the subsequent market volume response to a one standard deviation shock in market volume. (Panel B) shows the market volume response to a shock in market return, conditional on no change in market volume contemporaneously. (Panel C) presents the market return response to a shock in market return. (Panel D) shows the response of market return to a shock in market volume, conditional on no change in market volume contemporaneously.



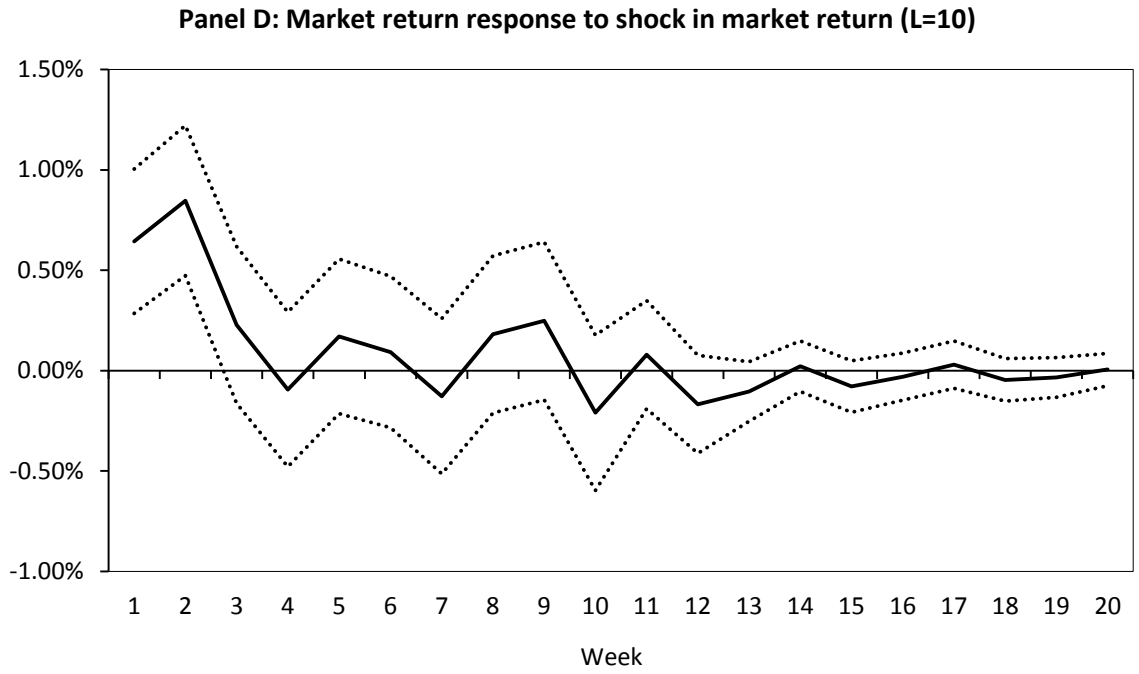


Figure 1. Continued.