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SPECULATIVE TRADING AND RETURNS: EVIDENCE FROM ESTONIAN STOCK MARKET

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Abstract

This thesis attempts to create a full overview of speculative trading. We look at the extent of speculative trading on the market wide level, the characteristics of investors who engage in speculative trading and the effects of speculative trading. To distinguish speculative trades from non-speculative we use a definition proposed by Barber and Odean (2002). To examine the effect of speculative trading on the market, we use a modified Statman, Thorley and Vorkink (2006) model on return-volume relation. We find 58% of all trades in NASDAQ OMX Tallinn stock exchange between 2004 and 2010 can be classified as speculative. Institutions are found to be the most speculative; however the speculativeness of individual investors has increased significantly over our sample period. Men are more speculative than women and domestic investors are more speculative than foreign investors. Speculativeness increases with investor size, but diminishes with investor age. We also find that increased level of speculative purchases explain the return-volume relation. Speculative traders were found to react to past stock returns, but were not found to have an effect on future stock returns.

Keywords: Speculative trading, return-volume relation, stock returns, investor behavior, investor bias, Estonian stock market, NASDAQ OMX Tallinn, the Baltics

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Table of Contents

List of Tables

1. Introduction

For a man on the street, the word “speculative” brings about suspicion and negative emotions, especially, for people in the Baltics. In the world of finance, it is a topic that has been of interest to academics and professionals alike for many years and has gained a reputation as being a controversial one. Putting it in simple words – speculative traders are investors that buy and sell their stocks not due to liquidity needs but rather to “switch” between different stocks, hoping to increase their returns compared to just holding a constant portfolio. To distinguish between speculative traders and other investors we use a definition proposed by Barber and Odean (2002) which states that speculative trades are “all profitable sales of complete positions that are followed by a purchase within three weeks and all purchases made within three weeks of a speculative sale”.

According to the Efficient Markets Hypothesis (EMH) this “selling and buying” action should be pointless, meaning that it should not result in higher returns. According to the EMH, all available information is already incorporated into prices, and it is impossible to predict the future movements of stocks, suggesting that active portfolio management would not yield any excess returns. In a world with microstructure frictions this trading becomes even more futile, due to the existence of transaction costs, in the form of bid-ask spreads, broker fees and commissions.

Previous literature has looked at speculative trading from different angles, for instance, Barber and Odean (2000) examined speculative trades and their returns, arriving at a conclusion that excessive trading reduces, not boosts your wealth, therefore it is pointless. Other works have looked at the characteristics of speculative traders – Barber and Odean (2001) arrived at a conclusion that men are more speculative than women and Chui, Titman and Wei (2010) found evidence that investors in countries with higher individualism levels tend to engage more in speculative trading.

Although there are some works which touch upon speculative trading from different perspectives, up till now there is no academic paper creating “the full picture” of speculative trading on an individual stock exchange. In our work we plan to fill these gaps and examine speculative trading, starting from examining the extent of speculative trading on a market-wide level to understanding what type of investors engage in speculative trading and what effects these speculative traders leave on the market as a whole. In our work we use a unique dataset, which contains information on all transactions made in NASDAQ OMX Tallinn stock exchange between 2004 and 2010 including information about several characteristics, such as investor type, gender and age (in the case of individual investors), and whether the investor is foreign or domestic.

In order to measure the effects of speculative trading we develop a hypothesis that return-volume relation is caused by speculative traders acting as positive feedback traders. Return-volume relation is an increase in trading volume following a period of high returns that has been observed on stock exchanges around the world. The existing literature, for example Statman, Thorley and Vorkink (2006) and Griffin, Nardari and Stulz (2007), acknowledges the phenomenon, but it has not yet been linked with speculative trading. In order to test this, we use a modified methodology proposed by Barber and Odean (2002) to divide the trade volumes of an investor in speculative and non-speculative. Afterwards, we use a modified version of the model used by Statman et al. (2006), to investigate how speculative traders react to shocks in returns.

Based on our research focus, our main research question is stated as follows: *To what extent return-volume relationship is driven by speculative trading in Estonian stock market?* We establish two sub research questions: *What is the extent of speculative trading on Estonian stock market? What are the characteristics of speculative traders on Estonian stock market?*

Our research contributes to the existing academic literature in several aspects. First of all we create a thorough investigation on the speculative trading. By employing our unique dataset we will be able to specify speculative trader age, type, size and other characteristics. Therefore we will both re-check robustness of previous works and find new evidence about characteristics that have not yet been described in academic papers. Moreover, due to our approach we are able to assess how many trades out of all trades are based on speculative motives, thus estimating the level of speculative activity on a market wide level. This is an area that has not yet been fully explored. Furthermore, we assess the return-volume relation and develop a linkage between speculative traders and return-volume relation, which allows an empirical decomposition of this widely observed phenomenon on a market-wide level. Lastly, we contribute to the scarce existing knowledge of Estonian stock market.

Our work is constructed as follows: in Section II we present the existing knowledge about speculative trading, develop a link between speculative trading and return-volume relation; in Section III we state the hypotheses; in Section IV the main features of Estonian stock market are presented; in Section V we describe the data that will be used in our research; in Section VI the methodology used is described; Section VII presents the results which are later discussed in Section VIII; Section IX concludes.

2. Literature review

In this section we review the relevant previous research done in the field of speculative trading, investor biases and return-volume relationship. First, we discuss empirical evidence on the motives for trade and specify the definition of speculative trading used in several research papers. We also touch upon the linkage between the willingness to speculate and investor overconfidence. Lastly, the evidence for the return-volume relation is discussed, along with the possible causes mentioned by academic papers. Most of the causes are linked to individual investor biases and overconfidence, setting the link from speculative trading to return-volume relation.

2.1. Incentives for speculative trading

Before trying to understand what is speculative trading and when and why investors are willing to engage in speculative trading, we start by discussing the main incentives to trade in general. Several authors, such as Milgrom and Stokey (1982), Kyle (1985), Stoffmann (2011), Barber and Odean (2002), distinguishes between two reasons for trading, namely, due to the need for liquidity and the willingness to trade on private information about the stock market. Liquidity needs can be described as a general wish to invest savings in stock market or divest from the market, for example, to buy a house or a car. Trading on information (or perceived information) means that an investor sells a stock and buys another stock due to some private information, in other words "switch" stocks, due to the belief that the other stock will yield higher returns (Stoffmann, 2011).

The abovementioned motivation, namely, the trade on information, can be called speculative. In their paper Barber and Odean (2002) propose a definition that speculative trading is "all profitable sales of complete positions that are followed by a purchase within three weeks and all purchases made within three weeks of a speculative sale". The definition is used also in earlier work of Odean (1999) and in other academic research e.g. Dorn, Huberman and Sengmeuller (2008). Barber and Odean (2002) admit that the proposed definition cannot perfectly identify all speculative trades; however they assume that the trades that are identified by the definition are most likely speculative. Stoffmann (2011) also uses this definition of speculative trading; however he reduces the time span from three weeks to three days. The underlying idea is that