Investor Behavior and Volatility Asymmetry

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Declaration:

Hereby I declare that this doctoral thesis, my original investigation and achievement, submitted for the doctoral degree at Tallinn University of Technology has not been submitted for any academic degree.

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Investorite käitumine ning volatiilsuse asümmeetria

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Introduction

Behavioral finance is defined as the study of how psychology affects finance (Shefrin 2002). Behavioral finance has its roots in the works of Kahnemann and Tversky (1979, 1992), who brought the concept of psychology, especially the decision making under uncertainty, to economic science. During the two recent decades behavioral finance has attracted growing attention among both the academics and practitioners. But it still remains debated whether the emotions and cognitive errors (if they exist at all) are common to investors, cancel out at market level (as proposed by traditional finance) and whether the efficient market hypothesis and the assumption of investors being rational should hold (and to which degree).

Behavioral finance has not been able to convincingly answer all the criticism of Eugene Fama, the developer of the efficient market hypothesis, presented in his paper "Market efficiency, long term returns, and behavioral finance" (Fama 1998). But there seems to be a shift from traditional finance towards behavioral finance and even Eugene Fama has been quoted admitting that stock prices could be "somewhat irrational" (Hilsenrath 2004). Recent turbulent times in financial markets and periods deemed as "bubbles" in retrospect seem to be accelerating the shift or at least arising further questioning about the rationality of investors.

According to Shefrin (2002) there are three main themes or areas of disagreement between supporters of behavioral finance and the views of traditional finance. Firstly, behavioral finance claims that investors use heuristics (simplified rules of thumb) in their decision making which causes different biases. Secondly, behavioral finance claims that in addition to making objective decisions based on risk and return, investors are influenced by how such decisions are framed. This contradicts the frame independent view of decision making assumed by traditional finance. Thirdly, behavioral finance believes that heuristic-driven biases and

framing effects drive market prices away from fundamental values, whereas traditional finance assumes that markets are efficient.

Another approach would be to divide behavioral finance into micro and macro level (see e.g. Pompian 2006). The micro level examines behaviors or biases of investors, while the macro level detects and describes anomalies in the efficient market hypothesis.

Current thesis takes the approach of behavioral finance and focuses on the investor stock market behavior, thus the micro level of behavioral finance. The thesis presents the results and background of three papers accepted for publication (Talpsepp 2010a and 2010b; and Dzielinski, Rieger and Talpsepp 2010) and one paper currently under review with revisions (Talpsepp and Rieger 2010). The papers focus on two different aspects of stock market "anomalities": namely the disposition effect and the volatility asymmetry. The disposition effect is the behavioral characteristic of investors to realize their winning positions early and keep holding losing positions too long. Volatility asymmetry means that volatility during falling market conditions tends to be higher compared to volatility during rising market prices.

As the results of the four papers in the thesis show, the two different empirical observations (the disposition effect and the volatility asymmetry) share a common factor of being influenced by behavioral characteristics and biases of especially individual investors. In addition to traditional finance explanation, different reactions to positive versus negative news (that can be summarized as framing effects) also play a common role for both the disposition effect and the volatility asymmetry. Connections of the investor behavior and the empirical observation of asymmetric volatility (which does not necessary have to be related to market inefficiencies) are also studied.

The disposition effect is studied in my two papers accepted for publication. The paper "Reverse Disposition Effect of Foreign Investors" (Talpsepp 2010a) focuses on the difference of local and foreign investor behavior based on a comprehensive dataset of Estonian stock market transactions. Talpsepp (2010a)

provides the first empirical documentation and further explanation of the reverse disposition effect for a clearly distinct investor group. It also provides a wide range of out of sample tests for previously proposed explanations of the disposition effect. The paper has been accepted for publication in the Journal of Behavioral Finance. The results of the paper have been presented at the Euro Working Group on Financial Modelling 46th Conference, San Jose, Costa Rica 2009. The paper has been accepted for conference presentation at the 1st World Finance Conference 2010, to be held in Viana do Castelo, Portugal May 2010. Part of the preliminary results of the paper was also presented at Economies of Central and Eastern Europe: Convergence, Opportunities and Challanges Conference, Tallinn, Estonia 2009; and results have been discussed at the seminars at Tallinn University of Technology and the University of Zurich.

The paper "Does Gender and Age affect Investor Performance and the Disposition Effect?" (Talpsepp 2010b) uses a subsample of the same Estonian dataset as Talpsepp (2010a), but focuses more on individual investor differences of stock market behavior and performance based on the distinction at the age and the gender level. The contribution of Talpsepp (2010b) is providing further empirical evidence of the connections between the disposition effect bias, trading intensity and performance for different gender and age groups. Both of the papers studying the disposition effect (Talpsepp 2010a and 2010b) use the same survival analysis methodology but slightly different data and regression setups and subsampling. Both of the papers are empirical in nature, but Talpsepp (2010a) uses also numerical simulation to test the theoretical model predictions. Talpsepp (2010b) has been accepted for publication in journal: Research in Economics and Business: Central and Eastern Europe, Vol. 2, No. 1. Part of the preliminary results has been presented at Economies of Central and Eastern Europe: Convergence, Opportunities and Challanges Conference, Tallinn, Estonia 2009; and results have been discussed at seminars at the Tallinn University of Technology and the University of Zurich.

Volatility asymmetry is studied in the papers "Volatility asymmetry, news and private investors" (Dzielinski, Rieger and Talpsepp 2010) and "Explaining Asymmetric Volatility around the World (Talpsepp and Rieger 2010). The contribution of the papers is providing tests of various hypothesis of the causality of volatility asymmetry and proposing individual investor market participation level as a possible new factor explaining the asymmetry. Dzielinski, Rieger and Talpsepp (2010) has been accepted for publication as a chapter in "News Analytics in Finance Handbook" to be published by John Wiley & Sons. Dzielinski, Rieger and Talpsepp (2010) consists of 4 sections: 1. Introduction, 2. What causes volatility asymmetry, 3. Who makes markets volatile?, and 4. Conclusions. Section 2 presents the main results of Talpsepp and Rieger (2010) with some additional insights into the matter using the same international data as Talpsepp and Rieger (2010). Section 2 is written and has calculations and graphics made by Tõnn Talpsepp. Section 3.1 is written and has calculations and graphics made by Michal Dzielinski. Section 3.2 studies the linkage between volatility and market participation of both individual and institutional investors based on a comprehensive transaction dataset of the Estonian stock market. Section 3.2 is written and has calculations and graphics made by Tõnn Talpsepp. Prof. Marc Oliver Rieger has been responsible for supervising the work and putting together and finalizing the text and writing most of the introduction and conclusion part of the paper based on the results produced by T. Talpsepp and M. Dzielinski.

The paper "Explaining Asymmetric Volatility around the World" (Talpsepp and Rieger 2010) gives a more thorough and detailed treatment of volatility asymmetry. Talpsepp and Rieger (2010) has been resubmitted with revisions to the Journal of Empirical Finance, but had not been finally accepted for publication at the time of writing (April 2010). Thus, Talpsepp and Rieger (2010) is not included as an appendix to the thesis. Still, the current thesis presents some of the theoretical and methodological background that is included in Talpsepp and Rieger (2010) but has been omitted from Dzielinski, Rieger and Talpsepp (2010) for brevity. The results of Talpsepp and Rieger (2010) and thus part of the results

of Dzielinski, Rieger and Talpsepp (2010) were presented at the German Economic Association Annual Congress 2009, Magdeburg, Germany 2009; the 16th Annual Meeting of German Finance Association, Frankfurt, Germany 2009; CARISMA Annual Conference 2010, London, United Kingdom 2010. The paper has been accepted for presentation at the 8th INFINITI Conference on International Finance, to be held in Dublin, Ireland June 2010. The results have been discussed at different seminars held at the University of Zurich, the Tallinn University of Technology and the University of Bielefeld. Talpsepp and Rieger (2010) has been written (including studying the theory, choosing and applying the methodology, gathering data and writing down the results) by Tõnn Talpsepp under the supervision of Prof. Marc Oliver Rieger. Prof. Rieger's invaluable contribution has kept the author of the current thesis on track and given valuable suggestions as well as corrections when necessary.

The rest of the thesis is organized as follows: Section 1 gives an overview of the theoretical background, used methodologies and results of the papers Talpsepp (2010a); Talpsepp (2010b). Section 2 gives an overview of the theoretical background, used methodologies and results of the papers Dzielinski, Rieger and Talpsepp (2010) with complementation from Talpsepp and Rieger (2010) where necessary. Concluding section draws parallels between the topics of the disposition effect and volatility asymmetry.

1. Disposition effect

The current section summarizes the background information, methodology and results of the disposition effect research presented in Talpsepp (2010a and 2010b).

1.1 Related literature

A detailed overview of the disposition effect literature is also given in Talpsepp (2010a and 2010b). The current section summarizes and combines the overview presented in those two papers.

The bias of liquidating winning positions too early and holding losing positions too long is known as the disposition effect and was first documented by Shefrin and Statman (1985). The effect is widely explained by the prospect theory of Kahneman and Tversky (1979). According to the prospect theory utility curve, investors consider marginal gains less valuable than marginal losses when the market price is above the reference point and consider marginal gains more valuable than marginal losses when investors' positions are in loss. However, recent work of Hens and Vlcek (2006); Barberis and Xiong (2009); Kaustia (2009) show that the prospect theory based explanation does not hold for a large number of cases and under certain conditions the reverse disposition effect is more likely than the disposition effect. Other disposition effect explanations include: the hypothesis that investors follow the contrarian strategy and believe that stocks revert to the mean (Barber and Odean 1999); rebalancing needs (Lakonishok and Smidt 1986); transaction cost minimization (Harris 1988); and mental accounting combined with backward looking optimization (Hens and Vlcek 2006).

The disposition effect as well as the reverse disposition effect can be explained by taking into consideration the prospect theory S-shaped value function, given as:

$$v(x) = \begin{cases} x^\alpha, & x \geq 0 \\ -\lambda(-x)^\beta, & x < 0 \end{cases} \tag{1}$$

where x is the gain with respect to the reference point, λ is the coefficient for loss aversion, and α and β are coefficients for risk aversion and risk seeking. Usually investors are considered being risk-averse for gains, which makes them realize gains early. At the same time investors tend to be risk-seeking in losses, making them take an additional risk when in a loss and thus not liquidate losing positions.

Hens and Vlcek (2006) argue, however, that the standard prospect theory explanation holds for the disposition effect only ex-post, especially for less loss averse investors. Hens and Vlcek (2006) show that risk averse investors with low loss aversion (who would be expected to exhibit the disposition effect according to the prospect theory explanation) would not invest in the risky stock in the first place. Barberis and Xiong (2009) show that in some cases the prospect theory predicts the disposition effect, but in other cases it can also predict the reverse disposition effect. Kaustia (2009) reaches similar conclusions and points out that it is easier to obtain a prediction for a reverse disposition effect than the disposition effect.

The first empirical evidence of the disposition effect was found by Schlarbaum, Lewellen and Lease (1978). One of the most prominent works in the area is Odean (1998), who suggests that investors who expect the losers to outperform the winners are, on average, mistaken. Gender differences have been studied by Barber and Odean (2001) and Feng and Seasholes (2008). Shapira and Venezia (2001) show that both professional and individual investors exhibit the disposition effect. The same is found by Grinblatt and Keloharju (2000, 2001, 2001b). Locke and Mann (2005) show that full-time traders on the Chicago Mercantile Exchange also exhibit the disposition effect but their performance does not seem to be negatively affected by that. The effect for professional traders is also recorded by Locke and Zhan (2005), Garvey and Murphy (2005), amd Haigh and List (2005).

Kumar (2009) shows that behavioral biases are stronger when there is greater market-wide uncertainty and Leal, Armada and Duque (2008) report a higher degree of the disposition effect during bull market. Frazzini (2006) finds

that investors under-react to positive news announcements, which can cause them to sell positions early. Krause, Wei and Yang (2006) report the disposition effect for buy strategies and a reverse disposition effect for sell strategies.

Feng and Seasholes (2005), Chen et al. (2004) and Choe and Eom (2006) show that more sophisticated and experienced investors exhibit the disposition effect to a smaller degree than less sophisticated investors. Dhar and Zhu (2006) and Brown et al. (2006) found the same reduced disposition effect for wealthier investors and Dhar and Zhu (2006) also report the reduced disposition effect for investors in professional occupations.

The disposition effect has been found in experimental studies by Weber and Camerer (1998), Strobl (2003) and Weber and Welfens (2007). Weber and Welfens (2007) also find that most investors exhibit the disposition effect but the degree varies across investors. Moreover, investors with a reverse effect also exist.

1.2   Methodology

The disposition effect analysis uses survival analysis (Cox proportional hazard model) to measure the existence of the disposition effect. Survival analysis methodology is also used in similar recent papers of Feng and Seasholes (2005) and Stoffman (2007). Both fixed and time-varying covariates are included in the hazard model to measure the probability that an investor will sell his or her current stock position. Survival analysis offers a number of advantages over logit methodology and ratio analysis (two methods which are also used in Talpsepp 2010a and 2010b). The advantage of survival analysis is that it is a statistical model of how long a stock is typically held in a portfolio. In comparison to ratio analysis, it uses data of all trading days, not only data of sell decisions (common to *PGR-PLR* ratio analysis). Survival analysis offers an easy way to interpret results and takes into account the price path of the stock in the portfolio. Additional advantages are pointed out by Feng and Seasholes (2005).

Using logistic regressions (similarly to Grinblatt and Keloharju 2000) would be an alternative approach and this is also used in the follow up paper

Talpsepp, Vlcek and Wang (2010). Survival analysis and logistic regressions are similar in the sense that they use binary outcome variables and allow for categorical or continuous predictor variables. The main difference and advantage of survival analysis is using the time dimension of the data, which allows an examination of the relationship of timing and occurrence of outcomes to multiple predictors. Logit analysis would focus only on occurrence. The used Cox proportional hazard model also allows censored observations, meaning that the data can be analyzed before all participants have experienced the terminal event (in this particular case, the sale of the stock position).

The hazard rate is estimated by maximum likelihood from the following equation:

$$h(t, p, X, Z_t) = p\lambda t^{p-1} \exp(X\beta + Z_t\gamma + \varepsilon_t) \tag{2}$$

where h is the hazard rate; β and γ are the vectors of coefficients for the covariates; $p\lambda t^{p-1}$ is referred to as the baseline hazard. The term $\exp(X\beta + Z_t\gamma + \varepsilon_t)$ allows both time-invariant and time-varying covariates, where X and Z_t are respectively the vectors of fixed and time-varying covariates. The hazard rate is the probability of selling a stock position at time t, conditional on holding a stock until time t-1. I only report hazard ratios which are equal to $\exp(\beta)$ and $\exp(\gamma)$. The hazard ratio can be regarded as the change in the probability of the terminal event (sale of stock) corresponding to changes in the covariates (different investor, stock and market specific characteristics).

Cox proportional hazard model does not impose any structure on the baseline hazard, and Cox's (1972) partial likelihood approach allows estimation of the coefficients for covariates without estimating the baseline hazard. Thus, a baseline hazard (baseline probability of the sale of stock) is not calculated, but the focus is on factors influencing the overall hazard. Details about estimating the proportional hazard model can be found in Cox and Oakes (1984).

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The *PGR-PLR* ratio analysis of Odean (1998) is also used, which counts realized gains, realized losses, paper gains, and paper losses for each day a position is sold from an account. An investor is regarded to be disposition effect biased when the aggregate proportion of realized gains is greater than the aggregate proportion of realized losses.

The calculation of *PGR-PLR* analysis uses:

RG - Number of realized gains for the sample or an investor group

PG - Number of paper gains for the sample or an investor group

RL - Number of realized losses for the sample or an investor group

PL - Number of paper losses for the sample or an investor group

The proportion of gains realized (PGR) and the proportion of losses realized (PLR) is calculated from:

$$PGR = \frac{RG}{RG + PG} \qquad (3)$$

$$PLR = \frac{RL}{RL + PL} \qquad (4)$$

A positive difference between the proportion of gains realized and the proportion of losses realized ($PGR - PLR > 0$) is assumed to indicate the disposition effect. The significance of the difference is tested with a *t*-test, where the standard error is

$\sqrt{\frac{PGR(1-PGR)}{RG+PG} + \frac{PLR(1-PLR)}{RL+PL}}$.

1.3 Data

A dataset including all transactions on Nasdaq OMX Tallinn from January 1, 2004 till June 30, 2008 is used in Talpsepp (2010a) and Talpsepp (2010b). The data includes over 0.5 million transactions for a total of 24,153 different accounts.

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Talpsepp (2010b) uses a subsample of the dataset and analyses 242,000 transactions for 20,758 different individual investor accounts.

The overall dataset is comprehensive, meaning that it includes all trades made during the period on the Tallinn stock exchange. The provided data is anonymous and includes the account ID-s, the transaction date, the price, the security and the type of the investor. Individual investors can be classified by gender, age and nationality (classified as domestic and foreign). Institutional investors can be classified by their institution type and origin (classified as domestic and foreign).

The dataset includes also starting portfolios for all accounts. I make a comparison of the reference price and the current market price for each stock in each investor's portfolio, for every trading day in the sample. Thus, trading decisions, realized and paper gains and losses for each position and each investor for every trading day are recorded. Such a data setup results in over 11 million observations that are used in the analysis.

The data setup uses a similar approach to Shapira and Venezia (2001), Feng and Seasholes (2005). The stock position is recorded when the first purchase after 1 January 2004 takes place and ending when the position goes to zero. The position could be built up with multiple purchases and liquidated with multiple sells. The reference price is the volume-weighted average purchase price.

I compare the reference price to the current market price range of each stock in each investor's portfolio for every trading day in the sample to record whether the position is in gain or loss; and the number of realized or paper gains and losses on days when a sell occurred.

Similarly to Feng and Seasholes (2005), I come up with two variables: the "Trading gain indicator" (TGI) and the "Trading loss indicator" (TLI). The TGI takes a value of 1 when a position is sold or trading at a gain on a given day or 0 otherwise. The TLI takes a value of 1 when a position is sold or trading at a loss on a given day or 0 otherwise. As I record the TGI or the TLI for each position of each account and for every trading day, a total of over 11 million observations are used

in the subsequent survival analysis. Such a large number of observations helps to improve the reliability of the results (Talpsepp 2010a). Due to a slightly different data setup with a lower frequency of recording gains and losses, the *PGR-PLR* ratio analysis uses about 900,000 observations. In the survival analysis, in addition to investor and market specific fixed and time-varying covariates, I also use interaction terms of the TGI and the TLI to investor and market related variables, which enables to get more insight into the analysis. The same approach is used by Feng and Seasholes (2005).

1.4 Results

The contribution to the disposition effect literature by the papers of Talpsepp (2010a and 2010b) firstly consists in having a dataset that contains all trades for all investors of a stock market (see e.g. Grinblatt and Keloharju 2000, 2001 and 2001b). Such a dataset has only been available for the Finnish stock market and all other previous studies have been able to study subsamples of discount brokers, which can potentially include a bias in data selection.

In Talpsepp (2010a) I provide evidence that a group of foreign investors who play an identifiable role on the stock exchange not only clearly distinguishes itself from domestic investors (like found also by Grinblatt and Keloharju (2001, 2001b) and Frino, Johnstone and Zheng (2004)) but also seems to exhibit the reverse disposition effect. Thus, the main contribution of Talpsepp (2010a) is the first empirical documentation (and some additional insights) of the reverse disposition effect for a large and important investor group and further empirical out of sample tests for most of the previous findings in the literature without any bias of taking subsamples of the data.

Current literature lacks detailed analysis of the account size, risk level and trading intensity of different age groups and concentrates on gender differences in an emerging market setup in western cultural environment, which can have clear implications on investor behavior (see e.g. Hens and Wang 2007). Talpsepp (2010b) studies the behavior of individual investors, gender and age differences in

more detail with a focus on the disposition effect bias and its connection with trading performance. Talpsepp (2010b) provides empirical evidence that the disposition effect bias, trading intensity and performance results differ across gender and age groups. A higher level of the disposition effect bias translates into a lower portfolio return, which is also negatively affected by higher trading intensity.

Recent criticism of the explanation of the disposition effect based on the prospect theory argues that there exist cases when the prospect theory should predict the disposition effect and cases when it should predict the reverse disposition effect. The existence of the disposition effect is supported by a large number of empirical findings, but the reverse disposition effect is not. The results of Talpsepp (2010a) show that there are distinct investor groups for which either the disposition or the reverse disposition effect can prevail in the same market and that is obtained in a case where market wide results would indicate the prevalence of the disposition effect. The diverse behavior of different investor groups can be caused by clear distinctions in behavioral characteristics that can be transformed into the prospect theory value function parameterization, which can at least partly explain the completely opposite behavior under not too different parameterization (shown by Hens and Vlcek (2006); Barberis and Xiong (2009); Kaustia (2009) and confirmed by numerical simulations run in Talpsepp (2010a)).

The reverse disposition effect of foreign investors may partly be explained by a higher loss aversion compared to local investors, which makes them liquidate losing positions relatively early. Also differences in risk aversion; risk seeking behavior and expected risk level can produce the disposition effect for local investors and the reverse disposition effect for foreign investors. Another explanation includes the higher level of sophistication of foreign investors as increased experience and sophistication generally decreases the disposition effect bias for also other investor groups. Talpsepp (2010a) finds that: "*Longer holding periods, slightly higher adjusted trading frequency and possibly reduced loss and risk aversion (possibly caused by familiarity bias) could in fact also help to explain the disposition effect for local investors in the recent models. The results give an*

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insight that there could also exist prospect theory based models that, when incorporating clear differences of investor groups, could explain the puzzle for a larger proportion of investors."

Overall, the results of the Estonian stock market show the prevalence of the disposition effect but to a smaller degree than found for some other markets. Going into more detail with the disposition effect biased investors, the results show that investor sophistication seems to reduce the bias for most of the investor groups. The results of Talpsepp (2010b) show that there is a negative correlation between the disposition effect and the portfolio performance as more disposition effect biased investors show worse results (still, some exceptions exist). In addition to the disposition effect bias, there seems to exist a difference in trading behavior as foreign and non-individual investors seem driven by momentum strategies, whereas local and individual investors seem to be generally contrarian in their trading.

Gender and age distinctions (as presented in Talpsepp 2010b) show that the performance of female investors is better than male investors even when adjusted for risk. The better performance of female investors holds despite the fact that the disposition effect bias of female and male investors is very similar. Worse performance is associated with a higher trading intensity of men and younger investors who seem to harm their portfolio performance with overtrading (there are similar findings in Barber and Odean (2001)). Older investors trade less and also show better performance results. Both the larger disposition effect bias and the worse performance results of young investors can be partly caused by less experience and sophistication of the younger as the results indicate. All the results are obtained by running a large number of different regressions with different setups and controlling for a large number of demographic and market wide variables (such as past returns, stock specific dummy variables etc). A total number of different control variables in the regressions presented in Talpsepp (2010a and 2010b) amounts to around 80 when also counting the interaction terms with the "Trading gain indicator" and the "Trading loss indicator".

2. Volatility asymmetry

This section summarizes with additional detail the background information and methodology of the volatility asymmetry literature and used methodology partly also presented in Talpsepp and Rieger (2010) and Dzielinski, Rieger and Talpsepp (2010). A short summary of the results of Dzielinski, Rieger and Talpsepp (2010) and Talpsepp and Rieger (2010) is presented as well.

2.1 Related literature

Numerous studies have found that volatility in equity markets appears to be asymmetric as returns and conditional volatility are negatively correlated (see overview by Bekaert and Wu (2000)).

The first studies to document the finding are by Black (1976) and Christie (1982) who attempt to explain the asymmetry with leverage effect, meaning that a drop in the value of the stock increases financial leverage by reducing the value of equity, which makes the stock riskier and increases its volatility. However, Schwert (1989) points out that although aggregate leverage is significantly correlated with volatility, it explains only a small part of the movements in volatility.

Another well documented hypothesis explains the effect by the existence of time-varying risk premiums as presented in the works of Pindyck (1984); Engle, Lilien and Robbins (1987), French, Schwert, and Stambaugh (1987); Campbell and Hentschel (1992). The time-varying risk premium theory explains return shocks by changes in conditional volatility. Furthermore, Glosten et al. (1993) and Nelson (1991) argue that across time there is no theoretical agreement about the relationship between returns and volatility within a given period of time and that either a positive or a negative relationship between current stock returns and current volatility is possible. Also Bekaert and Wu (2000); and Li, Yang and Hsiao (2005) point out that the negative relationship between market volatility and the expected market return immediately implies that the time-varying risk premium theory cannot be valid to explain the stock market behavior. Bansal and Yaron

(2004) and Drechsler and Yaron (2009) show that variability in equity prices can largely be explained by fluctuations in expected growth rates and risk premium which implies that the time-varying risk premium explanation cannot be left aside.

Early empirical evidence have conflicting findings as French, Schwert, and Stambaugh (1987) and Campbell and Hentschel (1992) find the relation between volatility and the expected return to be positive, while Turner, Startz, and Nelson (1989), Glosten, Jagannathan, and Runkle (1993), and Nelson (1991) find the relation to be negative. The number of earlier mixed results is extended by Pindyck (1984) and Poterba and Summers (1986).

Most of the more recent studies find an insignificant relationship between the returns and conditional variance in international stock markets (Baillie and DeGennaro, 1990; Choudhry, 1996; De Santis and Imrohoroglu, 1997; Li et al. 2005; Shin 2005). Although French et al. (1987) document a significant positive relationship between US stock market returns and the conditional variance of these returns, Baillie and DeGennarro (1990) report that such a positive relationship is weak and almost nonexistent in the US stock market. Similarly, Theodossiou and Lee (1995); DeSantis and Imrohoroglu (1997); and Lee, Chen and Rui (2001) also find a positive but insignificant relationship between stock market returns and the conditional variance in many other international stock markets. DeSantis and Imrohoroglu (1997) find evidence of a statistically significant risk premium for only three of fourteen emerging markets under the assumption of fully segmented markets.

Bollerslev and Zhou (2006) show that empirical results for risk premiums will depend on structural parameters for realized volatilities. In further investigation of high-frequency data Bollerslev, Litvinova and Tauchen (2005) find correlations between absolute high-frequency returns and current and past high-frequency returns to be significantly negative for several days, while the reverse cross-correlations between absolute returns and future returns are generally negligible.

Among papers investigating volatility asymmetry Bekaert and Harvey (1997) provide some evidence of a leverage effect for emerging markets. Fraser and Power (1997) find statistically significant evidence of a leverage effect for the U.K., Japan, and Malaysia. Brooks et al. (2000) find evidence of leverage in equity indices for ten mature markets. Jayasuriya, Shambora and Rossiter (2005) report asymmetry in both mature and emerging markets. Selcuk (2005) finds significant negative correlation between shocks to the stock market index and shocks to volatility, which would suggest the existence of a leverage effect.

Among papers studying the causastion behind volatility asymmetry, Sentana and Wadhwani (1992) propose that stop-loss orders and portfolio insurance are consistent with positive feedback trading. They also discuss the effect of margin positions which may have to be liquidated due to price declines and thus lead to higher volatility. Figlewski and Wang (2001) argue that a firm's leverage usually stays near a certain level rather than changes constantly which seems to be the case for volatility asymmetry, thus the leverage effect cannot explain the asymmetry. It is supported by Bekaert and Wu (2000) who find more support for volatility feedback than leverage.

McQueen and Vorkink (2004) develop a theoretical preference-based equilibrium asset pricing model, which explains both volatility clustering and asymmetry by a feedback effect Aydemir, Gallmeyer and Hollified (2005) quantify the leverage effect by using an equilibrium asset pricing model and find that financial leverage is economically not significant at market level and at firm level it just partially explains variations in volatility.

Further, counter to the leverage-based explanation, asymmetry is generally larger for aggregate market index returns than for individual stocks (see, e.g., Kim and Kon (1994), Tauchen, Zhang and Liu (1996), and Andersen, Bollerslev, Diebold and Ebens (2001)). Hens and Steude (2009) show with experimental financial markets data that the leverage effect seems to exist even when there is no financial leverage present.

2.2　Methodology

The asymmetric power GARCH (APARCH) model of Ding, Granger and Engle (1993) coupled with skewed Student's *t*-distribution is chosen to estimate volatility of all markets. There is a wide range of models (see e.g. Poon and Granger (2003)) that could be used for the task when using daily returns. The APARCH model is used in similar works of Brooks (2000, 2007) as well as Jayasuriya, Shambora and Rossiter (2005). The asymmetric power GARCH model coupled with a generalized asymmetric Student's *t* distribution has been shown by Mittnik and Paolella (2000) and Giot and Laurent (2004) to deliver relatively (compared to other models) very accurate VaR forecasts relying on volatility out of sample forecasting.

Haas, Mittnik and Paolella (2004) have found the APARCH model coupled with the asymmetric Student's *t*-distribution as well as mixed-normal GARCH models to produce better VaR prediction results than more simple GARCH models. Extension to the model is offered by Paolella and Steude (2007) by getting even better VaR prediction results with using different weighting functions of the observation data.

Hansen and Lunde (2005) found when analyzing the IBM stock data that the best overall performing model was the APARCH(2,2) model with *t*-distributed errors and mean zero; among other models, also V-GARCH specification (which is less sensitive to outliers) did quite well contrary to E-GARCH model that performed surprisingly poorly. It should be noted that realized intraday returns were used for calculations.

The main advantage of the APARCH model is that it nests various models among which the general GARCH model of Bollerslev (1986) features a conditional variance equation, as well as the model of Taylor (1986), which features a conditional standard deviation equation.

In the volatility asymmetry study no ARMA orders nor constants are used in the equations. It enables to get more stable results with smaller standard errors for parameter estimations when using rolling time windows for international data. After testing various combinations of different ARMA and APARCH orders (also

including constants in equations), the final choice of the model is the APARCH(1,1) model without constants and ARMA orders which enabled to obtain results with quite a small number of observations (1000 observations for each rolling time window) and relatively stable results. Another advantage of using the APARCH (1,1) model is an easier interpretation of the model as the APARCH equation becomes:

$$\sigma_t^\delta = \alpha(|\varepsilon_{t-1}| - \gamma\varepsilon_{t-1})^\delta + \beta\sigma_{t-1}^\delta \tag{5}$$

where α, γ, β and δ are parameters to be estimated. The conditional standard deviation is given by σ_t and γ reflects volatility asymmetry where a positive value means that past shocks ε_{t-1} have a larger impact on current conditional volatility when the shocks are negative compared to shocks being positive.

Despite using skewed t-distribution and imposing no restrictions on the parameters in Equation 8, GARCH type models do not fit all samples of data well, as on occasions there is no stable solution for the parameters and the model is said to be non-convergent or unstable. Mostly non-convergent estimates occur when data includes large jumps in the prices or the sample size is too small. The paper deals with the problem by utilizing two different outlier detection methods and removing captured jumps; and also using Gaussian kernel with the size of 4 standard deviations as a weighting function for the input data. The use of outlier detection methods and kernel weighting improves the stability of estimations of the APARCH model significantly.

To detect jump locations efficiently, wavelets methods are employed, which are powerful for detecting jumps as demonstrated in Wang (1995). A wavelet based approach as proposed by Fan and Wang (2007) is used to detect jumps in the data, so that jump locations and sizes could be estimated. With the wavelet transformation, the information about jump locations and jump sizes is stored at high-resolution wavelet coefficients. With jump locations and sizes being

estimated, they are removed from the observed data, resulting in jump adjusted data.

The second outlier detection method of Lee and Mykland (2008) uses local volatility in a predefined time window to test for jump components in returns. Jumps are captured studying the volatility condition prevailing at the time of the tested return. In times of high volatility, an abnormal return is bigger than an abnormal return in times of low volatility. Hence, Lee and Mykland (2008) study the properties of the ratio of the tested return over a measure of local volatility. They derive an asymptotic test for the statistic and a rejection region under the null of no jump at the tested time, proposing a powerful, parsimonious methodology that allows testing whether any return contains a jump component, its location and size.

The used outlier detection methods were designed for use on intraday data and have shown superior results compared to other methods on intraday data. The average number of eliminated observations amounts to 1-2% for most countries and robustness checks (see Talpsepp and Rieger 2010) show that volatility asymmetry estimations are not qualitatively affected by eliminating jumps.

Using Gaussian kernel weighting function enables to improve the stability of APARCH estimations further and to get volatility asymmetry estimates for a qualitatively shorter time period as the used moving time window gets more weight from observations in the center of the window.

2.3 Data

Nominal returns instead of excess returns are used to estimate volatility. Numerous studies (e.g. Baillie and DeGennarro, 1990; Nelson, 1991; Choudhry, 1996; Lee et al., 2001) argue that using excess returns (stock returns minus risk free return) instead of nominal stock returns produces little difference in estimation and inference in this line of research. Also Galadera and Faff (2004) noted that under different market regimes, classifying data by sign (positive or negative) of excess returns instead of nominal returns does not make a significant difference when

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using GARCH (1,1) to model volatility. For better comparability all returns are measured as the log difference of the price in U.S. dollars of the MSCI index data obtained from Thomson's Datastream for a total of 49 counties. The sample starts from 1980 for developed countries and from 1987 or later for emerging markets.

2.4 Results

The aim of the volatility asymmetry research is to test various explanations that have been suggested as a cause for asymmetric volatility. As the literature overview shows, various hypotheses have been proposed but the causes of the asymmetry still remain unclear. The contribution to the literature is testing the hypothesis, by using improved methods for the asymmetry estimation and having a sample with a large number of countries and a relatively long time span. This enables to test the hypothesis with cross sectional as well as time series and panel data, which has not been done before. Recent findings of Hens and Steude (2009) show that volatility asymmetry exists even in experimental setups, which suggests that there could be behavioral factors influencing the asymmetry. Thus, Dzielinski, Rieger and Talpsepp (2010) and Talpsepp and Rieger (2010) go one step further to test empirically whether behavioral factors can influence volatility asymmetry. Recent research (see e.g. Tetlock 2007) has shown that media has the power to influence investor sentiment and prices in the stock market, which can have implications also on volatility asymmetry.

The results for time series of volatility asymmetry measures for 49 countries are obtained by repeatedly estimating the APARCH model for each country. Using a moving time window with the size of 1000 observations for APARCH model estimations (with the described jump detection and kernel weighting) enables to capture the time series of the asymmetry. The obtained parameter gamma from Equation 7 is of particular interest as it is used as the main measure of volatility asymmetry. After obtaining the asymmetry measures, a

further adjustment is still used as the asymmetry measures are correlated to the market returns (see Talpsepp and Rieger (2010) for more detail).

As the different volatility asymmetry estimates confirm each other in most cases, it is concluded that developed countries tend to have a higher level of asymmetry although the level of asymmetry changes substantially over time. A number of possible factors (as suggested in the previous literature) that can drive volatility asymmetry are tested after obtaining the asymmetry measures.

The leverage effect tests (Talpsepp and Rieger 2010) show a positive significant relationship between the private debt level of a country to the GDP and the asymmetry. This is contradicted by the fact that we did not find any significant impact of the average debt to equity ratio of the listed companies of a country on volatility asymmetry, which should be a better measure of leverage. In conclusion, we cannot find support for the pure leverage effect in our data. We also test a well documented hypothesis of time varying risk premium but do not find support for that either.

Tests with panel data and with a number of market development measures (including GDP/capita, different published market development and efficiency indexes) show that a higher level of economic development and market efficiency is coupled with a higher level of volatility asymmetry, which is a surprising finding.

We test the hypothesis that the ability to short-sell securities can cause asymmetry and find a significant positive relationship between the level of asymmetric volatility and the feasibility of short-selling. Although short selling is generally feasible in more developed countries, the correlation between GDP per capita and the feasibility of short selling does not bias the positive impact of short selling on asymmetric volatility in most of the used regression setups. However, short selling cannot be the main factor influencing volatility asymmetry as most of the fluctuations in the asymmetry measures cannot be explained by the changing conditions of short selling.

The results of Dzielinski, Rieger and Talpsepp (2010) concentrate on the impact of the news and individual investors on the volatility asymmetry. The results show that more news is generally correlated with having a larger share of bad news which is especially true for stocks with more coverage on average (both media and analyst coverage). Dzielinski, Rieger and Talpsepp (2010) test both media coverage (media penetration) and analyst coverage (number of analysts covering stocks on average) effect on international data. The results show a significant positive correlation between asymmetric volatility and both media penetration and analyst coverage. The problem is that both media penetration and analyst coverage are also correlated with the level of market development and because of that media penetration becomes insignificant in different multiple regression setups but the analyst coverage variables are still both statistically and economically significant when controlling for a number of control variables. The results indicate that analysts and the media can cause volatility asymmetry. Previous literature suggests that individual investors are more likely to be influenced by the news and have larger behavioral biases that can cause volatility asymmetry.

Dzielinski, Rieger and Talpsepp (2010) use two variables: ownership concentration and market capitalization/GDP to measure the share of individual investors in the market. The results report a positive correlation in both cross sectional and time series data, meaning that the more individual investors are present in the market, the higher the volatility asymmetry.

Dzielinski, Rieger and Talpsepp (2010) propose a model where media report predominantly bad news. The effect is stronger when analyst coverage and media reports are more frequent. A large number of bad news items lead to overreaction of mostly private investors whose trading then increases the volatility. Thus, a larger proportion of individual and on average less sophisticated investors on the market increases the volatility asymmetry. The model is supported by the connections found between increased volatility and greater keyword search activity on Google which is most likely conducted by individual investors. Also Estonian

transaction data shows that times with high volatility coincide with times where many investors trade on the market. Additional evidence is provided in Talpsepp and Rieger (2010) which also uses a direct variable describing the market participation of individuals on cross sectional international level and has some confirming evidence from time series data.

Conclusions

In the ongoing "battle" between behavioral finance and traditional finance, the results of the thesis present empirical evidence in favor of behavioral models. The disposition effect related research has enabled to give some empirical weight to the recent behavioral models and the volatility asymmetry study has found support for behavioral factors that stand together with traditional explanations.

To once more summarize the conclusions of Talpsepp (2010a and 2010b); we can see clear differences in the behavior of different investor groups. Although most of the investors are disposition effect biased, foreign investors seem to exhibit the reverse disposition effect. There are not too big differences between individual and institutional and between female and male investors in respect to the disposition effect. The younger investors trade more and are more affected by the disposition effect although experience seems to decrease the bias.

The prospect theory based explanation of the disposition effect has recently received criticism for requiring an unrealistic parameterization for the disposition effect and could instead produce the reverse of the disposition effect for most cases. Empirical results of Talpsepp (2010a) combined with theoretical modeling indicate that there exist prospect theory based models that could explain the puzzle for a larger proportion of investors, when incorporating differences of investor groups (e.g. reduced loss and risk aversion of local investors caused by familiarity bias).

The results of trading activity on the Estonian stock market (as presented in Talpsepp 2010a and 2010b) show that we can distinguish between the sophistication level of investors. Different types of investors follow different strategies (either contrarian or momentum driven for individual and institutional investors) and show different performance results. As the literature overview shows, the same principles apply to international stock markets where we can assume different trading styles and behavior of individual and institutional (or more and less sophisticated) investors.

International stock markets are studied in the volatility asymmetry part of the thesis. The results show that at the country level, economic development, to some extent the feasibility of short selling and level of financial leverage can cause volatility asymmetry. Individual investor market participation combined with the presence of analysts and media coverage can be one of the factors resulting in higher volatility asymmetry.

The results show that more news is generally associated with a large share of negative news which affect investor sentiment. The more influenced are generally the less sophisticated individual investors. In a negative sentiment, bad news is more amplified, which can result in higher volatility asymmetry. In case of good news and positive sentiment, the amplification effect is reduced by the shrinkage of the news flow.

In conclusion, the existence of the disposition effect and volatility asymmetry can be caused by behavioral factors which remain in the empirical models even after controlling for different other factors. Those behavioral factors incorporate the decision framing by investors who react differently to positive and negative news and can frame losses and profits differently depending on whether being in a gain or loss.

Despite the evidence presented in the current thesis and the papers referred to, still further empirical proof and improvement of theoretical models is required to confront the skepticism of supporters of the traditional finance paradigm. Further research in the disposition effect field could focus on improving current theoretical models based on either prospect theory or incorporating other factors into the models to explain the phenomena for a larger number of cases. Empirical work could include complementing trading data with survey data of investor attitudes towards risk-taking and take into account the attributes of the investments such as the news and financial data. Both theoretical and empirical work (with improved, more detailed and longer time series data) could be conducted for the volatility asymmetry topic.

The disposition effect related papers (Talpsepp 2010a and 2010b) have their follow-up in a current working paper "Closer Look at the Disposition Effect: Speculating in Gains, Waiting in Losses." (Talpsepp, Vlcek and Wang 2010). As Talpsepp, Vlcek and Wang (2010) uses logit methodology in its empirical part based on the same Estonian dataset, part of its results act as a confirming robustness check of the survival analysis based methodology findings of Talpsepp (2010a and 2010b).

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Appendix 1

Reverse Disposition Effect of Foreign Investors

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Talpsepp, T. 2009. Reverse Disposition Effect of Foreign Investors, 44th Meeting of EURO Working Group on Financial Modelling, San Jose, Costa Rica, 6-9 December 2009, Conference presentation

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Reverse Disposition Effect of Foreign Investors

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Abstract

The paper analyses the tendency of investors to realize gains too early and the reluctance to liquidate losing positions. Analysis is based on the complete transaction data of the Estonian stock market. The Cox proportional hazard model along with ratio analysis is used to measure the disposition effect. I find presence of the disposition effect on the market but contrary to other investor groups, foreign investors seem to exhibit a "reverse disposition effect" that can be caused by different behavioral characteristics compared to local investors, especially risk aversion. Foreign investors are more driven by momentum strategies whereas local investors pursue the contrarian approach. Experience and investor sophistication seem to decrease the disposition effect.

1. Introduction

Numerous studies have identified the tendency of investors to realize winning positions too early and be reluctant to realize losses. The bias is known as the disposition effect that was first documented by Shefrin and Statman [1985]. Various hypotheses have been offered but underlying causes for such behavior still remain unclear.

The disposition effect has widely been explained by the prospect theory of Kahneman and Tversky [1979]. According to that investors regard possible further gains less valuable than losses when having a winning position; and the other way round when facing a loss. However, recent work[1] shows that the prospect theory based models have a hard time predicting the disposition effect ex-ante. This is because investors would not buy such risky assets in the first place that can cause the disposition effect under their behavioral characteristics. In addition, recent work shows that the prospect theory based explanation is more likely to predict the reverse of the disposition effect rather than the disposition effect. Current empirical studies have identified the disposition effect for all studied international stock and real estate markets as well as executive stock option exercise, but the reverse disposition effect has not been identified[2] for a distinguishable market or investor group.

Interpretation of the recent prospect theory based theoretical models poses a question whether there are investor groups behaving according to the more likely predictions of the models and thus can prevailingly exhibit the reverse disposition effect. Current empirical findings do not show the reverse disposition effect biased investors. If there were, we could study the traits distinguishing such investors and

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[1] Hens and Vlcek [2006]; Barberis and Xiong [2009]; Kaustia [2009] show that the prospect theory based explanation can hold only for a very small number of cases.
[2] Krause, Wei, Yang [2009] report the reverse disposition effect for extremely short term trading and certain trading strategies using a newly defined measure to capture the effect.

possibly offer more insights into the matter, to see if and how well prospect theory based models can predict the disposition effect related portfolio allocation and trading decisions. Empirical existence of the reverse disposition effect would mean that controversial results of prospect theory based models can still accord to empirical findings and there could be powerful factors having different influence on the decisions of different investor groups.

To obtain results for various investor groups which enable to study the disposition effect in more detail, I use a complete dataset from the Estonian stock market. Data includes details of *all* trades made from 2004 till July 2008 on the Tallinn stock exchange. Such a comprehensive dataset has only been available for the Finnish stock market and none of the other previous studies have been able to study all transactions of a stock exchange but used subsamples of discount brokers instead. Work on Finnish data mostly concentrated on larger stocks, whereas the current paper analyses every single trade for every stock that gives a unique perspective to the results obtained.

Equipped with such a comprehensive dataset, I provide the first empirical evidence that indeed a large investor group of foreign investors seem to exhibit the reverse disposition effect. As foreign investors play an identifiable role on the stock exchange, this enables to draw the focus of the study on differences between local and foreign investors in more detail. The findings enable to offer insights into the determinants that can cause a very clear behavioral distinction of foreign investors from the whole sample and all previous empirical findings that can have its roots in the differences of risk aversion. The propensity of local traders to be more prone to the disposition effect has been previously discussed by Grinblatt and Keloharju [2001, 2001b] and Frino, Johnstone and Zheng [2004] for different markets. This paper makes an addition to the list by offering some new insights into the matter in a case when the disposition effect behavior of foreign investors is even further from local investors.

The main contribution of the paper is the first empirical documentation of the reverse disposition effect for a large and important investor group. The paper

provides further empirical out of sample tests for most of the previous findings in the literature and stands out as an up to date comprehensive study of trading behavior without any bias of taking subsamples of the trading universe.

The paper is organized as follows: Section 2 gives an overview of both theoretical and empirical studies concerning the disposition effect; Section 3 describes the used dataset and methodological aspects. Results are provided in Section 4 and concluding remarks in Section 5.

2. Previous studies

2.1. Theoretical models

The prospect theory [Kahneman and Tversky 1979] explanation of the disposition effect suggests that investors regard the acquisition price of securities as their reference point. According to the prospect theory utility curve, investors consider marginal gains less valuable than marginal losses when the market price is above the reference point and consider marginal gains more valuable than marginal losses when investors' positions are in loss. Thus, investors are more prone to liquidate winning positions and are reluctant to sell losing positions.

Among recent critics of the prospect theory based explanation, Hens and Vlcek [2006], Barberis and Xiong [2009] and Kaustia [2009] all show that the prospect theory based explanation could hold only for some cases but might not hold for the majority. At the same time Barberis and Xiong [2009] and Kaustia [2009] show that under certain conditions the reverse disposition effect is more likely than the disposition effect.

Alternative explanations of the disposition effect suggest that the phenomena can be explained by a contrarian strategy with a belief that all stocks revert to the mean [Barber and Odean 1999], a rebalancing need or transaction cost minimization. The contrarian approach makes the assumption that past winners tend to underperform past losers. The diversification explanation suggests that investors respond to large price fluctuations by rebalancing their portfolios to restore previous diversification [Lakonishok and Smidt 1986]. Transaction cost

minimization explanation suggests that investors avoid selling losers to reduce transaction costs which are relatively higher for lower priced stocks [Harris 1988].

The disposition effect and also the reverse disposition effect implication could be reached by taking into consideration the results projected by the prospect theory S-shaped value function, given as:

$$v(x) = \begin{cases} x^{\alpha}, & x \geq 0 \\ -\lambda(-x)^{\beta}, & x < 0 \end{cases} \tag{1}$$

where x is the gain with respect to the reference point, λ is the coefficient for loss aversion, and α and β are coefficients for risk aversion and risk seeking. Usually investors are considered being risk-averse for gains which makes them realize gains early. At the same time investors tend to be risk seeking in losses making them take an additional risk when in a loss and thus not liquidate losing positions.

However, Hens and Vlcek [2006] use a two-period analytical model combined with numerical examples to argue that the standard prospect theory explanation is sound only ex-post, especially for less loss averse investors. The ex-post disposition effect assumes that the investment has already taken place. They show that risk averse investors with low loss aversion would not invest in the risky stock in the first place. Only a few combinations of high returns in losses and relatively lower returns in gains would produce the ex-ante disposition effect for investors with previously mentioned prospect theory value parameters. Hens and Vlcek [2006] offer alternative explanations for the disposition effect that include backward looking optimization combined with different mental accounts for realized and paper gains and losses.

With a different theoretical model, Barberis and Xiong [2009] show that the link between the prospect theory and the disposition effect is not always present: in some cases, the prospect theory does predict the disposition effect; but in other cases, it predicts the reverse disposition effect. The prospect theory doesn't explain the disposition effect in cases when the number of trading periods is low

and when expected risky asset returns are high. However, when asset returns are low, risk averse investors would generally not invest in such assets.

Barberis and Xiong [2009] show that with Tversky and Kahneman [1992] parameterization and a two-period model the prospect theory value function would produce the reverse disposition effect as the investor increases positions after gains in stock prices and the expected return is not very low. They argue that taking more risk after a gain is the investor's optimal strategy. This occurs when the initial period expectation of the potential gain is larger than that of the potential loss which is the factor making the investor take the position in the first place.

For the Barberis and Xiong [2009] model, the disposition effect could be more likely produced for high frequency traders with a high number of periods in mind. High number of periods smoothes the investor's utility function, thus lowering the risk aversion. In such a case the investor is willing to buy assets with a relatively low expected return and takes only small positions after gains.

Kaustia [2009] reaches similar conclusions with a numerical approach. He finds that for higher expected returns and exogenous reasons to sell, the disposition effect could hold in cases when the loss aversion as well as the risk seeking parameter is clearly lower than estimated by Tversky and Kahneman [1992]. He also points out that it is easier to obtain a prediction for a reverse disposition effect with varying prospect value function parameters within realistic intervals.

As shown by all previously mentioned works criticizing the prospect theory explanation, there are many different prospect theory value function parameter combinations that most of the times would not produce a sale of the position but on occasions can produce the disposition effect or the reverse disposition effect. Also probability weighting from the prospect theory can influence the outcome. In addition to the prospect theory parameters, the emergence of the effects is affected by market wide variables such as the expected return of the stock and expected probabilities and distribution of the returns. Such a variety of different parameter values which can be different for various groups of

investors can easily cause a situation where some investors exhibit the disposition effect and some the reverse disposition effect.

2.2. Empirical studies

Individual and professional investors

Numerous empirical results support the existence of the disposition effect. The earliest evidence can be found in Schlarbaum, Lewellen and Lease [1978], for retail brokerage clients. In further detailed individual investor related works, Odean [1998] finds that individual investors in the USA demonstrate a significant preference for selling winners and holding losers, except in December when tax-motivated selling prevails. Such a behavior does not appear to be motivated by a desire to rebalance portfolios. Additionally Odean [1998] suggests that investors who expect the losers to outperform the winners are, on average, mistaken. Further, Barber and Odean [2000] show that individual investors in the USA trade too frequently which is harmful to their wealth.

Shapira and Venezia [2001] show that both professional and individual investors (based on Israeli data) exhibit the disposition effect, although the effect is stronger for independent investors. Grinblatt and Keloharju [2001] found evidence (based on Finnish data of both individual and professional investors) that investors are reluctant to realize losses; engage in tax-loss selling activity; and that past returns and historical price patterns affect trading.

Locke and Mann [2005] found that the Chicago Mercantile Exchange full-time traders hold onto losses significantly longer than gains, but do not show any evidence of costs associated with such a behavior. Further, Locke and Zhan [2005] and Garvey and Murphy [2005] show that the duration of unprofitable trades is longer than that for profitable trades across the day for professional US day-traders. Coval and Shumway [2005] show that proprietary traders on Chicago Board of Trade (CBOT) are highly loss-averse taking above average afternoon risk after suffering morning losses. Haigh and List [2005] show that professional traders

recruited from CBOT exhibit a stronger degree of myopic loss aversion than undergraduate students in an experimental study.

Market wide variables

Among works taking into account trading and market wide variables, an early USA based study of Ferris, Haugen and Makhija [1988] examined the disposition effect in terms of trading volume. They found that in addition to being a determinant of year-end volume, the disposition effect is also a determinant of volume levels throughout the year. Kumar [2005] shows that behavioral biases are stronger when there is greater market-wide uncertainty, as reflected by higher mean stock-level volatility and higher unemployment rate. He found that investors are more overconfident and disposition effect biased when stocks are more difficult to value. Leal, Armada and Duque [2008] also report a higher degree of the disposition effect during periods of bull market than bear market for Portugal.

Frazzini [2006] investigates whether the disposition effect induces under-reaction to news, leading to return predictability. He found that investors did under-react to news announcements and therefore large unrealized capital gains had higher subsequent returns and generated a predictable price drift.

Investor sophistication

Feng and Seasholes [2005] show with Chinese data that investor sophistication and trading experience eliminate the reluctance to realize losses as sophisticated investors are clearly less susceptible to the disposition effect than the average investor in the sample. Trading experience weakens the disposition effect but it does not eliminate it entirely. The finding is supported by Chen et. al. [2004] with similar Chinese data. Dhar and Zhu [2006] found empirical evidence that wealthier and individual US investors in professional occupations exhibit less disposition effect. Krause, Wei and Yang [2009] find evidence of the disposition effect for buy strategies, but they report a reverse disposition effect for sell and short-term strategies for Chinese investors.

Experimental setup

Weber and Welfens [2007] found that the degree of the disposition effect varies considerably on an individual level as most investors exhibit the disposition to some degree, although investors with a reverse effect exist. In an experiment setup, they found that Investors who started with a positive disposition effect decreased their bias over time, while those investors with a negative initial disposition effect also drifted towards the no-disposition effect benchmark.

Experimental analysis of Weber and Camerer [1998] confirms the existence of the disposition effect in an artificial setup. Strobl [2003] demonstrates that rational investors can exhibit disposition effects even in a world without taxes, transaction costs, and portfolio rebalancing needs.

3. Data and methodology

3.1. Data

I use data provided by Nasdaq OMX Baltic that includes *all* transactions on Nasdaq OMX Tallinn (OMXT) which is the only stock exchange in Estonia. The data consists of transactions for a total of 22 listed companies, which is a comprehensive list of all companies that have had their shares traded on the Estonian stock exchange during that period. OMXT can be characterized as a small emerging market stock exchange with a market capitalization of about 3 billion EUR during the viewed period and market capitalization/GDP of around 30%. Around 45% of the market capitalization of OMXT was held by foreign investors at the end of the period. Its small size imposes some liquidity constraints for active trading on especially larger institutional investors.

The observed time period starts from 1 January 2004 and ends on 30 June 2008 and includes *all* transactions made with Estonian listed companies. Data consists of 567,000 transactions for 24,153 different accounts (see Table 1). As Estonian law allows multiple accounts for all investors, the number of actual different investors is somewhat smaller than 24,153. The provided data is anonymous and includes account ID-s, trade date, price, security and type of

investor. Investor type data enables to distinguish between domestic (Estonian residents) and foreign investors, financial institutions, government related accounts, investment funds, corporations and individuals. Individual investors can be additionally classified by gender and age.

Table 1. Breakdown of the number of different accounts.

	Num. of local	Num. of foreign	Foreign %	Total
Individual investors	20 212	777	3.7%	**20 989**
Institutional investor	3 057	107	3.4%	**3 164**
Government related	27	0	0.0%	**27**
Fund	24	0	0.0%	**24**
Nominee	4	29	87.9%	**33**
Client account	0	10	100.0%	**10**
Total	**23 269**	**884**	**3.7%**	**24 153**

Although the list includes all transactions made on the stock exchange during the observed period, some transactions that do not go through the exchange system are not recorded and recognized in the dataset. Such transactions usually include security transfers from one account to another, which do not require monetary payments[3]; also repurchasing agreements and alike. It should be noted that when change of ownership occurs, the transaction goes generally through the stock exchange system and is recorded in the dataset. The transactions that are not recorded in the dataset can be regarded as exceptions and such a small number of trades cannot influence the results of a very large sample.

The provided data also includes starting portfolios for all accounts on the date of 1 January 2004. This enables me to calculate the starting market value of all portfolios, but *not* purchasing prices for the portfolios. For calculations presented in the paper, I construct portfolios with purchasing prices for all accounts discarding the existing positions before 1 January 2004 for which the purchasing price is not known. Such an approach still enables to calculate the reference price needed for testing for the disposition effect and is consistent with the methodology

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[3] e.g. one entity is the controlling owner of two different accounts and transfers securities from one account to another

used e.g. in Odean [1998], Grinblatt and Keloharju [2001]. The average purchasing price of the position is used as the reference price and it is compared to the closing market price of each security in the portfolio for each trading day for each account. All prices are adjusted for stock splits and dividends.

I use the total market value of the portfolio as one of the experience indicators. For such calculations I do not discard portfolios that existed before 1 January 2004 but calculate the total portfolio value for each investor for each trading day and use it as one variable in subsequent survival analysis.

To measure the average return over the observed period, aggregate data of different investor groups is used. Portfolio return (see Table 2) is measured as an annual money-weighted return which allows to weight periods of more invested funds more heavily and is justified over time-weighted average return as most participants in the market can diversify the portfolio with foreign assets, and depending on their market expectations, can increase or decrease the amount of invested funds, which affects their return. OMXT index realized an average annual return of 17.23% over the observed period and this can be viewed as a benchmark.

Table 2. Portfolio return and proportion of total assets by investor groups.

Portfolio return	Investor type	Proportion of total assets
17.63%	Institutions	83.14%
16.65%	Private investors	16.86%
21.06%	Foreign investors	45.00%
14.56%	Local investors	55.00%
15.26%	Local private investors	15.20%
31.61%	Foreign private investors	1.66%
14.22%	Local institutional investors	39.80%
20.65%	Foreign institutional investors	43.35%
0.00%	Government related	0.06%
16.30%	Funds	1.59%
29.43%	Nominee accounts	29.76%
-0.41%	Client accounts	6.83%

3.2. Survival analysis methodology

Similarly to Feng and Seasholes [2005] and Soffman [2007], the paper uses survival analysis to measure the existence and magnitude of the disposition effect. In addition, I use ratio analysis as a confirmation of the results which enables me to make the results comparable with the widest possible number of studies.

I use a Cox proportional hazard model with both fixed and time-varying covariates to measure the probability that an investor will sell its current stock position. Survival analysis offers a number of advantages over previously widely used ratio analysis and Logit methodology. The advantages include being a statistical model of how long stock are typically held in a portfolio; using data of all trading days in comparison to only using data of sell decisions (common to *PGR-PLR* ratio analysis); offering an easy way to interpret results; taking into account the price path of the stock in the portfolio (other approaches may give incorrect inferences in cases in which capital gains or losses vary over time), as pointed out by Feng and Seasholes [2005].

I calculate the hazard rate, the probability of selling at time *t* conditional on holding a stock until time *t-1*, where the hazard rate *h* and the vector of coefficients β and γ for the covariates are obtained by maximum likelihood estimation of the following equation:

$$h(t, p, X, Z_t) = p\lambda t^{p-1} \exp(X\beta + Z_t\gamma + \varepsilon_t) \qquad (2)$$

where $p\lambda t^{p-1}$ is referred to as the baseline hazard. The term $\exp(X\beta + Z_t\gamma + \varepsilon_t)$ allows both fixed and time-varying covariates where X and Z_t are respectively the vector of fixed and time-varying covariates.

I use the specification where some of the independent variables (covariates) are constant (fixed covariates) and others can vary over time. Independent variables can represent investor, stock and market specific characteristics. Similarly to Feng and Seasholes [2005], I use interaction of both

fixed and time-varying covariates to the trading loss or gain indicator variable (TLI and TGI) to capture the bias of investors.

For the different coefficients of covariates, I only report hazard ratios which are equal to $\exp(\beta)$ and $\exp(\gamma)$. Hazard ratio can be regarded as a change in the hazard rate corresponding to the changes in covariates.

Cox proportional hazard model does not impose any structure on the baseline hazard, and Cox's [1972] partial likelihood approach allows to estimate the coefficients for covariates without estimating the baseline hazard. As the data contains partial liquidations and positions that are not closed by the end of the viewed period, the advantage of the method is that it also allows for censored observations necessary for such a setup. Details about estimating the proportional hazard model can be found in Cox and Oakes [1984].

3.3. Ratio analysis

Similarly to Odean [1998] I use *PGR-PLR* analysis that counts each realized gain, realized loss, paper gain, and paper loss for each day a position is sold from the account. The disposition effect is regarded to be present when the aggregate proportion of gains realized is greater than the aggregate proportion of losses realized. Although criticized by Feng and Seasholes [2005] as not taking into account the price path of the security, such an approach can also be applied on cross sectional level aggregating realized and paper gains or losses of certain investor groups. *PGR-PLR* ratio analysis results are reported in this paper only when discrepancies with survival analysis are found.

PGR-PLR analysis can be defined as:

RG - Number of realized gains for the sample for investor group

PG - Number of paper gains for the sample for investor group

RL - Number of realized losses for the sample for investor group

PL - Number of paper losses for the sample for investor group

The counts are used to calculate the proportion of gains realized, labeled as PGR, and proportion of losses realized, labeled as PLR:

$$PGR = \frac{RG}{RG + PG} \tag{3}$$

$$PLR = \frac{RL}{RL + PL} \tag{4}$$

A positive difference (*PGR - PLR*) is assumed to indicate the disposition effect.

A *t*-test is used for testing the statistical significance of the differences in the proportions of PGR and PLR. A significant difference means that investors exhibit a propensity to hold losing stock too long and to sell winning stock too early. The standard error for the difference in the proportions of PGR and PLR is

$$\sqrt{\frac{PGR(1-PGR)}{RG+PG} + \frac{PLR(1-PLR)}{RL+PL}}.$$

3.4. Data setup

For setting up the data for survival analysis, I define a stock position as starting (similarly to Shapira and Venezia [2001], Feng and Seasholes [2005]) when the first purchase after 1 January 2004 takes place and ending when the position goes to zero[4]. The definition allows a position to build up with multiple purchases and also liquidate the position with multiple sells. The volume-weighted average price is regarded as the reference price and a sell is recorded every time a sell takes place until the balance goes to zero.

For each stock in each investor's portfolio, for every trading day in the sample, I make a comparison of the reference price to the current market price of the stock to see whether the investor incurs realized or unrealized loss or profit for

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[4] As accounts include stocks before 1 January, the investors are seemingly able sell more stock than my definition of the position and therefore such selling transactions are discarded.

the specified stock. Reference price is the known average purchasing price of the security and the current market price is the range of market price on the respective trading day. Feng and Seasholes [2005] report that using different approaches to calculate the purchasing price (highest, average, first, latest purchasing price) do not produce any differences in results and I follow their approach.

When comparing the reference price to the market price, a loss is recorded only when the reference price is higher than the highest price of the day and a gain is recorded when the reference price is lower than the lowest price of the day. If no transactions have occurred, a closing price of the previous day is used for the market price. If a sell occurs, the selling price is used instead of the day's price range. For each position, regardless of whether it is still open or has been liquidated on the given day (a sell has occurred), respectively a paper or realized return is calculated for each day. For calculating the returns, the reference price and the closing price (or selling price) of the day are used.

Based on whether a loss or gain is recorded for a given position, I use two variables, namely the "Trading gain indicator" (TGI) and the "Trading loss indicator" (TLI). The TGI takes a value of 1 when a position is realized or trading at a gain on a given day or 0 otherwise. The TLI takes a value of 1 when a position is realized or trading at a loss on a given day or 0 otherwise.

As I record the TGI or the TLI for each position of each account and for every trading day a total of over 11 million observations are used in the subsequent survival analysis. Such a large number of observations help to improve the reliability of the results.

The ratio analysis uses fewer observations, as I use the methodology of Odean [1998] who records observations only on dates when a sale has occurred and this reduces the observations from 11 million to about 900,000. Realized and paper gains and losses are still calculated by using the reference price obtained as described previously and which is compared to the latest market price range.

4. Results

To estimate the existence of the disposition effect, I use the estimations obtained from the hazard model. The model (Equation 1) uses a dependent indicator variable that equals 1 for every day when the stock position is sold on that day, and 0 if there is no sale of the stock. Independent variables in different regressions include the TLI, the TGI and different demographic, market or stock specific variables, altogether over 40 different, mostly dummy indicator variables.

Most of the variables are market return specific to see how and which intervals of previous returns affect trading decisions. The choice of variables is based on previous studies. Different variables that have been reported to either affect the disposition effect or trading decisions are included in the current study. Similarly to Feng and Seasholes [2005], I interact demographic variables with the TLI (TGI) and include the interaction terms in the regressions as independent variables[5]. The interaction terms help to identify whether changes in demographic variables are correlated with changes in the investor's reluctance to realize losses and propensity to realize gains early. I still include demographic variables by themselves to act as controls, as different demographic groups may have different holding times on average.

Using a large number of market and stock return related variables enables to test the robustness[6] of the presented disposition effect results. Hence, I present a number regression setups to show that cross sectional differences in the disposition effect of investor groups persist and the corresponding hazard ratios do not qualitatively change much, even when including a large number or different control variables.

For survival analysis, I pool all investors together and estimate hazard ratios of different variables to capture the average effect across investors. To get

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[5] Using the interacted variables increases the total number of variables under different setups to over 60.

[6] Including a number of control variables enables to see it the disposition effect is really caused by holding/selling the position because of being in a loss/gain relative to other trading strategy or market and stock return related explanations.

more detailed results across the most important investor groups, I repeat the same procedures for subsamples of the data filtered by investor types or characteristics. I report the hazard ratios where a hazard ratio greater than 1 measures an increase in the conditional probability of a sale due to a change in the covariate and a ratio below 1 indicates a decrease in the probability of a sale due to the covariate[7].

On occasions *PGR-PLR* results are reported, they are obtained by sub-sampling the dataset filtered by different investor types or characteristics.

4.1. Complete dataset tests

Using only one covariate (either TLI or TGI), I test whether all investors in the sample exhibit the disposition effect on average. Table 3 reports the results of the hazard ratio of the TLI (REG 1) and the TGI (REG 4). The hazard ratio (0.77) of TLI, which is significantly smaller than 1, indicates that the average investor is prone to the disposition effect. The hazard ratio can be interpreted as there is (0.77-1=-0.23) a decrease in the hazard to sell the stock position when the price of the stock is below its reference price. The hazard rate of TGI indicates that there is a clearly (1.27-1=0.27) increased hazard rate to sell the position when the position trades for a gain.

I illustrate the interpretation of the hazard ratios with the following example. Let's make an assumption that the average time of the sale is approximately 25 days and use a simplification that the hazard rate of a sale for all investors is thus constantly 4% (which can be considered the baseline hazard) for each day. Hence, the hazard rate of 0.77 would mean a decrease of the hazard from 4% to 0.77×4%=3.08% and the hazard rate of 1.27 would increase the hazard to sell a gain to 4%×1.27=5.08% which are both also economically significant changes in probability.

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[7] E.g. a hazard ratio below 1 for the TLI indicates the presence of the disposition effect (decreased probability to sell a losing stock) and a hazard ratio above 1 for the TGI indicates an increased probability of selling a stock that has gained in value. The probabilities are measured against the baseline hazard rate of a sale.

To study the factors and cross sectional differences behind the disposition effect in more detail, a number of different (indicator) variables are used as covariates in different regressions. The results of the whole sample with different covariates can be seen in Table 3, results for the subsample of individual investors in Table 4 and for institutional investors in Appendix A.

Different variables included in the regressions include the TLI indicator (or the TGI indicator), an indicator variable for institutional investors (all non-individual investors); an indicator for male investors; an indicator for foreign investors; indicators of experience for the investor measured by the trades made since the beginning of the dataset; indicators for different age brackets of individual investors; variables for the gain/loss in the stock price for previous intervals; a variable for the portfolio size of the investor; a variable for the number of stocks in the portfolio; a variable for the current return on the position or indicators for different return intervals; indicators for different types of institutions; and indicators for different stock.

The results for e.g. REG 2 can be interpreted in a way that for example the hazard rate for a foreign institutional investor purely resulted from being in a loss is $0.744 \times 2.152 \times 0.927 = 1.48$.[8] The results from REG 3 and REG 6 show that investors exhibit the disposition effect even when controlling for different variables in most of the investor categories. The results show a distinction between individual and institutional (non-individual) investors where individual investors seem to be less biased, which is a surprising result, although the difference is very small making it qualitatively practically not-existent. A very clear distinction exists between local and foreign investors where foreign investors do not seem to be disposition effect biased. The differences between different investor classes are analyzed in more detail in the following subsections.

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[8] Considering also the coefficients of the control variables would increase the total probability of selling the position even further in the current example. From the example we see the increase of probability caused by the fact of being in a loss, *not* because of other cross sectional differences.

Table 3. Hazard model for selling the stock for the sample.

	REG 1			REG 2			REG 3		
	Haz. Ratio	Z-stat		Haz. Ratio	Z-stat		Haz. Ratio	Z-stat	
Variable									
TLI	0.774	-35.05	***	0.744	-31.85	***	0.420	-22.47	***
foreign* TLI				2.152	36.91	***	1.689	20.94	***
foreign				1.846	45.29	***	0.965	-2.30	**
instit.*TLI				0.927	-4.89	***	0.835	-6.62	***
instit.				2.891	112.04	***	2.668	59.98	***
male* TLI							1.086	3.49	***
male							1.753	39.68	***
return of the position							1.000	-2.29	**
Portf size*TLI							1.083	18.75	***
Portf size							1.180	65.00	***
No. of Stock*TLI							0.982	-7.76	***
No. of Stock							1.078	53.95	***

	REG 4			REG 5			REG 6		
	Haz. Ratio	Z-stat		Haz. Ratio	Z-stat		Haz. Ratio	Z-stat	
Variable									
TGI	1.270	32.86	***	1.317	29.74	***	2.254	21.10	***
foreign* TGI				0.467	-36.76	***	0.584	-21.54	***
foreign				3.958	87.74	***	1.643	25.30	***
instit.*TGI				1.089	5.51	***	1.186	6.27	***
instit.				2.665	80.35	***	2.239	37.09	***
male* TGI							0.913	-3.85	***
male							1.912	34.52	***
return of the position							1.000	-2.30	**
Portf size*TGI							0.927	-17.73	***
Portf size							1.275	71.02	***
No. of Stock*TGI							1.019	7.94	***
No. of Stock							1.058	29.16	***

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

Regressions 1-3 present the Trading Loss Indicator (TLI) as the main driver of selling decision (all other variables are interacted with the TLI where indicated). Regressions 4-6 present the Trading Gain Indicator (TGI) as the main driver of selling decision (all other variables are interacted with the TGI where indicated).

Table 4A. Hazard model for selling the stock for the subsample of individual investors.

	REG 7			REG 8			REG 9		
	All investors			**Local investors**			**Foreign investors**		
Variable	Haz. Ratio	Z-stat		Haz. Ratio	Z-stat		Haz. Ratio	Z-stat	
TLI	0.659	-6.17	***	0.605	-6.83	***	1.335	1.36	
return of the position	1.000	-1.53		1.000	-1.50		1.001	1.04	
Portf size×TLI	1.095	14.81	***	1.091	13.54	***	1.072	3.07	***
Portf size	1.029	8.09	***	1.025	6.75	***	1.148	9.93	***
Num. of Stock×TLI	0.950	-9.09	***	0.948	-8.88	***	0.949	-3.05	***
Num. of Stock	0.791	-74.26	***	0.798	-65.76	***	0.772	-28.73	***
foreign×TLI	1.423	9.90	***						
foreign	1.642	20.79	***						
male×TLI	0.973	-1.13		0.963	-1.53		1.229	1.81	*
male	1.464	26.11	***	1.421	23.55	***	1.917	8.27	***
age 21-30×TLI	0.919	-1.53		1.075	1.16		0.403	-6.59	***
age 31-40×TLI	0.857	-2.79	***	0.986	-0.22		0.421	-6.22	***
age 41-50×TLI	1.151	2.47	**	1.285	3.92	***	1.119	0.74	
age 51-60×TLI	1.026	0.43		1.140	1.97	**	1.246	1.27	
age 61-70×TLI	0.903	-1.64		1.047	0.67		0.397	-3.80	***
age over 70× TLI	0.921	-1.20		1.049	0.64		0.635	-1.16	
age 21-30	2.591	27.27	***	1.845	16.03	***	6.730	20.06	***
age 31-40	1.723	15.74	***	1.242	5.70	***	4.121	15.13	***
age 41-50	1.215	5.49	***	0.908	-2.46	**	1.341	2.87	***
age 51-60	1.075	1.96	**	0.818	-4.92	***	0.848	-1.46	
age 61-70	1.021	0.53		0.765	-6.39	***	0.926	-0.57	
age over 70	0.798	-5.50	***	0.600	-11.56	***	0.536	-3.26	***
exper. 6-10 trades×TLI	1.037	1.31		1.058	1.96	**	0.887	-1.05	
exper. 11-20 trades×TLI	0.930	-2.00	**	0.943	-1.55		0.870	-1.05	
exper. 21-30 trades×TLI	0.784	-5.35	***	0.782	-5.17	***	0.763	-1.66	*
exper. 31-40 trades×TLI	0.878	-3.28	***	0.889	-2.84	***	0.770	-1.95	*
exper. 41-50 trades×TLI	0.734	-6.66	***	0.817	-4.14	***	0.374	-6.40	***
exper. over 50 trades×TLI	0.817	-7.61	***	0.848	-5.97	***	0.554	-6.22	***
exper. 6-10 trades	1.487	23.71	***	1.492	23.28	***	1.276	3.28	***
exper. 11-20 trades	3.294	53.16	***	3.345	52.04	***	2.516	10.26	***
exper. 21-30 trades	5.380	59.81	***	5.421	57.91	***	4.412	13.51	***
exper. 31-40 trades	6.026	71.83	***	6.026	68.76	***	5.248	18.39	***
exper. 41-50 trades	9.140	76.79	***	9.038	73.25	***	7.300	18.89	***
exper. over 50 trades	20.342	180.05	***	20.712	174.78	***	14.512	40.19	***
price Δ t-1 day	2.581	4.89	***	2.623	4.78	***	3.307	1.67	*
price Δ t-2...t-5 days	4.199	18.56	***	4.417	18.42	***	3.097	3.90	***
price Δ t-6...t-10 days	23.286	48.44	***	27.118	49.93	***	2.972	3.59	***
price Δ t-11...t-20 days	15.608	41.01	***	17.214	41.03	***	5.088	5.85	***
price Δ t-21...t-30 days	23.271	60.67	***	25.750	60.31	***	8.594	10.73	***
price Δ t-31...t-40 days	24.067	66.98	***	26.091	66.16	***	9.035	11.43	***
price Δ t-41...t-60 days	0.087	-70.78	***	0.083	-69.16	***	0.119	-16.65	***

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

Regression 7 presents the Trading lain indicator (TLI) as the main driver of selling decision (all other variables are interacted with the TLI where indicated). Regression 8 presents hazard ratios for the subsample of local individual investors and Regression 9 presents hazard ratios for the subsample of foreign individual investors.

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Table 4B. Hazard model for selling the stock for the subsample of individual investors.

Variable	REG 10 All investors Haz. Ratio	Z-stat		REG 11 Local investors Haz. Ratio	Z-stat		REG 12 Foreign investors Haz. Ratio	Z-stat	
TGI	1.451	5.51	***	1.582	6.24	***	0.694	-1.73	*
return of the position	1.000	-1.54		1.000	-1.51		1.001	1.05	
Portf size×TGI	0.917	-14.19	***	0.921	-12.91	***	0.935	-2.94	***
Portf size	1.124	23.43	***	1.116	20.90	***	1.229	11.50	***
Num. of Stock×TGI	1.053	9.14	***	1.055	8.87	***	1.056	3.22	***
Num. of Stock	0.751	-61.76	***	0.756	-56.25	***	0.731	-21.73	***
foreign×TGI	0.691	-10.37	***						
foreign	2.352	32.63	***						
male×TGI	1.023	0.95		1.034	1.34		0.818	-1.77	*
male	1.429	18.46	***	1.371	15.81	***	2.345	10.50	***
age 21-30×TGI	1.072	1.25		0.915	-1.43		2.465	6.55	***
age 31-40×TGI	1.156	2.63	***	1.004	0.06		2.356	6.17	***
age 41-50×TGI	0.864	-2.58	***	0.772	-4.05	***	0.893	-0.75	
age 51-60×TGI	0.969	-0.52		0.871	-2.08	**	0.798	-1.31	
age 61-70×TGI	1.110	1.69	*	0.956	-0.66		2.567	3.88	***
age over 70×TGI	1.086	1.20		0.951	-0.67		1.616	1.22	
age 21-30	2.399	20.42	***	2.003	14.22	***	2.717	10.07	***
age 31-40	1.483	9.19	***	1.232	4.27	***	1.743	5.44	***
age 41-50	1.402	7.64	***	1.171	3.14	***	1.501	3.67	***
age 51-60	1.105	2.15	**	0.937	-1.24		1.059	0.44	
age 61-70	0.919	-1.73	*	0.801	-4.10	***	0.364	-5.01	***
age over 70	0.735	-5.61	***	0.630	-7.71	***	0.334	-3.20	***
exper. 6-10 trades×TGI	0.966	-1.26		0.946	-1.94	*	1.144	1.17	
exper. 11-20 trades×TGI	1.088	2.33	**	1.074	1.89	*	1.157	1.10	
exper. 21-30 trades×TGI	1.284	5.50	***	1.285	5.27	***	1.354	1.86	*
exper. 31-40 trades×TGI	1.138	3.27	***	1.123	2.80	***	1.320	2.08	**
exper. 41-50 trades×TGI	1.345	6.39	***	1.215	3.98	***	2.518	6.02	***
exper. over 50 trades×TGI	1.217	7.43	***	1.173	5.76	***	1.807	6.23	***
exper. 6-10 trades	1.540	19.74	***	1.577	20.14	***	1.123	1.33	
exper. 11-20 trades	3.040	39.10	***	3.129	38.28	***	2.181	8.09	***
exper. 21-30 trades	4.199	40.30	***	4.224	38.52	***	3.306	9.95	***
exper. 31-40 trades	5.288	54.67	***	5.355	52.24	***	4.002	14.08	***
exper. 41-50 trades	6.751	52.64	***	7.411	52.08	***	2.817	9.40	***
exper. over 50 trades	16.660	136.71	***	17.604	132.87	***	8.044	30.39	***
price Δ t-1 day	2.659	5.05	***	2.699	4.93	***	3.448	1.73	*
price Δ t-2...t-5 days	4.308	18.94	***	4.525	18.76	***	3.233	4.07	***
price Δ t-6...t-10 days	23.764	48.85	***	27.628	50.30	***	3.115	3.75	***
price Δ t-11...t-20 days	15.939	41.44	***	17.549	41.42	***	5.314	6.03	***
price Δ t-21...t-30 days	23.774	61.18	***	26.269	60.78	***	8.909	10.94	***
price Δ t-31...t-40 days	24.577	67.55	***	26.606	66.68	***	9.373	11.65	***
price Δ t-41...t-60 days	0.086	-71.34	***	0.082	-69.66	***	0.116	-16.87	***

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

Regression 10 presents the Trading gain indicator (TGI) as the main driver of selling decision (all other variables are interacted with the TGI where indicated). Regression 11 presents hazard ratios for the subsample of local individual investors and Regression 12 presents hazard ratios for the subsample of foreign individual investors.

4.2. Investor type

4.2.1. Foreign investors

To better see how the disposition effect can influence investors, I focus on the differences of investor groups. One of the main aims is to test if differences in trading behavior exist for distinguishable investor groups. As I observe a clear distinction between local and foreign investors, I focus the study to see whether foreign investors are less biased than domestic investors and whether the same forces are driving both foreign and domestic investors in terms of the disposition effect.

An interesting phenomenon emerges for foreign investors as they seem to react in the opposite way to the local investors in terms of the disposition effect. All regressions in Table 3 show that foreign investors tend to liquidate losing positions much more quickly than winning positions which is the complete opposite of the disposition effect. The same is true for a subsample of individual investors (see Table 4A and 4B) and institutional investors (see Appendix A).

Almost[9] all regression setups clearly support the reverse disposition effect of foreign investors. In general, foreign investors are not disposition effect biased in the traditional way, but reverse disposition effect biased. The only exception seems to be foreign institutions that do not classify under the nominee or client account types. Such institutions tend to act very similarly with the investment funds as they trade less and tend to hold losses longer than winning stock. As most foreigners belong either to the individual investor or the nominee or client account type, the general conclusion about the behavior of foreign investors is that, on average, they do not seem to exhibit the disposition effect but the reverse effect. Similar results are also produced by using *PGR-PLR* methodology (see Table 5).

We can see from the previous theoretical work (Section 2.1.) that differences in risk aversion in gains, risk seeking in losses, loss aversion as well as

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[9] When studying the effect on a subsample of institutional investors (see Appendix A), the largely nominee and client account dominated data starts to affect the foreign investor dummy as the nominee and client account dummies overlap with the foreign investor dummy variable.

expectations of market returns can greatly affect the investor's decision for holding or selling the position. The reasoning behind the reverse disposition effect behavior of foreign investors can be mostly in differences of the risk aversion and/or loss aversion compared to local investors. The tendency of foreign investors of being more risk averse as well as loss averse has been documented before[10]. However, if foreign investors have actually higher ability to take risk, they might end up in a situation when they are more risk and loss averse only in case of losses.

Foreign investors could assume higher level of risk related to their foreign (especially an emerging market) investments that would make them more loss averse and to expect higher returns. The ex-ante loss aversion of local investors can be reduced by familiarity bias that is generally regarded as the cause for the home bias of portfolio allocation. As foreign investors have invested to a partly unknown risky market, they know that prices on such a market can fall substantially and to protect their wealth, they feel compelled to liquidate losing positions more readily.

If foreign investors are momentum driven in a way that they take positions after significant price gains (that is what comes out of regressions containing previous period returns) they act in the exact way the model of Barberis and Xiong [2009] would predict - they exhibit the reverse disposition effect. A more momentum effect driven trading behavior of foreign investors corresponds to a more rational wealth allocation after a gain according to the model of Barberis and Xiong [2009]. As local investors do not take larger positions under the same circumstances, they either expect lower returns (which would justify their behavior) or act less rationally.

The higher level of wealth[11] and larger portfolio size should increase the foreign investors' ability to take risk. As I include the portfolio size as a covariate in the regressions, any effects from the increased availability of funds should be at

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[10] See e.g. Cooper and Kaplanis [1994] for the discussion of reduced risk aversion for local investors or Nilsen and Rovelli [2001].

[11] Tables 1 and 2 present that about 3.7% of investors are of foreign origin who hold about 45% of total assets; most foreign investors come from countries with higher GDP/capita ratio than the local.

least partly[12] described by that variable and excluded from the differences of investor types. Higher ability to take risk coupled with higher loss aversion (those characteristics are not mutually exclusive) can affect decisions on status quo or positive[13] news by resulting in higher required returns that makes such investors hold winning positions longer. The same might not apply for bad news.

Foreign investors can have an informational disadvantage compared to local investors which reduces their ability to react to news. As bad news gets generally more public attention, it reaches foreign investors relatively faster than good news. Regarding information availability, the Tallinn Stock Exchange belongs to Nasdaq OMX group that imposes similar requirements on listed companies as developed markets. All in all, foreign investors have exactly the same access to company press releases (published simultaneously in English and Estonian) than locals. The main real informational difference comes from other news sources (e.g. local mass media). If media accentuates bad news, this should affect more locals than foreigners.

But if foreigners are already convinced of their informational disadvantages, every bit of information that they receive might get amplified attention. As leveraged bad news involves a sale decision before price movements take place, the investors will liquidate whatever positions necessary. Informational disadvantage can be one important factor increasing foreign investors' loss aversion and thus decreasing their risk seeking behavior in losses. Also as being a relatively small and open economy, the Estonian market is greatly influenced by inflow of foreign institutional funds. During the time of bad news, foreign analysts tend to get clearly more cautious than local analysts which can have amplified effects on mostly foreign investors. Even if good news gets the same leveraged attention, foreign investors remain to hold winning positions for an extended time as their required return is high or if prices do not adjust promptly.

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[12] Both local and foreign investors can hold other assets not included in the data. Probably the proportion of other assets is clearly larger for foreign investors which don't allow making too bold conclusions based on that variable.

[13] Loss aversion doesn't affect the prospect value function on the positive side.

On average, foreign investors can also be considered as more sophisticated investors, since investing on other than the domestic market inherently requires increased sophistication or availability of funds. Previous studies (see Section 2.2.) as well as the results of the current work show that investor sophistication and trading experience can reduce the traditional disposition effect. Such characteristics can more readily describe the foreign investor group in comparison to the local investor group. This can more easily result in a situation where the differences in the loss or risk aversion can shift the trading behavior of foreign investors to the reverse disposition effect side.

Most of the nominee and client accounts (which are relatively big in size), hold investments for foreigners. This could mean that the investments of a relatively large number of foreign investors are managed or advised by professional money managers. As investments of nominee and client accounts are pooled together under a few accounts, it makes it more difficult to study the behavior of certain foreign investors which might affect the overall results compared to the situation when they trade independently. Depending on the institution, either individuals/institutions investing under the nominee account can make their own investment decisions or their assets are managed by professional money managers. As this might be the case for non-individual investor accounts (under which a majority of foreigners belong to the nominee or client account type), this is not the case for individual investors who exhibit the reverse disposition effect even more clearly. If the reverse disposition effect was caused by professional money managers, we would see similar tendencies for also local investment funds or institutional investors, which is clearly not the case.

The model of Barberis and Xiong [2009] shows that we could see the disposition effect for high frequency traders with high number of trading periods in mind. It could be argued that local investors might indeed have longer or more trading periods in mind when making their investment decisions as they do not intend to exit their home market permanently, which might be the case for foreign investors who switch their investments between a larger variety of markets.

Hazard ratios associated with foreign investor control dummies in different regressions show higher probability of trading for foreign investors when not considering whether their position is in loss or gain. Although it could indicate that foreign investors trade more frequently than local investors, we have to take into consideration their larger portfolio size and adjust the frequency accordingly. Appendix B presents the portfolio size and trading frequency for local and foreign individual and institutional investors.

As can be seen from the trading statistics, foreigners make more and slightly larger trades than local investors. When looking at the average yearly portfolio turnover ratio[14], we can see that this is quite similar for local and foreign individual investors (although foreigners seem to be slightly more frequent traders when adjusted for the portfolio size) but foreign institutions have clearly a smaller portfolio turnover. Clearly a larger portfolio turnover for local institutions could also be caused by the fact that some local institutions act as market makers but as the number is still smaller than for individual investors, this cannot explain the whole difference. Average holding periods are shorter for both foreign investor groups compared to their local counterpart, which confirms the assumption that local investors who seem disposition effect biased, have longer and more periods in mind when investing. The difference in trading frequency doesn't come out clearly as local and foreign individual investors have roughly the same trading frequency.

For a robustness test, I run a similar numerical simulation sensitivity analysis to Kaustia [2009] to check if the prospect theory would predict the reverse disposition effect under the previously discussed assumptions of the behavior of foreign investors. Although the model has a hard time predicting any sales at all, the sensitivity analysis implies that for the prediction of the reverse disposition effect, loss aversion coefficient can be (but not necessarily has to be) higher than for the prediction of the disposition effect. Tversky and Kahneman [1992] estimate risk aversion and risk seeking parameters to be equal but as this might always not

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[14] Average yearly portfolio turnover is calculated as average number of trades multiplied by average trade size, divided by average portfolio size for the corresponding investor group.

be the case, the sensitivity analysis also shows higher propensity for the reverse disposition effect especially in cases when $\alpha > \beta$ from Equation 1. In general, the sensitivity analysis offers possibilities for the previous discussion of differences in parameter values to hold for the prospect theory based explanation of the reverse disposition effect, but also shows combinations under which this might not be the case.

4.2.2. Institutional investors

Results from Table 3 show that although institutional investors tend to trade more they seem to have slightly increased propensity for the disposition effect compared to individual investors. But as the effect of the interaction term and the institutional investor control variable is the opposite, we cannot make very strong conclusions. The *PGR-PLR* results do not show a very clear distinction between individual and institutional investors either.

Institutional investor regressions include four different types of institutions: investment vehicles belonging to the government or public sector as one group (labeled public), nominee accounts, client accounts, investment funds (labeled fund) and all other non-private investors (See Appendix A for results).

An interesting result is the behavior of investment funds. Clearly, due to the low liquidity of the market, investment funds cannot trade frequently as their investable funds tend to be too big to be able to properly execute trades. This tendency to trade infrequently is reflected in a very low value of the hazard ratio for the control variables. At the same time one would expect that investment funds would be among the most sophisticated market participants of all. Regarding the disposition effect, this is not the case. In all setups, both for the whole sample and for the institutional investor subsample, interaction terms with both the TLI and the TGI show that investment funds are probably the single most distinguishable investor class that is prone to the disposition effect on both holding losers and selling winners.

However, this does not necessarily mean that funds show inferior returns. In an environment where prices generally appreciate in time (as it has been on average for the viewed period) holding both winning and losing positions tends to pay off in the end. But should such behavioral pattern remain unchanged in the time of crises, fund investors would be suffering significant losses in the short or medium term as funds would not tend to start liquidating positions when losses start to emerge.

4.3. Investor sophistication

Similarly to Feng and Seasholes [2005], I investigate whether investor sophistication can explain the differences in the level of the disposition effect that most investor classes exhibit. Feng and Seasholes [2005] discuss that emerging market investor sophistication can be quantified by the number of trades they have made, the age, the portfolio size and diversification[15]. In order to see the effect in my sample, I divide investors into age brackets, count the number of trades since the beginning of data, and calculate the value of the portfolio and the number of stock in the portfolio for each investor and for each trading day.

Larger portfolio size seems to decrease the bias and the results are robust under different regression setups. Interaction terms for trading experience imply an increased disposition effect bias for individual investors but are in most cases statistically and qualitatively not different from 1 for institutional investors or when other time dummies are introduced. Still, very clear cross sectional differences exist. Contrary to the results of Feng and Seasholes [2005], a larger number of stocks in the portfolio increase the disposition effect. It can be argued that the number of stocks in the portfolio is not the best indicator for diversification (or sophistication) as the number of available investable companies is very small and low liquidity can reduce the investable universe even further for larger and more sophisticated investors.

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[15] Feng and Seasholes [2005] included the number or trading rights as well, which cannot be applied for current data.

4.4. Trading style

I check for feedback trading to see whether investors are contrarians and sell winning and buy losing stock that might have nothing to do with the disposition effect. I include past returns for up to 60 trading days (about 3 months) before the transaction takes place. As the hazard ratios indicate, investor selling decisions are affected by the past returns of the securities, whereas most recent periods influence the selling decision the most. Although past returns do affect the selling decision, including the fact that such variables do not change coefficients for other indicators in the regressions and thus cannot be the cause for the disposition effect.

To further test whether investors are more momentum driven or contrarian, I also used positive and negative returns separately in the regressions for all investor types. When comparing hazard ratios of positive and negative returns for local and foreign investors, negative returns for the past 5 days affect the selling probability of local investors (making them short-term momentum driven) but the opposite is true for 5-40 day returns. Foreign investors seem to be slightly less momentum driven by the last 1-5 day returns but more momentum driven (selling decision more affected by negative returns) by other time intervals. Tables 4 and 5 present the effect where larger values for price change hazard ratios indicate contrarian and smaller values momentum driven behavior.[16]

Institutional investors as well as foreign investors tend to belong more to the momentum trader category. Based on the presented data and model setup, such classification can be arbitrary as buy decisions are not analyzed although Grinblatt and Keloharju [2001] report the same for Finish investors.

There seems to be a negative correlation between average returns over the period and the level of the disposition effect. Higher returns are shown by investor groups who exhibit either the reverse disposition effect or are less disposition effect biased. An alternative explanation for such a correlation is that momentum

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[16] Results for including negative and positive returns separately are available upon request. Current paper investigates only selling decisions and buying decisions are neglected which would require a separate event-study.

strategies work better on the Estonian market or investors with relatively very large asset base can influence the prices of a relatively small stock market, which makes them look less biased.

Table 5. Comparison of survival analysis and *PGR-PLR* analysis

| Investor type | Survival analysis | | *PGR-PLR* ratio analysis | | | | |
	Hazard ratio for TLI	Hazard ratio for TGI	PGR	PLR	PGR-PLR	T-stat	
All investors	0.774***	1.270***	0.314	0.289	0.025	-13.476	***
Institutions	0.724***	1.368***	0.213	0.202	0.011	-5.026	***
Individual investors	0.807***	1.214***	0.419	0.372	0.047	-17.061	***
Foreign investors	1.334***	0.741***	0.175	0.192	-0.017	5.566	***
Local investors	0.735***	1.337***	0.355	0.321	0.034	-15.583	***
Local private investors	0.781***	1.256***	0.420	0.371	0.049	17.113	***
Foreign private investors	1.372***	0.707***	0.406	0.384	0.022	2.210	**
Local institutional investors	0.627***	1.575***	0.261	0.237	0.023	7.449	***
Foreign institutional investors	1.568***	0.636***	0.135	0.153	-0.017	-5.557	***

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

Survival analysis presents hazard ratios for the Trading loss indicator (TLI) and the Trading gain indicator (TGI) used as the only covariate in filtered subsample regressions. PGR-PLR analysis presents the Proportion of gains realized (PGR) minus the Proportion of losses realized (PLR) for filtered subsamples.

5. Conclusions

The prospect theory explanation of the disposition effect has recently received criticism for not explaining the puzzle for most of the time and requiring the parameterization that is mostly not realistic. However, as the recent theoretical models show, there exist cases when the prospect theory should predict the disposition effect and cases when it should predict the reverse disposition effect. Although previous empirical research has not clearly identified that, my results of a comprehensive dataset show that there are distinct investor groups for which either the disposition or the reverse disposition effect can prevail. Such a complete opposite behavior can be caused by different behavioral characteristics. As also previous theoretical work shows, behavioral differences can be transformed into

the prospect theory value function parameterization, which can at least partly explain the complete opposite behavior under not too different parameterization.

The empirical data shows that a distinct foreign investor group seems to behave as quite accurately predicted by the prospect theory based model of Barberis and Xiong [2009]. However, foreign investors do not seem to exhibit the disposition effect but the reverse disposition effect. Such a behavior can partly be explained by a higher loss aversion of foreigner investors compared to local investors, which makes them liquidate losing positions relatively early. As discussed in Section 4.2. there could also be clear differences in risk aversion and risk seeking behavior as well as in the expected risk level, which all affect the trading decisions. Another explanation can be a higher level of sophistication of foreign investors as increased experience and sophistication seems to decrease the disposition effect as found in the current study as well as previously by Feng and Seasholes [2005].

Longer holding periods, slightly higher adjusted trading frequency and possibly reduced loss and risk aversion (possibly caused by familiarity bias) could in fact also help to explain the disposition effect for local investors in the recent models. The results give an insight that there could also exist prospect theory based models that, when incorporating clear differences of investor groups, could explain the puzzle for a larger proportion of investors.

Despite finding the reverse disposition effect of foreign investors, the results show that the disposition effect prevails on the Estonian stock market, however, to a smaller degree than found for some other markets. Individual investors seem to be slightly less prone to the disposition effect than institutional investors, whereas investment funds exhibit surprisingly high degree of reluctance to realize losses. Foreign and non-individual investors are more driven by momentum strategies in their trading whereas local and individual investors pursue the contrarian approach.

Other results include finding that experience and investor sophistication does seem to reduce the disposition effect bias even when controlling for different other demographic and market wide variables. The reverse disposition effect biased

investors seem to exhibit better performance results than the disposition effect biased investors.

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Appendix A. Hazard model for selling the stock for the subsample of non-individual investors

Variable	REG 13 Haz. Ratio	REG 13 Z-stat	REG 14 Haz. Ratio	REG 14 Z-stat	REG 15 Haz. Ratio	REG 15 Z-stat	REG 16 Haz. Ratio	REG 16 Z-stat	REG 17 Haz. Ratio	REG 17 Z-stat	REG 18 Haz. Ratio	REG 18 Z-stat	REG 19 Haz. Ratio	REG 19 Z-stat	REG 20 Haz. Ratio	REG 20 Z-stat
TLI	0.688	-5.15 ***	0.502	-10.32 ***	0.621	-32.11 ***			1.382	4.47 ***	1.907	9.69 ***				
TGI							0.724	-25.85 ***					1.588	31.29 ***	1.368	25.10 ***
foreign×TLI (TGI)					2.655	35.17 ***							6.275	85.65 ***		
foreign					2.381	49.31 ***							0.381	-34.80 ***		
public×TLI (TGI)	0.736	-0.83	0.713	-0.92					1.391	0.89	1.435	0.98				
public	0.701	-1.88 *	0.512	-3.54 ***					0.508	-2.13 **	0.360	-3.23 ***				
fund×TLI (TGI)	0.631	-1.95 *	0.833	-0.78					1.604	2.00 **	1.221	0.85				
fund	0.189	-14.41 ***	0.138	-17.29 ***					0.118	-10.36 ***	0.114	-10.60 ***				
nomineexTLI (TGI)	2.074	19.62 ***	1.893	17.00 ***					0.483	-19.60 ***	0.529	-16.98 ***				
nominee	0.420	-37.59 ***	0.473	-32.19 ***					0.871	-4.74 ***	0.894	-3.79 ***				
client. ×TLI (TGI)	1.362	5.80 ***	1.254	4.25 ***					0.738	-5.70 ***	0.802	-4.13 ***				
client.	0.597	-15.20 ***	0.655	-12.51 ***					0.810	-5.12 ***	0.819	-4.85 ***				
return of the position	0.999	-3.70 ***	0.999	-4.44 ***					0.999	-3.69 ***	0.999	-4.42 ***				
Portf size×TLI (TGI)	1.026	3.63 ***	1.031	4.48 ***					0.977	-3.24 ***	0.972	-4.12 ***				
Portf size	1.149	32.62 ***	1.262	59.01 ***					1.178	28.28 ***	1.300	47.34 ***				
Num. of Stock×TLI (TGI)	1.004	0.96	1.013	3.41 ***					0.996	-0.94	0.987	-3.45 ***				
Num. of Stock	1.112	47.80 ***	1.137	60.56 ***					1.116	33.91 ***	1.152	45.38 ***				
exper. 6-10 tr. ×TLI (TGI)	0.911	-1.46							1.097	1.45						
exper. 11-20 tr. × TLI (TGI)	0.935	-0.85							1.073	0.89						
exper. 21-30 tr. ×TLI (TGI)	0.972	-0.30							1.044	0.44						
exper. 31-40 tr. × TLI (TGI)	0.892	-1.45							1.129	1.54						
exper. 41-50 tr. × TLI (TGI)	1.081	0.89							0.930	-0.84						
exper. ov. 50 tr. × TLI (TGI)	1.109	2.16 **							0.900	-2.22 **						
exper. 6-10 trades	1.050	1.34							0.957	-0.83						
exper. 11-20 trades	1.217	4.29 ***							1.136	2.00 **						
exper. 21-30 trades	1.234	3.90 ***							1.188	2.17 **						
exper. 31-40 trades	2.228	17.39 ***							1.978	10.69 ***						
exper. 41-50 trades	2.168	15.10 ***							2.334	12.13 ***						
exper. over 50 trades	3.942	49.80 ***							4.373	38.03 ***						
price Δt-1 day	1.444	1.37							1.464	1.42						
price Δt-2…t-5 days	10.028	24.36 ***							10.112	24.48 ***						
price Δt-6…t-10 days	8.042	19.56 ***							8.134	19.69 ***						
price Δt-11…t-20 days	7.538	20.50 ***							7.624	20.65 ***						
price Δt-21…t-30 days	8.162	27.33 ***							8.241	27.48 ***						
price Δt-31…t-40 days	7.085	26.56 ***							7.152	26.72 ***						
price Δt-41…t-60 days	0.241	-26.84 ***							0.239	-27.01 ***						

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

Regressions 13-16 present the Trading loss indicator (TLI) as the main driver of the selling decision (all other variables are interacted with the TLI where indicated) for the subsample of non-individual investors. Regressions 17-20 present the Trading gain indicator (TGI) as the main driver of the selling decision (all other variables are interacted with the TGI where indicated) for the subsample of non-individual investors.

Appendix B. Trade size and frequency.

	Local individual investors	Foreign individual investors	Difference between foreign and local invest.	Local institutional investors	Foreign institutional investors	Difference between foreign and local invest.
Avg. num. of sales	5.49	12.38	2.3	38.80	415.48	10.7
Avg. num. of purchases	5.50	13.46	2.4	34.05	538.36	15.8
Avg. sale size in EUR	2 227	3 168	1.4	8 361	6 893	0.8
Avg. purchase size in EUR	1 985	2 294	1.2	9 191	6 151	0.7
Avg. num of trades	10.99	25.84	2.4	72.84	953.83	13.1
Avg. trade size in EUR	2 106	2 713	1.3	8 749	6 474	0.7
Avg. portfolio size in EUR	4 473	13 192	2.9	155 469	2 886 162	18.6
Avg. yearly turnover of the portfolio	1.15	1.18	1.0	0.91	0.48	0.5
Avg. holding period	68.29	52.15	0.8	37.87	14.16	0.4

All figures are presented for the whole sample period (i.e. 4.5 years) except for the Average yearly turnover of the portfolio. Difference between foreign and local investors presents how many times does the figure for foreign investors exceed the figure for local investors.

Appendix 2

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

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

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Abstract

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

1. Introduction

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

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

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

trading intensity and performance results tend to differ across gender and age groups; whereas, a higher level of the disposition effect bias translates into lower portfolio return, which is also negatively affected by higher trading intensity.

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

2. Related Literature

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

2.1. United States

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

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

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

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

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

2.3. Europe

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

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

Weber and Welfens (2007) analyse individual level disposition effects by using both account level German online broker data, as well as a controlled laboratory experiment. They find that the degree of the disposition effect varies considerably on an individual level, as most investors exhibit the disposition to

some degree, although investors with a reverse effect exist. In an experiment setup, they find that investors who started with a positive disposition effect decreased their bias over time, while those investors with a negative initial disposition effect also drifted towards the no-disposition effect benchmark. The results show that investors with higher income, as well as more trading experience, are less prone to the disposition effect; whereas, investors with aggressive investment strategies tend to exhibit a relatively high disposition effect.

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

2.2. Asia and Oceania

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

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

Feng and Seasholes (2005) investigate investor sophistication and trading experience based on Chinese discount broker data from 1999 to 2000. They show that investor sophistication and trading experience eliminate the reluctance to realise losses; as sophisticated investors are clearly less susceptible to the disposition effect than the average investor in the sample. Feng and Seasholes (2008) also document that men hold larger portfolios, trade more intensively and

make slightly larger trades than women, although they do not find difference in the performance of genders.

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

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

3. Methodology

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

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

An alternative approach would be to use logistic regressions (as used in Grinblatt and Keloharju 2000). Both survival analysis and logistic regressions use binary outcome variables and allow for categorical or continuous predictor variables and are thus quite similar in their setup. The main difference and advantage of survival analysis comes from bringing in the time dimension to the analysis and thus allowing to examine the relationship of both timing and occurrence of outcomes to multiple predictors, rather than focusing only on occurrence. Another advantage of survival analysis is that it allows for censored observations, meaning that data can be analysed before all participants have

experienced the terminal event. The same is true when the entry time for participants is not simultaneous.

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

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

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

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

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

Survival analysis is accompanied with *PGR-PLR* ratio analysis that counts the number of realised gains and losses, as well as unrealised gains and losses on days when a selling transaction takes place for the portfolio. The counts are used to

calculate the proportion of gains realised, labelled as *PGR*, and the proportion of losses realised, labelled as *PLR*. The *PGR* and *PLR* for the sample or an investor group are defined as:

$$PGR_i = \frac{RG_i}{RG_i + PG_i} \tag{3}$$

$$PLR_i = \frac{RL_i}{RL_i + PL_i} \tag{4}$$

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

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

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

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

For every trading day in the sample, for each stock in each investor's portfolio, I make a comparison of the reference price to the current market price of the stock to see whether the investor incurs realised or unrealised loss or profit for

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

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

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

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

4. Individual Investor Account Data and Trading

I use a dataset provided by Nasdaq OMX Baltic. The data includes all transactions on Nasdaq OMX Tallinn (OMXT) for all domestic and foreign individual investors

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

4.1. Investor Age and Gender

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

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

4.2. Investor Portfolios and Performance

The provided data includes starting portfolios for all accounts with the date of 1 January 2004, as well as portfolios with monthly intervals. This enables the calculating of the monthly average market value of all portfolios grouped by investor gender and age (see Table 1). Although the average portfolio size for men somewhat exceeds female portfolios (7,278 EUR vs. 5,573 EUR), interesting

patterns can be observed among different age groups. For the investors at the age of 21-40 years, the portfolio size for male and female investors is quite similar. For male investors the portfolio size seems to increase with the increase of age, which can be logically affected by the fact that before retirement individual investor wealth should generally be growing. Female investors, on the other hand, do not exhibit such a pattern and their portfolio size starts to decrease after the age of 50, which can be affected by women being less overconfident (see Barber and Odean, 2001), which makes them more conservative towards approaching retirement time and decreases their exposure to the stock market.

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

Table 1. Trading and Account Statistics of the Estonian Market

	Number of accounts		Average portfolio size (EUR)		Average portfolio beta		Average annual return	
	Female	*Male*	*Female*	*Male*	*Female*	*Male*	*Female*	*Male*
Total	**6 673**	**14 085**	**5 573**	**7 278**	**1.027**	**1.019**	**23.0%**	**15.0%**
Age under 21	377	714	4 469	2 637	1.178	1.134	19.8%	6.0%
Age 21-30	931	3 657	2 890	2 115	1.063	1.063	3.6%	-0.1%
Age 31-40	1 482	4 195	4 060	4 518	1.105	1.037	13.3%	7.4%
Age 41-50	1 063	2 163	7 200	11 762	0.988	0.992	22.4%	16.3%
Age 51-60	1 015	1 367	5 795	11 932	1.056	1.000	19.8%	17.7%
Age 61-70	1 028	1 076	4 728	13 083	0.945	0.916	31.2%	16.3%
Age over 70	771	909	4 052	10 226	1.084	0.988	35.9%	22.7%

	Average amount of a purchase (EUR)		Average amount of a sale (EUR)		Average num. of puchases per account		Average num. of sales per account	
	Female	*Male*	*Female*	*Male*	*Female*	*Male*	*Female*	*Male*
Total	**1 985**	**2 017**	**2 292**	**2 284**	**3.3**	**7.0**	**3.7**	**6.7**
Age under 21	1 340	900	1 684	1 127	2.7	2.8	2.5	2.5
Age 21-30	1 136	1 377	1 439	1 483	3.0	6.9	3.0	6.7
Age 31-40	1 681	1 823	2 042	2 013	3.0	7.5	3.4	7.3
Age 41-50	2 537	2 565	2 720	2 697	4.6	8.4	5.0	7.9
Age 51-60	2 122	2 802	2 652	3 576	3.8	7.3	3.9	6.8
Age 61-70	2 073	2 644	2 271	3 181	3.0	6.3	3.5	6.3
Age over 70	2 301	2 626	2 447	3 365	2.7	4.6	3.9	5.0

	Average holding period		Average stock days per account		Stock days/avg holding period	
	Female	*Male*	*Female*	*Male*	*Female*	*Male*
Total	**91.0**	**61.7**	**384.1**	**468.0**	**4.2**	**7.6**
Age under 21	90.2	73.6	370.6	368.2	4.1	5.0
Age 21-30	75.5	46.2	299.8	342.6	4.0	7.4
Age 31-40	99.9	56.8	378.5	457.1	3.8	8.1
Age 41-50	68.4	70.5	385.8	579.3	5.6	8.2
Age 51-60	104.6	78.9	483.5	565.8	4.6	7.2
Age 61-70	108.6	79.1	427.5	559.2	3.9	7.1
Age over 70	94.7	107.5	307.3	579.3	3.2	5.4

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

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

Older investors seem to show superior results for both female and male investors. This cannot be explained by more trading experience; as the Estonian stock market was opened in the second half of 1990's and before 1990's Estonian

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

investors didn't even have a theoretical possibility of investing in foreign markets, nor the experience of a market economy. So there cannot be any differences in trading experiences among older than 40 year old investors. The main differences in performance can be affected by differences in trading intensity and holding period lengths as discussed in the next subsection.

4.3. Transaction and Trading Characteristics

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

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

Stock days per account and stock days divided by the average holding period show that men clearly hold more stocks in their portfolio, which more than compensates the shorter holding period and results in the higher number of stock

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days despite a shorter holding period (ceteris paribus, a longer average holding period should result in a greater number of stock days per account).

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

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

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5. Disposition Effect Results

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

Different variables for the regressions include the TLI (or the TGI); an indicator for male investors; indicators for the experience of an investor measured by the trades made since the beginning of the dataset; indicators for different age brackets; variables for the gain/loss in the stock price for previous intervals; a variable for the portfolio size of an investor; a variable for the number of stocks in the portfolio; a variable for the current return on the position or indicators for different return intervals; and indicators for different stock. For survival analysis, I pool all investors together and estimate hazard ratios of different variables to capture the average effect across investors. The hazard ratio below zero for the Trading loss indicator (TLI), along with the hazard ratio of above zero for the

Trading gain indicator (TGI), indicate the presence of the disposition effect (i.e. decreased probability to sell a losing stock and an increased probability to sell a winning stock). Hazard ratios for other variables show an increased or decreased probability of selling the position resulting from that variable. The probabilities are measured against the baseline hazard rate of a sale.

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

5.1. The Disposition Effect Bias

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

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variable with the TLI is below one (0.947) and the interaction term with the TGI is above one (1.052).

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

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

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

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

Table 2. Hazard Model for Trading Intensity

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

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

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

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

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

The model in Table 2 presents hazard ratios associated with different variables that can affect selling decisions.

Survival analysis in Table 3 presents hazard ratios for the Trading loss indicator (TLI) and the Trading gain indicator (TGI) used as the only covariate in filtered subsample regressions. PGR-PLR analysis presents the Proportion of gains realized (PGR) minus the Proportion of losses realized (PLR) for filtered subsamples.

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

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

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

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

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

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

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

Results of previous studies show that the disposition effect tends to decrease in December due to tax selling motivations. As usually the tax year ends with the calendar year and only realised profits are taxed (as it is in Estonia), it could be beneficial for investors to realise losses that could offset tax obligations

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

from realised gains. Such an activity could be conducted throughout the year, but as Odean (1998) shows, for US investors it will increase in December.

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

5.2. The Disposition Effect and Performance

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

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

explanation for such a correlation is the differences in trading strategies that can also affect the disposition effect.

Table 5. Correlation Between Portfolio Returns and the Disposition Effect

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

The TLI* and the TGI* is calculated based on baseline the TLI and the TGI values and corresponding interaction terms with age group dummies and the TLI and the TGI from Table 4. The TLI, the TGI and PGR-PLR is calculated from age group subsamples.
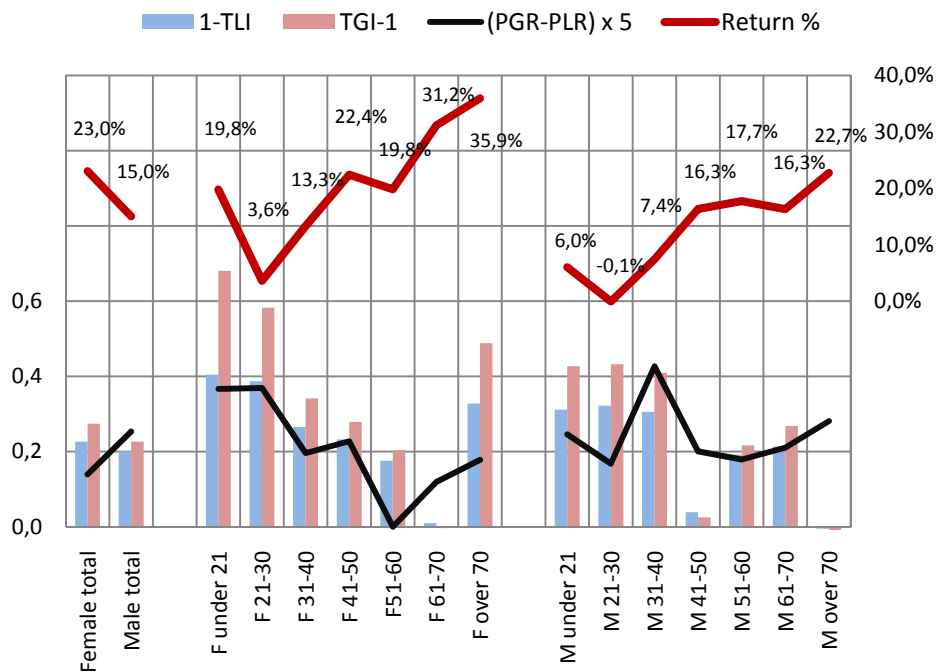
Figure 1. Correlation Between Portfolio Returns and the Disposition Effect

6. Conclusions

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

- The portfolios of female investors perform clearly better than the portfolios of male investors, even when adjusted for risk.

- Older investors clearly outperform younger investors in both female and male groups.

- A longer holding period, less trading intensity and fewer stocks in the portfolio is associated with female investors.

- The disposition effect bias is very similar for female and male investors when controlling for a different market, trading, performance and investor sophistication related variables.

- There is a negative correlation between the disposition effect and the portfolio performance, as less biased investors generally show better results.

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

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

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Appendix 3

Volatility asymmetry, news and private investors

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Talpsepp, T., Rieger, M.O. 2009. Explaining Asymmetric Volatility around the World, CARISMA Annual Conference 2010, London, UK, 1-3 February 2010, Conference presentation

Talpsepp, T., Rieger, M.O. 2009. Explaining Asymmetric Volatility around the World, 16th Annual Meeting of German Finance Association (DGF), Frankfurt, Germany, 8-10 October 2009, Conference presentation

Talpsepp, T., Rieger, M.O. 2009. Explaining Asymmetric Volatility around the World, German Economic Association Annual Congress 2009, Magdeburg, Germany, 8-11 September 2009, Conference presentation

Volatility asymmetry, news and private investors

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Abstract

Volatility is typically higher in down markets. Using an international comparison of volatility asymmetry and an analysis of a complete set of stock market transactions, we show that this effect, known as "leverage effect", is most likely driven by overreaction of private investors to bad news. This result is supported by our observation that an increase in attention to negative news (as measured by an increase in Google searches for keywords related to the macroeconomy like "recession") can predict a subsequent increase in volatility

1. Introduction

When prices drop, volatility increases. This general observation was most noticeable during the recent financial crisis, where following stock market drops the volatility reached record values. The effect has been most widely explained by changes in leverage and existence of time varying risk premiums. It is therefore sometimes called "leverage effect", but we will use the more neutral name volatility asymmetry, since so far no clearly recognized explanation exists.

In this article we investigate the potential relation between the occurrence of volatility asymmetry, news and private investors. In Section 2 we summarize results from a study comparing volatility asymmetry in 49 countries worldwide (Talpsepp & Rieger 2009). The study shows that volatility asymmetry is most

pronounced in highly developed markets and in particular in markets with high participation of private investors. Moreover, we find that markets with many financial analysts actually show higher volatility after downturns. These results suggest that private investors might react nervously to bad news. We show that times of high news concentration are typically times of many bad news, thus the overreaction of private investors to bad news will likely lead to the observed asymmetry in the volatility.

Further evidence for this relationship between news, private investors and volatility asymmetry is reported in Section 3.1: volatility of the S&P 500 increases after an increase in the number of Google searches for specific keywords related to the macroeconomy like "recession". It seems plausible that this is caused by private investors getting nervous and subsequently overreacting on the stock market, leading to an increase in the volatility.

To cross-validate our results, we study market data on trades of private and institutional investors from a stock exchange in Section 3.2. The special feature of this data set is that it entails all transactions on the stock market (in Estonia), thus we have no selection bias in the data. We demonstrate that at times where many private investors trade, volatility is higher, which is confirming our theory

2. What causes volatility asymmetry?

Increased volatility while market prices drop is referred to as volatility asymmetry. The current section summarizes some of the results of Talpsepp & Rieger (2009) on measuring and empirically investigating various causes of volatility asymmetry.

2.1. Measuring volatility asymmetry

There is a number of approaches to measure volatility asymmetry. We can derive the asymmetry from different types of volatility estimation models. A direct approach compares volatility of up and down markets (which has its drawback when linking different market periods to corresponding volatility). We favored to use more of an ad hoc model that already incorporates the asymmetry estimation in

its original setup. The choice can also depend on data availability and the exact research focus.

Although current literature on volatility (see e.g. Andersen, Bollerslev & Diebold (2003)) has shifted to using realized volatility from intraday returns, such data is not available for all markets and longer time periods. As we study a wide range of markets for a long time period, we use the asymmetric power GARCH (APARCH) model of Ding, Granger & Engle (1993) with asymmetric t-distribution. There is a wide choice of GARCH type models (see e.g. Poon & Granger (2003)) that could be used for the task when using daily returns. But as the APARCH model contains an asymmetry parameter it is one of the most natural choices for this task. Additionally, APARCH proved to deliver very accurate VAR forecasts compared to other models, especially when using asymmetric t-distribution.

We used the following specification of the APARCH model:

$$\sigma_t^\delta = \alpha(|\epsilon_{t-1}| - \gamma\epsilon_{t-1})^\delta + \beta\sigma_{t-1}^\delta \qquad (1)$$

where α, γ, β and δ are the APARCH parameters to be estimated. We are mainly interested in the asymmetry parameter γ only. It reflects the volatility asymmetry and takes values from -1 to 1. If there were no asymmetry (meaning that volatility is the same for down market periods and up market periods) the estimated γ would be zero. A positive value of γ means that volatility is higher in bear markets and that is exactly what results show for almost all countries during most of the time

Using GARCH type models has disadvantages when the time span is relatively short (usually less than 2000 observations) and/or return data contains

jumps. To cope with such problems we use outlier detection methods with kernel weighting for model input returns[1].

Handling jumps is one of the key problems that need to be addressed when applying more popular GARCH type models. Eliminating jumps enables us to receive more stable results with higher reliability and only a small loss of approximately 1-2% of data. Eliminating jumps could be a high price to pay when trying to forecast volatility in turbulent times. But our tests show that when estimating volatility asymmetry, removing jumps from data does not change the quality of the asymmetry estimate and thus does not have any significant impact on the results.

2.2. Volatility asymmetry comparison

To compare volatility asymmetry in different countries, we use daily stock market returns from the 49 country Morgan Stanley Capital International (MSCI) index provided by Thomson's Datastream. We include all data that is available in our sample. For a better comparison we use MSCI index returns measured in U.S. dollars. As a proxy for volatility asymmetry we use gammas obtained by repeatedly estimating Equation (1) for each country with a moving time window. Using a moving time window of a size of 1000 observations gives us a unique time series dataset of the volatility asymmetry for each country. As described in Talpsepp & Rieger (2009) we adjust the obtained measures for volatility asymmetry to exclude an impact of different return patterns. The adjustment also allows for a better comparison of the estimated volatility asymmetry across countries. We still use both adjusted and unadjusted measures for volatility asymmetry (both time series and cross sectional data) for testing different factors that can cause the asymmetry. When comparing volatility asymmetry across countries we can conclude that developed countries tend to have a higher level of

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[1] Please see Talpsepp & Rieger (2009) for details of the APARCH model and additional measures taken to ensure better stability of the estimated parameters to cope with short time spans.

asymmetry. The United Stated ranks first in all measures. Japan, Germany and France rank among the first 10 in all categories and the UK is also in the top of the table. The only emerging market with a relatively high level of asymmetry in most specifications is Mexico.
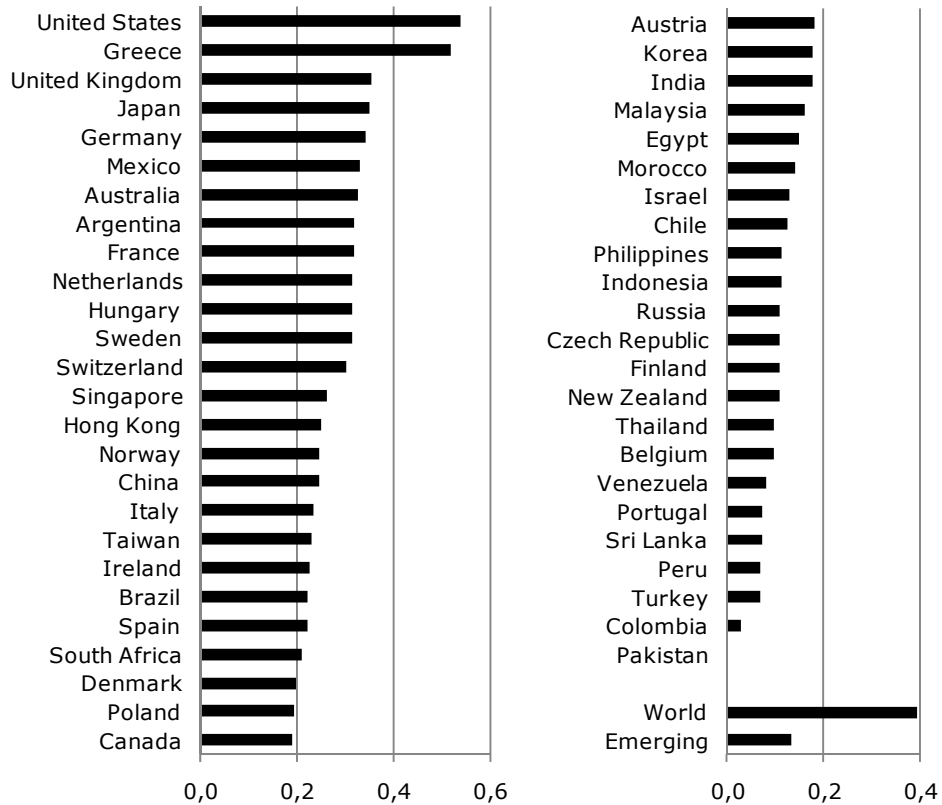

Figure 1. The level of volatility asymmetry.

Results show that the level of asymmetry changes in time quite remarkably. Some of the major fluctuations of the estimated gammas are caused by extreme fluctuations in market prices which can still not be captured by the APARCH model (despite outlier detection). But the increase in asymmetry seems to be facilitated especially during turbulent market situations as can be seen during the Asian crises and the burst of the technology bubble. Trend analysis captures an

increasing volatility asymmetry for 40 of the 49 studied markets. Hence, although volatility asymmetry might be considered a market inefficiency and thus should be fading in time, our results show an increasing asymmetry. This gives us a first clue about what can drive asymmetry.
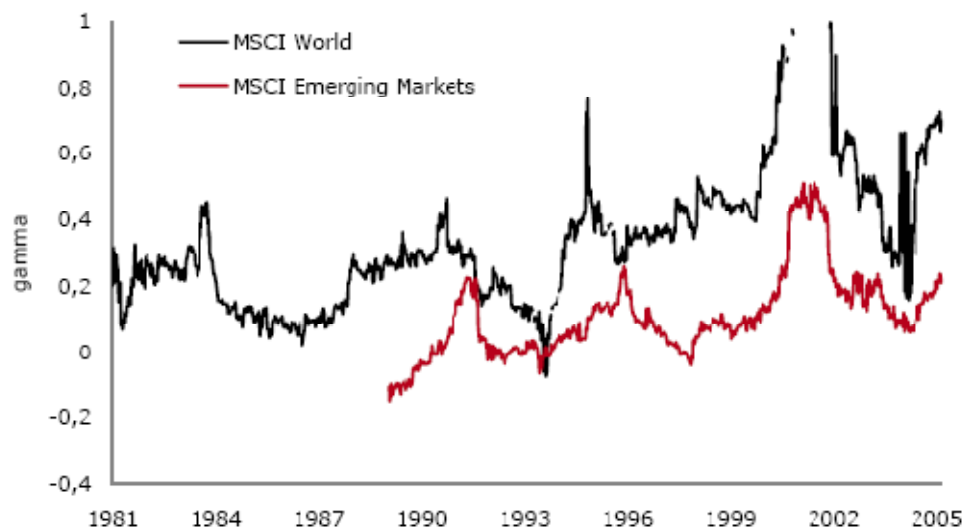
Figure 2. Time dynamics of volatility asymmetry (gamma) for MSCI World and MSCI Emerging Markets Index. Values over zero indicate asymmetry where volatility is higher when prices fall, values below zero mean that volatility is higher when market goes up.

2.3. Market wide causes for volatility asymmetry

In Talpsepp & Rieger (2009) a number of factors that should drive volatility asymmetry based on the findings and prepositions in the literature has been tested, in particular financial leverage (Black 1976). However not much support for the pure leverage effect has been found in our data, similarly no support for the time varying risk premium as an explanation was found (see further discussion in Talpsepp & Rieger (2009)).

As our findings show that the level of volatility asymmetry tends to be increasing in time and can differ significantly across countries, it is natural to wonder whether the economic development or structure can play a role in explaining the differences in asymmetry. We test a number of more or less direct measures of market development (including GDP/capita, different published market development and efficiency indexes, etc.) under different regression setups to check the hypothesis. All our test results indicate that the level of asymmetry is not related to a lack of market efficiency: quite the contrary, a higher level of economic development and market efficiency is associated with a higher level of volatility asymmetry!

This is certainly a surprising result that we want to understand in the remainder of this paper.

2.4. Volatility asymmetry, news and individual investors

Recent research has argued that media has the power to influence investor sentiment and thus prices on the stock market (see e.g. Tetlock (2007)). Hence, information obtained from media might potentially cause volatility asymmetry.

In fact volatility asymmetry is positively related to analyst coverage in the data (Talpsepp & Rieger 2009). This links back to the role of media in financial markets, since analyst opinions are generally transmitted by different media channels. What are then the characteristics of media coverage time series that could shed light on this relationship? In a forthcoming working paper Dzielinski, Steude & Subasi (n.d.) look at the daily media sentiment for the constituents of the Dow Jones 30 index in the period from January 2007 to September 2009. The quantities under consideration are the share of positive respectively negative news in the total for the given day. Sentiment scores are taken from Newssift, an online tool powered by the Financial Times. Interestingly, there is often a significant positive correlation between the share of negative news and the number of news overall, and conversely higher share of positive news is associated with a lower number of news overall. Furthermore, this effect appears to be more pronounced for stocks,

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which have more news on average. Therefore, stocks that are more covered on average (without differentiating between analysts and other media) are also more susceptible to the "negative news bias". The ideal argument would thus go as follows: more news means predominantly more bad news, which makes investor reactions more pronounced, when there is downward pressure on prices.

International data allows to measure media penetration and it turns out that it is strongly correlated with volatility asymmetry. However, media penetration is also closely correlated with the level of market development and might not always tell the best story about stock market media coverage. Thus when including both GDP/capita and media penetration in the same regression, the impact of media seems to disappear. This can be of course somewhat deceiving as a clear link between the development of the country and the level of asymmetry is much harder to explain than the link between impact of media and asymmetry. However, the impact of media on volatility would be much easier to capture within a market if we had reliable data on news flow.

Table 1. Log-log regressions on volatility asymmetry (adjusted gamma)

	Coef.	Robust Std. Err.	t-stat		Coef.	Robust Std. Err.	t-stat	
Analyst coverage	0.449	0.107	4.21	**	0.588	0.115	5.1	**
Media penetration	-1.947	1.157	-1.68		0.710	0.277	2.57	*
GDP/capita	0.686	0.284	2.42	*				
Stock market capitalization/GDP	0.228	0.104	2.19	*				
Const.	-0.515	2.534	-0.2		-6.125	1.071	-5.72	**
N	40				40			
R-squared	0.71				0.62			
F stat.	27.2				32.41			

International data still allows us to further test the hypothesis of news having a significant impact on volatility asymmetry: analysts are an important source of information for investors and could potentially influence their sentiment. We would expect analysts to discover the shortcomings of companies and media to communicate their discoveries. In case of good news, analysts might not get the same media attention as in the case of disappointing news. Thus we might expect to see the co-influence of media and analysts to volatility asymmetry. As there are usually more analysts in developed markets, the conclusion also fits the finding of higher volatility asymmetry in developed markets.

As already mentioned, our data shows a significant positive correlation between asymmetric volatility and analyst coverage. The effect is still present when controlling for other factors e.g. the level of GDP/capita and media. We conclude that better coverage of listed companies helps to draw more attention to possible shortcomings in a firm's operations in case of bad news and helps to react more quickly to the news. The finding is also supported by previous work of Hong, Lim & Stein (2000) who argue that stocks with a low coverage tend to react less precisely to bad news compared to high coverage stocks.

Our results indicate that analysts and media could cause volatility asymmetry but this can only happen if they can persuade at least some investors to trade more erratically during down moves. The question is, who these investors might be? Hens & Steude (2009) suggest that volatility asymmetry can be caused by investors' preferences. Shefrin (2005) proposes biased expectations as a possible explanation. Since individual investors are more prone to be biased than institutional investors, we would expect large volatility asymmetry in markets where the share of individual investors is higher. This might be the situation for more developed markets.

We use two parameters to capture the share of individual investors in the market: ownership concentration and market capitalization/GDP. We find a significant negative impact of ownership concentration on volatility asymmetry. The finding indicates that countries where ownership concentration of listed

companies is low (implying that there are more individual investors who are likely to be less experienced and/or informed), have a higher level of asymmetry. We also use market capitalization divided by GDP as a proxy for share of private investors in the market. Here, we find a positive correlation: the more individual investors in the market the higher volatility asymmetry.

Based on these results we hypothesize that in case of bad news a higher absolute number of investors will be selling and pushing prices down more quickly, thus increasing volatility during periods when prices fall. This could be the explanation for a different behavior of investors after prices fall or rise, which would be consistent with the ideas of Hens & Steude (2009) and Shefrin (2005). It would also be consistent with the assumption that more analysts and media attention in case of bad news can cause asymmetry.

3. Who makes markets volatile?

3.1. Google and volatility

So far we have seen that the degree of volatility asymmetry is linked to two characteristics of the financial market in question: the share of private investors and the number of stock analysts. The aim of the following section is to illustrate in a more detailed way how private investors can impact the stock market and discuss a convenient metric of their behavior. This exercise might be helpful to portfolio managers, who are often concerned about the "little man's" actions, which are argued to be more susceptible to swings of mood, especially in periods of market stress.

There are reasons to believe, frequently based on insights from behavioral finance, that private investor demand is more attention-driven than a systematic investment approach should be. Private investors tend to follow simple heuristics, like picking stocks they have positive associations with or the ones recommended by friends or neighbors. This does not necessarily imply (as some would be happy to believe) that they will inevitably be driven out of the market. In a rather provocative experiment Gigerenzer (2007) showed that asking random people on

the street for stocks they know and subsequently investing into them can be a very successful strategy. But even if the simple investment strategies fail in the long run, the next generation of inexperienced investors will readily replace their frustrated predecessors. The reliance on simple heuristics of many investors implies, however, that looking at the typical array of a stock analyst's indicators, be it fundamental or technical, is not likely to say much about the direction private investors are headed in, simply because it is not what they themselves look at.

A sizeable number of studies have attempted to address this issue. Barber & Odean (2008) name extreme returns, trading volume and news and headlines as suitable indicators, which have been developed to a varying extent in the literature. Especially news and headlines proved to be very fertile grounds for research, originating in numerous event studies (Liu, Smith & Syed (1990), Barber & Loeffler (1993), Ferreira & Smith (1999), Arena & Howe (2008)), through time series and cross-sectional regressions (Mitchell & Mulherin (1994), Fang & Peress (2009)) and developing into the kind of linguistics-based analysis presented in this volume (Tetlock (2007)). Other authors examined factors derived more from a corporate finance point of view, such as the size of the advertising budget (Grulon, Kanatas & Weston (2004), Dong (2008), Chemmanur & Yan (2009)).

None of the above however is a direct measure of attention; they are all proxies, which run into the fundamental problem of distinguishing between active and passive effects or in marketing parlance, between push and pull.

To understand the difference, consider the following simple case of trying to predict the number of guests at a party. One might take the number of invitations sent as a (passive) estimate, but few would argue that the number of positive confirmations (which involve an active response from the addressee) would do a much better job.

Certainly, proxies are ubiquitous in economics and finance, where many phenomena are not directly observable at all, and they rest on the assumption (motivated by theory or empirical findings) that the active and passive effects are robustly correlated. In situations largely depending on human psychology like

attention or sentiment such correlations might however prove illusory or unstable over time. Therefore, in such circumstances direct measures are of particular value.

We argue that such a direct measure exists in the case of private investor attention, based on internet usage. It is presently rather uncontroversial to assume that most people rely on the internet for information, also concerning investment, and they get to that information by using search engines. Tracking the flow of search queries thus arguably brings one as close as it gets to what is on people's minds. This is exactly the kind of information that Google offers through a service called Google Trends, where weekly time series (starting January 2004) of the popularity of any given search term are available for inspection and download. Looking at search terms relevant from the investment viewpoint has the potential to correctly identify topics capturing private investors' attention and thus give clues as to their future actions. The fact that Google presently accounts for around 70% of global searches certainly adds weight to this hypothesis. Da, Engelberg & Gao (2009) give essentially the same argument and show how Google Trends can be relevant on the individual stock level. Using Russell 3000 as the universe, they report a statistically significant relationship between the increase in the search frequency for a stock ticker symbol and the subsequent increase in private buy orders submitted for that stock. Furthermore, they show how this contributes to large first-day returns and long run underperformance of IPO stocks. Their study is an important step towards documenting the merits of Google Trends in capturing private investor demand and we build on these findings to illustrate the resulting market impact.

Instead of focusing on individual stocks we take a different approach based on themes (or keywords) related to the macroeconomy. We argue that increased interest in those themes reflects uncertainty of private investors concerning the macroeconomic outlook, which might induce increased trading on their part. Correspondingly, to measure the financial impact we look at the returns, volatility and implied volatility of the most popular US index, the S&P 500. We chose to concentrate on three themes: "recession", "oil price" and "inflation" for the period

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from January 2004 to September 2009. We decided to concentrate on searches originating in the US only, given the considerable home bias, characteristic for private investors worldwide. Google Trends values are calculated as an index and the user can choose between fixed and relative scaling. The first approach applies the average of search traffic in a fixed time period (generally January 2004) as a reference value, while otherwise the average for the whole specified time period is used. While this might seem like a technicality, it gains importance when applying Google Trends to backtesting. In this kind of setup one has to be especially careful to clean out any information one could not have had in the past, a problem also known as filtration. However, downloading one year of Google Trends data with relative scaling implies knowing the average for the whole year also throughout the year, which is logically inconsistent. We therefore use fixed scaling in this analysis.

Another controversy, which Da et al. (2009) have to deal with is whether the searches they analyze are indeed linked to investment intentions, as opposed to looking to buy the company's products for instance and they argue that searching for a company ticker rather than its name is strong enough an indication.

We claim that this is not an important issue for us because of the highlevel focus of our study. According to an ICI (Investment Company Institute) report, half of American households owned stocks in the year 2005, either directly or through mutual funds. Therefore, greater uncertainty about macro themes among the general public is likely to find its way through to the stock market. This argument is further reinforced by the fact that we concentrate only on big moves in search interest.

In methodological terms our analysis belongs to the event-study type, pioneered for the stock market by Brown & Warner (1985). Accordingly, we define an event as a net weekly change in the Google Trends score, which falls in the top 5% of largest changes up to date (consider again the filtration problem). To establish at least some history, we sacrifice the initial 50 observations, which correspond to around one year of data. We are therefore left with 250 observations,

or roughly 5 years, for the analysis. Running the above procedure for all three themes returns 18 events for "recession", 14 for "oil price" and 15 for "inflation". We then investigate what happens to cumulative returns, realized volatility and implied volatility (as measured by the VIX) of the S&P 500 in the time window of -20 to +60 days around each event. Figures 3-5 show the average development for each theme respectively. As can be seen, each event is on average preceded by a dip in the cumulative returns.

There are two factors to explain this effect. For one, private investors might be expected to react with a lag. For other, the results published by Google Trends, and consequently the rates of change we computed, relate to the week just ended, so the few days preceding each event might already be influenced by intra-week activity of private investors. Notwithstanding, there is an immediate further drop in the first days after the event, followed by a negative drift for almost the remainder of the time window. The impact on realized and implied volatility is basically the mirror image of the impact on returns, consistent with the volatility asymmetry evidence. However, the scale of this impact is considerably larger making it an even more interesting phenomenon.
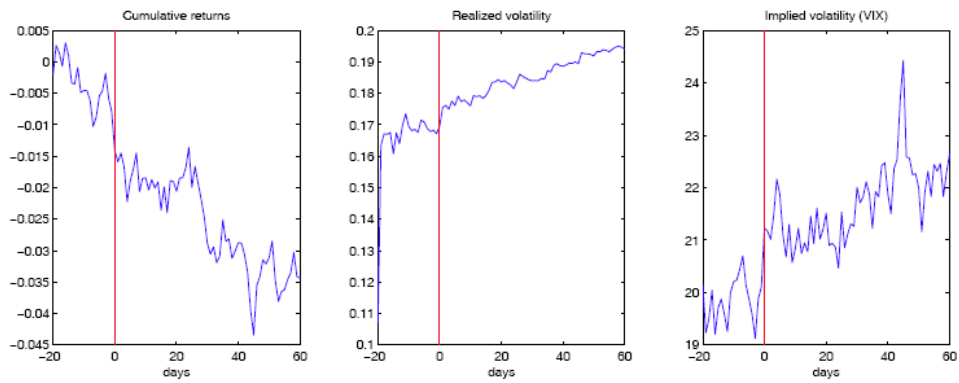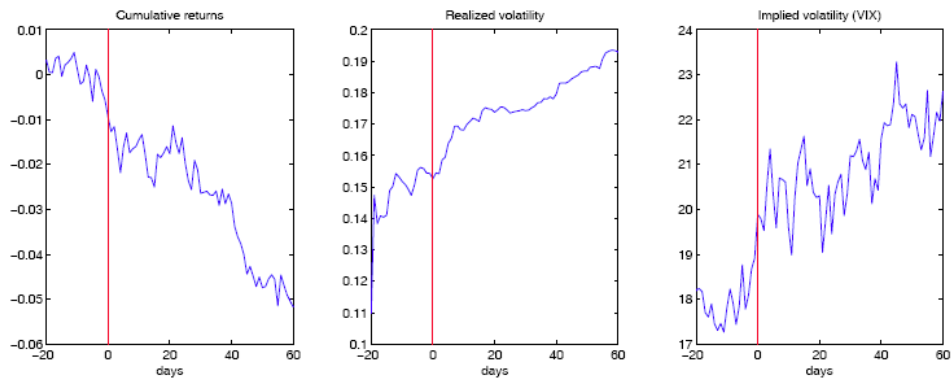
Figure 3. Theme "recession".
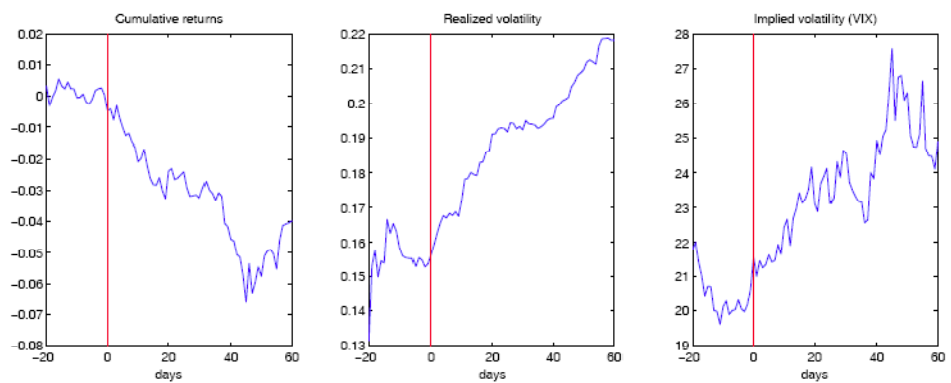

Figure 4. Theme "oil price".

Figure 5. Theme "inflation".

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3.2. Who is in the market when it becomes volatile?

When observing volatile markets, the question arises, who is in the market when it becomes volatile? According to the theory we have built so far, the increase in volatility should be caused by private investors and thus we would expect to see them on the market.

To check this we used a dataset of the Estonian stock market Nasdaq OMXT. We study this dataset, since it has a unique feature: it includes all transactions on the market and moreover allows us to identify all distinct investors in the market at different times and distinguish between individual and institutional investors, as well as locals and foreigners. We would expect to see more individuals trading on the market when the market becomes more volatile.

The first task is to measure volatility asymmetry in the OMXT index for the period we have the transaction data for (i.e. 2004-2008). Surprisingly we do not observe any asymmetry for the period by using similar APARCH models as we used for our international comparison. Our previous data shows that such cases exist especially in emerging markets. Estonia is a small emerging market with a relatively short history of stock exchange, so this observation does not contradict the findings of our international study. Particularly, there is very low or sometimes practically non-existent analyst coverage of the listed companies; and the market is quite young (remember the increasing trend of the asymmetry). In any case we can still see who is in the market when it becomes volatile.

For the lack of a volatility index, we estimate the volatility from an APARCH model. We count the number of individual and institutional investors as well as new investors who enter the market. We calculate the share of individual investors, the share of trades done by individual investors, and the share of turnover generated by individual investors compared to the market total.

As can be seen from the chart, individual investor participation remains quite stable during the whole period although fluctuations are quite noisy around the mean. We clearly observe, however, that the number of investors correlates strongly with volatility. This means that when markets become very volatile, the

number of investors who participate increases. Although increased volatility can have a self feeding effect that forces more investors to enter the market, we can assume that new important information represents one of the most significant causes of such behavior.
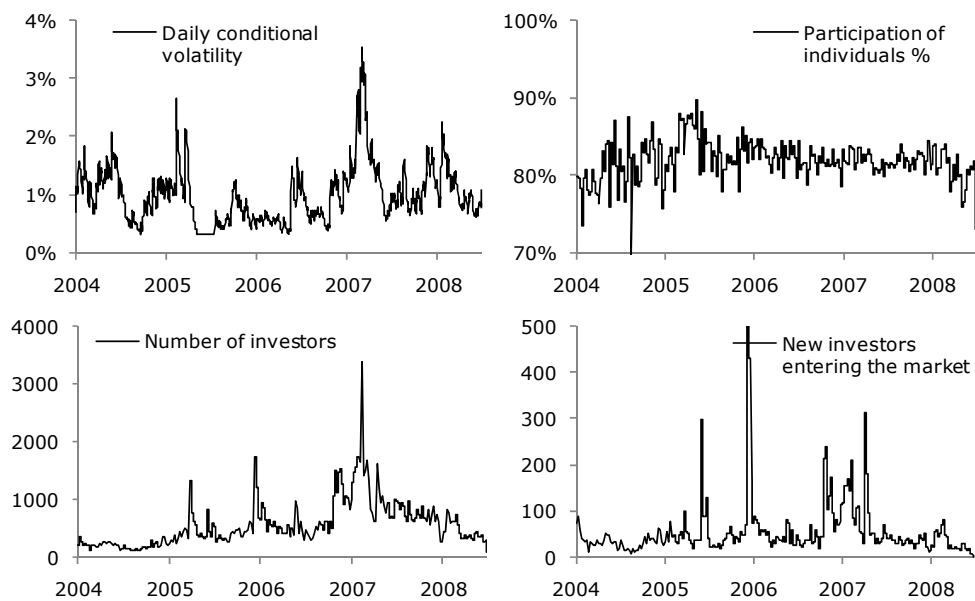

Figure 6. Correlation between volatility and investor market participation for Estonian stock market.

Situations of higher volatility force market participants at market sidelines to enter the market. The more developed a market, the more investors might be at the sidelines at any given time. We would also expect to see a higher proportion of the number of individual investors in more developed markets. As bad news tend to receive more media attention, this is amplified especially in down market conditions when investors start rushing into liquidating their positions.

4. Conclusions

Why is volatility higher in down markets? We proposed in this article a model that explains this asymmetry starting from the observation that news tend to be asymmetric as well (compare Fig. 7): media report predominantly bad news, as our analysis showed. The effect should be stronger, where analyst coverage and media reports are more frequent, and this can be observed in international data on volatility asymmetry.

A large number of bad news than leads to overreaction of (predominantly) private investors increasing the volatility, thus a larger proportion of private and on average less sophisticated investors on the market increases the volatility asymmetry as well. Also this effect can be found in international data on volatility asymmetry, where mostly countries with large numbers of private investors score high. Countries that have large numbers of private investors and sophisticated financial markets with good analyst coverage and news flow have therefore the highest levels of volatility asymmetry, e.g. the USA, UK and Japan.

Given that, it is not a surprise that globally volatility asymmetry increases over time, as more and more private investors enter markets and the news flow increases.

The model is supported by two further pieces of evidence: firstly, the number of Google searches for certain keywords related to the macroeconomy like "recession" is a predictor for high volatility. This demonstrates directly that private investors (who are most likely the majority among the Google users) influence volatility, and also shows the proposed causality. Second, investigating a full sample of stock market trades of a country (Estonia) we could see that times with high volatility coincide with times where many investors trade on the market. The new investors that enter in these times are usually the less professional investors. Our model suggests that their trading increases the volatility.
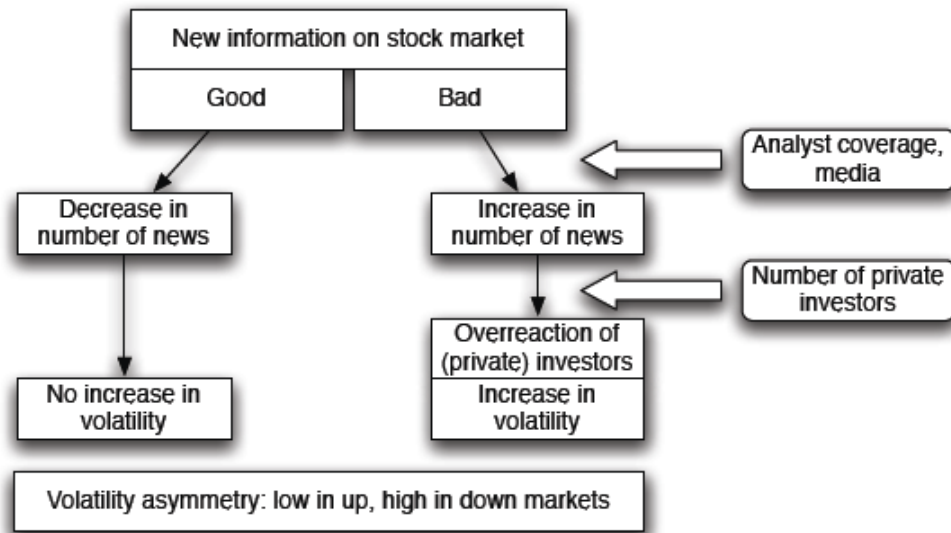
Figure 7. Functional sketch explaining how news reaction of private investors can lead to asymmetric volatility.

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19. Talpsepp, T. & Rieger, M. O. (2009), Explaining asymmetric volatility around the world, Working paper.

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Appendix 4

ELULOOKIRJELDUS

1. Isikuandmed
   Ees- ja perekonnanimi: Tõnn Talpsepp
   Sünniaeg ja -koht: 24.06.1982, Tallinn
   Kodakondsus: Eesti

2. Kontaktandmed
   Aadress: Trummi 23-2, 12617 Tallinn
   Telefon: 53429200
   E-posti aadress: tonn.talpsepp@ttu.ee

3. Hariduskäik

Õppeasutus (nimetus lõpetamise ajal)	Lõpetamise aeg	Haridus (eriala/kraad)
Tallinna Tehnikaülikool	2005 - …	Finantsökonoomika doktoriõpingud
Zürichi Ülikool	2007 - 2008	Šveitsi panganduse instituut, Rahandus, doktoriõpingud
Tallinna Tehnikaülikool	2004	Rahvamajandus, majandusteaduste magistrikraad (MA)
Tallinna Tehnikaülikool	2004	Rahvamajandus, bakalaureusekraad (BA)

4. Keelteoskus (alg-, kesk- või kõrgtase)

Keel	Tase
Eesti keel	emakeel
Inglise keel	kõrgtase
Vene keel	algtase
Saksa keel	algtase
Soome keel	algtase

5. Täiendusõpe

Õppimise aeg	Täiendusõppe läbiviija nimetus
2007-2009	CFA Institute, USA Chartered Financial Analyst

09.2007-01.2008	University of Zurich, Šveits Doktoriõpingud Swiss Banking Institute juures külalisdoktorandina, Swiss-Baltic Foundation stipendiumil
08.2007	Helsinki School of Economics, Soome Doktorikursus käitumuslikus rahanduses
2006-2007	Tartu Ülikool Doktoriõpingud külalisdoktorandina

6. Teenistuskäik

Töötamise aeg	Tööandja nimetus	Ametikoht
09.2005-…	Tallinna Tehnikaülikool	Lektor, Rahanduse ja panganduse õppetool, Majandusteaduskond
09.2007-06.2008	Tallinna Tehnikaülikool	Erakorraline teadur, Majandusteaduskond, Majandusuuringute teaduskeskus
01.2004-02.2006	AS Hansapank	Analüütik, Eesti krediidiriski osakond, Riskijuhtimine

7. Teadustegevus

Talpsepp, T. 2010. Reverse Disposition Effect of Foreign Investors. Journal of Behavioral Finance, ilmumas.

Talpsepp, T. 2010. Does Gender and Age affect Investor Performance and the Disposition Effect? Research in Economics and Business: Central and Eastern Europe, Vol 2, No. 1, ilmumas.

Dzielinski, M., Rieger, M.O., Talpsepp, T. 2010. Volatility asymmetry, news and private investors. News Analytics in Finance Handbook, John Wiley & Sons, ilmumas.

Talpsepp, T., Rieger, M.O. 2010. Explaining Asymmetric Volatility around the World. Esitatud koos parandustega: Journal of Empirical Finance, otsus ootel.

Talpsepp, T. 2009. Are Foreign Investors Less Biased than Domestic Investors. Economies of Central and Eastern Europe: Convergence, Opportunities and Challanges, Conference Proceedings, Tallinn, Estonia, 2009.

Karilaid, I., Talpsepp, T. 2010. Liquidity problems and policy implications during the recent financial crisis in the Baltic-Scandinavian region: ex ante empirical

study. Discussions on Estonian Economics Policy (Articles), 18, Berliner Wissenschafts-Verlag, Mattimar, ilmumas.

Talpsepp, T., Vlcek, M., Wang, M. 2010. A Closer Look at the Disposition Effect: Speculating in Gains, Waiting in Losses. Working Paper, University of Zurich.

Talpsepp, T. 2004. Credit risk assessment of local governments, Master thesis, Tallinn: Tallinn University of Technology, 99 lk.

Talpsepp, T. 2004. Factors influencing income base of Estonian local governments, Bachelor thesis, Tallinn: Tallinn University of Technology, 89 lk.

Konverentsiettekanded

Talpsepp, T., Rieger, M.O. 2010. Explaining Asymmetric Volatility around the World, INFINITI conference on international finance, Dublin, Ireland, 14-15 juuni 2010, konverentsiettekanne.

Talpsepp, T. 2010. Reverse Disposition Effect of Foreign Investors, 1st World Finance Conference 2010, Viana do Castelo, Portugal, 26-28 mai 2010, konverentsiettekanne.

Talpsepp, T., Rieger, M.O. 2009. Explaining Asymmetric Volatility around the World, CARISMA Annual Conference 2010, London, UK, 1-3 veebruar 2010, konverentsiettekanne.

Talpsepp, T. 2009. Reverse Disposition Effect of Foreign Investors, 44th Meeting of EURO Working Group on Financial Modelling, San Jose, Costa Rica, 6-9 detsember 2009, konverentsiettekanne.

Talpsepp, T., Rieger, M.O. 2009. Explaining Asymmetric Volatility around the World, 16th Annual Meeting of German Finance Association (DGF), Frankfurt, Germany, 8-10 oktoober 2009, konverentsiettekanne.

Talpsepp, T., Rieger, M.O. 2009. Explaining Asymmetric Volatility Around the World, German Economic Association Annual Congress 2009, Magdeburg, Germany, 8-11 september 2009, konverentsiettekanne.

Talpsepp, T. 2009. Are Foreign Investors Less Biased than Domestic Investors. Economies of Central and Eastern Europe: Convergence, Opportunities and Challanges, Tallinn, Estonia, 14-16 juuni 2009, konverentsiettekanne.
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8. Kaitstud lõputööd

Ksenia Tšahhirov, magistrikraad (teaduskraad), 2008, (juh) Tõnn Talpsepp, Riskijuhtimine suuruselt keskmises Eesti ettevõttes, Tallinna Tehnikaülikool, Rahanduse ja panganduse õppetool.

Marja Zaglada, magistrikraad (teaduskraad), 2006, (juh) Tõnn Talpsepp, Krediidiriski hindamine: Eesti kohalike omavalitsuste näitel, Tallinna Tehnikaülikool, Rahanduse ja panganduse õppetool.

Ivar Malm, magistrikraad, 2008, (juh) Tõnn Talpsepp, The concept of Efficient market hypotesis and market efficiency testingi in the case of Tallinn Stock Exhange, Tallinna Tehnikaülikool, Rahanduse ja panganduse õppetool.

Anna Krasnova, magistrikraad, 2006, (juh) Tõnn Talpsepp, Väärtpaberiportfelli koostamine kolmeastmelise investeerimisprotsessi kasutamisel, Tallinna Tehnikaülikool, Rahanduse ja panganduse õppetool.

Anu Kraam, magistrikraad, 2006, (juh) Tõnn Talpsepp, Pankade eluasemelaenuportfellide areng ning tootetingimustega vastuolus olevate eluasemelaenude analüüs SEB EÜP's, Tallinna Tehnikaülikool, Rahanduse ja panganduse õppetool.

9. Teadustöö põhisuunad

Ühiskonnateadused ja kultuur, Majandusteadus (Käitumuslik rahandus, turgude efektiivsus, volatiilsus)

10. Teised uurimisprojektid

Topograafilised lained, pinnahoovuste muutlikkus ning vee ja ainevahetus Soome lahes, ETF5869, 01.01.04 - 31.12.07

Appendix 5

CURRICULUM VITAE

1. Personal data
   Name: Tõnn Talpsepp
   Date and place of birth : 24.06.1982, Tallinn

2. Contact information
   Address: Trummi 23-2, 12617 Tallinn
   Phone: 53429200
   E-mail: tonn.talpsepp@ttu.ee

3. Education

Educational institution	Graduation year	Education (field of study/degree)
Tallinn University of Technology	2005 - …	Financial economics, PhD studies
University of Zurich	2007-2008	Swiss Banking Institute, Finance, PhD studies
Tallinn University of Technology	2004 - 2004	MA in Economics
Tallinn University of Technology	2000 - 2004	BA in Economics

4. Language competence/skills (fluent; average, basic skills)

Language	Level
Estonian	mother tongue
English	fluent
German	basic skills
Russian	basic skills
Finnish	basic skills

5. Special Courses

Period	Educational or other organisation
2007-2009	CFA Institute, USA Chartered Financial Analyst
09.2007-01.2008	University of Zurich, Switzerland Doctoral studies at the Swiss Banking Institute

	as a visiting student, Swiss-Baltic Net shcolarship
08.2007	Helsinki School of Economics, Finaland Doctoral course in behavioral finance
2006-2007	University of Taru Doctoral studies as a visiting student

6.   Professional Employment

Period	Organisation	Position
09.2005-…	Tallinn University of Technology	Lecturer, Department of Economics, Chair of Finance and Banking
09.2007-06.2008	Tallinn University of Technology	Extraordinary Researcher, School of Economics and Business Administration, Centre for Economic Research
01.2004-02.2006	AS Hansapank	Analyst, Estonian Credit Risk Department, Risk Management

7.   Scientific work

Talpsepp, T. 2010. Reverse Disposition Effect of Foreign Investors. Journal of Behavioral Finance, forthcoming.

Talpsepp, T. 2010. Does Gender and Age affect Investor Performance and the Disposition Effect? Research in Economics and Business: Central and Eastern Europe, Vol 2, No. 1, forthcoming.

Dzielinski, M., Rieger, M.O., Talpsepp, T. 2010. Volatility asymmetry, news and private investors. News Analytics in Finance Handbook, John Wiley & Sons, forthocoming.

Talpsepp, T., Rieger, M.O. 2010. Explaining Asymmetric Volatility around the World. Submitted with revisions to: Journal of Empirical Finance, decision pending.

Talpsepp, T. 2009. Are Foreign Investors Less Biased than Domestic Investors. Economies of Central and Eastern Europe: Convergence, Opportunities and Challanges, Conference Proceedings, Tallinn, Estonia, 2009.

Karilaid, I., Talpsepp, T. 2010. Liquidity problems and policy implications during the recent financial crisis in the Baltic-Scandinavian region: ex ante empirical

study. Discussions on Estonian Economics Policy (Articles), 18, Berliner Wissenschafts-Verlag, Mattimar, forthcoming.

Talpsepp, T., Vlcek, M., Wang, M. 2010. A Closer Look at the Disposition Effect: Speculating in Gains, Waiting in Losses. Working paper, University of Zurich.

Talpsepp, T. 2004. Credit risk assessment of local governments, Master thesis, Tallinn: Tallinn University of Technology,99 pages.

Talpsepp, T. 2004. Factors influencing income base of Estonian local governments, Bachelor thesis, Tallinn: Tallinn University of Technology, 89 pages.

Conference presentations

Talpsepp, T., Rieger, M.O. 2010. Explaining Asymmetric Volatility around the World, INFINITI conference on international finance, Dublin, Ireland, 14-15 June 2010, Conference presentation.

Talpsepp, T. 2010. Reverse Disposition Effect of Foreign Investors, 1st World Finance Conference 2010, Viana do Castelo, Portugal, 26-28 May 2010, Conference presentation.

Talpsepp, T., Rieger, M.O. 2009. Explaining Asymmetric Volatility around the World, CARISMA Annual Conference 2010, London, UK, 1-3 February 2010, Conference presentation.

Talpsepp, T. 2009. Reverse Disposition Effect of Foreign Investors, 44th Meeting of EURO Working Group on Financial Modelling, San Jose, Costa Rica, 6-9 December 2009, Conference presentation.

Talpsepp, T., Rieger, M.O. 2009. Explaining Asymmetric Volatility around the World, 16th Annual Meeting of German Finance Association (DGF), Frankfurt, Germany, 8-10 October 2009, Conference presentation.

Talpsepp, T., Rieger, M.O. 2009. Explaining Asymmetric Volatility Around the World, German Economic Association Annual Congress 2009, Magdeburg, Germany, 8-11 September 2009, Conference presentation.

Talpsepp, T. 2009. Are Foreign Investors Less Biased than Domestic Investors. Economies of Central and Eastern Europe: Convergence, Opportunities and Challanges, Tallinn, Estonia, 14-16 June 2009, Conference presentation.

8. Defended theses

Ksenia Tšahhirov, Master's Degree, 2008, (sup) Tõnn Talpsepp, Risk management in a middle size Estonian enterprise, Tallinn University of Technology, Chair of Finance and Banking.

Marja Zaglada, Master's Degree, 2006, (sup) Tõnn Talpsepp, Credit Risk Assessment: Measuring Credit Risk of Estonian Local Governments, Tallinn University of Technology, Chair of Finance and Banking.

Ivar Malm, Master's Degree, 2008, (sup) Tõnn Talpsepp, The concept of Efficient market hypotesis and market efficiency testingi in the case of Tallinn Stock Exhange, Tallinn University of Technology, Chair of Finance and Banking.

Anna Krasnova, Master's Degree, 2006, (sup) Tõnn Talpsepp, Using three level investment process in securities portfolio formation, Tallinn University of Technology , Chair of Finance and Banking.

Anu Kraam, Master's Degree, 2006, (sup) Tõnn Talpsepp, Dynamics of the Banks' housing loan portfolios and analysis of housing loans in conflict with product terms and conditions in SEB Eesti Ühispank, Tallinn University of Technology , Chair of Finance and Banking.

9.   Main areas of scientific work/Current research topics

Culture and Society, Economics (Behavioral finance, market efficiency, volatility)

10.   Other research projects

Topographic waves, the variability of the surface currents and the water and matter exchange in the Gulf of Finland, ETF5869, 01.01.04 - 31.12.07

Abstract

Investor Behavior and Volatility Asymmetry

The current thesis takes the approach of behavioral finance and focuses on the investor stock market behavior presenting the results and background of Talpsepp (2010a and 2010b), Dzielinski, Rieger and Talpsepp (2010) and Talpsepp and Rieger (2010). The focus is on the disposition effect and volatility asymmetry. The disposition effect is the behavioral characteristic of investors to realize their winning positions early and keep holding losing positions too long. Volatility asymmetry means that volatility during falling market conditions tends to be higher compared to volatility during rising market prices. The two different empirical observations share a common factor of being influenced by behavioral characteristics and biases of especially individual investors.

Although most of the investors are disposition effect biased, foreign investors seem to exhibit the reverse disposition effect. The differences are not too big between individual and institutional and between female and male investors in respect to the disposition effect. Younger investors trade more and are more affected by the disposition effect although experience seems to decrease the bias. We can distinguish between the sophistication level of investors and the trading style resulting in distinguishable performance results. Empirical results combined with theoretical modeling indicate that despite recent criticism, prospect theory based models could explain the disposition effect for a larger proportion of investors when incorporating differences of investor groups (e.g. reduced loss and risk aversion of local investors caused by familiarity bias).

International stock markets are studied in the volatility asymmetry part of the thesis. The results show that in addition to the level of economic development, possible slight influence of short selling and leverage, also individual investor market participation combined with the presence of analysts and media coverage can have a positive impact on volatility asymmetry. More news is generally associated with a larger share of negative news which starts to affect the investor

sentiment and bad news gets more amplified attention, which can cause volatility asymmetry. In case of good news and sentiment, the amplification effect is reduced by the shrinkage of the news flow.

In conclusion, the existence of the disposition effect and volatility asymmetry can be caused by behavioral factors, which remain in the empirical models even after testing for different other factors. Decision framing causes investors to react differently on positive and negative news. It can also cause seeing losses and profits differently, depending on whether being in a gain or loss.

Kokkuvõte

Investorite käitumine ning volatiilsuse asümmeetria

Käesolev töö lähtub käitumusliku rahanduse vaatenurgast ning keskendub investorite käitumuslikele aspektidele. Töös võetakse kokku tulemused ning avatakse detailsemalt teoreetilist tausta ja kasutatud metodoloogiaid artiklitest: Talpsepp (2010a ja 2010b), Dzielinski, Rieger ja Talpsepp (2010) ning Talpsepp ja Rieger (2010).

Käesolev töö keskendub kahele küllaltki eraldiseisvale teemale, mida ühendavad käitumuslikud aspektid, mis mängivad rolli mõlema vaadeldud teema juures. Töös keskendutakse dispositsiooniefektile ning volatiilsuse asümmeetriale. Dispositsiooniefekt kujutab endast käitumuslikku nähtust, kus investorid realiseerivad kasumis investeerimispositsioone liiga kiiresti, kuid hoiavad kahjumis positsioone liiga kaua. Volatiilsuse asümmeetria kujutab endast finantsturgudel valitsevat asümmeetriat, mille kohaselt turgude langedes on hindade volatiilsus suurem, võrreldes olukorraga, mil turud tõusevad. Kuigi tegemist pole otseselt haakuvate efektidega, võib mõlema eksisteerimist vähemalt osaliselt seletada käitumusliku rahanduse valdkonda kuuluvate teguritega, mille hulka kuuluvad peamiselt erainvestorite käitumuslikud erisused ning kõrvalekaldumine ratsionaalsetest otsustest.

Antud töö on suures osas empiiriline, kuid kasutab dispositsiooniefekti käsitlevas osas leitud käitumismalli seletamiseks ja simuleerimiseks ka varem avaldatud teoreetilisi mudeleid. Dispositsiooniefekti empiirilised tulemused baseeruvad Tallinna Börsi detailsel tehinguinfol, mis võimaldab eristada erinevaid investorite gruppe. Tulemused näitavad, et enamik investoreid on mõjutatud dispositsiooniefektist ehk kipub realiseerima kasumeid selgelt kiiremini kui kahjumeid. Antud tulemused vastavad mujal maailmas läbiviidud sarnaste uuringute tulemustele. Varasemates töödes pole aga identifitseeritud vastupidist käitumist dispositsiooniefektile, mis on nähtav välisinvestorite tegutsemises. Antud leid on ka üheks uueks aspektiks, milles seisneb antud töö panus antud valdkonna

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kirjandusse. Ülejäänud empiirilised tulemused näitavad, et dispositsiooniefekti osas ei eksisteeri väga olulisi erinevusi era- ja institutsionaalsete investorite vahel ning ka erisused nais- ja meesinvestorite vahel on küllaltki väikesed. Detailsem uurimine näitab siiski, et grupeerides investoreid ka vanuse järgi ning vaadeldes investeerimiskogemuse mõju investorite käitumisele, tulevad erisused erinevate gruppide vahel lisaks kohalike ja välisinvestorite erisustele välja ka vanuse ja sooliste gruppide vahel. Nooremad investorid ja ka meessoost investorid teevad rohkem tehinguid ning on ka dispositsiooniefekti poolest rohkem mõjutatud. Kokkuvõttes tähendab see, et nooremate ja meessoost investorite portfellide tootlused kipuvad vähem dispositsiooniefektist mõjutatud gruppidele alla jääma. Samas, mida rohkem on tehinguid tehtud, seda vähem ollakse dispositsiooniefektist mõjutatud ehk kogemus vähendab antud efekti.

Peamiselt on dispositsiooniefekti eksisteerimist seletatud Kahnemani ja Tversky (1979) perspektiiviteooria (*prospect theory*) käsitlusega. Samas on viimase aja teaduskirjandus näidanud, et perspektiiviteoorial baseeruv teoreetiline käsitlus ei seleta efekti suure hulga parameetrite puhul ning antud teoorial baseeruvat mudelit aluseks võttes on arvestataval hulgal juhtudel tõenäolisem jõuda dispositsiooniefektile vastupidisele efektile. Antud töö tulemused näitavad, et viimase aja kriitikast hoolimata võivad ka perspektiiviteoorial baseeruvad mudelid antud efekti paremini kirjeldada, kui mudelisse lülitada investorite erisusi. Antud töö tulemused kirjeldavad dispositsiooniefektile vastandlikku käitumist (ehk investor realiseerib kaotavad positsioonid kiiremini kui võitvad positsioonid) välisinvestorite puhul erisustega riski ja kaotuse ebemeeldivust kirjeldavates parameetrites. Kohalikel investoritel võivad antud parameetrilised näitajad olla perspektiiviteoorias tavapäraselt eeldatutest väiksemad tänu koduturu näilisele familiaarsusele.

Dispositsiooniefekti uurivas osas ilmnes ning ka varasemas kirjanduses on hulgaliselt näiteid ja põhjendusi era- ja institutsionaalsete investorite käitumise erisustest, kusjuures just erainvestorid on rohkem mõjutatud erinevatest käitumuslikest mallidest, mis kipuvad tähendama eristumist traditsioonilise

rahanduse ratsionaalsuse eeldusest. Antud nihked hinnangutes võivad olla ka üheks teguriks, mis kirjeldab volatiilsuse asümmeetria eksisteerimist enamikul finantsturgudel, mille uurimisele keskendub töö teine osa.

Volatiilsuse asümmeetriat käsitlev osa keskendub erinevate teoreetilises kirjanduses väljapakutud tegurite empiirilisele testimisele, sest senini puudub kirjanduses üksmeel, mis tegurid volatiilsuse asümmeetriat põhjustavad. Volatiilsuse asümmeetriat käsitleva osa uudsus peitub võimalikult laiapõhjalise valimi kasutamises (vaadeldakse 49 riigi andmeid). Lisaks ka varasemas kirjanduses kasutatud ristandmetele kasutatakse antud töös ka aegridu ja paneelandmeid, mida senine volatiilsuse asümmeetriat puudutav kirjandus käsitlenud pole. Volatiilsuse asümmeetria arvutamiseks kombineeritakse erinevaid meetodeid, mis koos kasutades võimaldavad kokkuvõttes leida asümmeetria aegridu, mida seni pole olnud võimalik kasutada.

Empiirilised tulemused näitavad, et volatiilsuse asümmeetria on mõjutatud riigi arengutasemest (mida kõrgemalt arenenud riik, seda kõrgem asümmeetria). Lisaks omavad väikest mõju ka aktsiate lühikeseks müügi võimalus ning finantsvõimenduse tase. Samas kontrollides ka muude erinevate potentsiaalsete faktorite mõju, jääb empiirilisse mudelisse ka erainvestorite osakaal turul, mis koos analüütikute ning meedia mõjuga näib seletavat vähemalt osaliselt volatiilsuse asümmeetriat. Empiirilised uuringud näitavad, et mida rohkem uudiseid finantsturgudele teatavaks tehakse, seda suurem on negatiivsete uudiste osakaal. Halvad uudised hakkavad negatiivselt mõjutama investorite meelsust ning lähtuvalt käitumusliku rahanduse põhimõtetest võivad hakata põhjustama otsuste raamistamist (*framing*) lähtuvalt meelestatusest. Seega saavad negatiivsed uudised võimendatud tähelepanu, mis eriti erainvestorite tehingute tõttu põhjustab volatiilsuse asümmeetriat. Sama võiks kehtida ka positiivsete uudiste puhul, kuid positiivse meelestatuse tingimustes kipub uudistevoog oluliselt väiksemaks jääma kui negatiivsetes tingimustes.

Kokkuvõttes võib järeldada, et nii dispositsiooniefekt kui ka volatiilsuse asümmeetria võivad vähemalt osaliselt olla põhjustatud investorite käitumuslikest

erisustest ning kõrvalekalletest traditsioonilise rahanduse mõistes ratsionaalsetest otsustest ka grupi tasandil. Antud käitumuslikud faktorid sisaldavad otsuste raamistamist, mis realiseerub erinevates reageeringutes positiivsetele ja negatiivsetele uudistele ning omades erinevat kasulikkuse funktsiooni olenevalt sellest, kas omatav aktsiapositsioon on parasjagu kasumis või kahjumis.

DISSERTATIONS DEFENDED AT
TALLINN UNIVERSITY OF TECHNOLOGY ON
ECONOMICS

1. **August Aarma**. Segmented analysis of bank customers and banking information: Estonian case. 2001.

2. **Enn Listra**. The development and structure of banking sector: retail banking in Estonia. 2001.

3. **Tatyana Põlajeva**. The comparative analysis of market's attractiveness. 2001.

4. **Tuuli Tammeraid**. Modeling flow of funds for Estonia. 2002.

5. **Ivo Karilaid**. The choice in general method for investment and performance evaluation. 2002.

6. **Hele Hammer**. Strategic investment decisions: evidence from survey and field research in Estonia. 2003.

7. **Viljar Jaamu**. The methods and instruments for solving the banking crisis and development of the banking sector in Estonia. 2003.

8. **Katri Kerem**. From adoption to relationships: Internet banking in Estonia. 2003.

9. **Ly Kirikal**. Productivity, the malmquist index and the empirical study of banks in Estonia. 2005.

10. **Jaanus Raim**. The PPP deviations between Estonia and non-transitional countries. 2006.

11. **Jochen Sebastian Heubischl**. European network governance – corporate network systematic in Germany, the United Kingdom and France: an empirical investigation. 2006.

12. **Enno Lend**. Transpordiühenduse ja logistikasüsteemi interaktsioon (Saaremaa ja Hiiumaa näitel). 2007.

13. **Ivar Soone**. Interrelations between retail service satisfaction and customer loyalty: A holistic perspective. 2007.

14. **Aaro Hazak**. Capital structure and dividend decisions under distributed profit taxation. 2008.

15. **Laivi Laidroo**. Public announcements' relevance, quality and determinants on Tallinn, Riga, and Vilnius stock exchanges. 2008.

16. **Martti Randveer**. Monetary policy transmission channels, flexibility of the economy and future prospects of the Estonian monetary system. 2009.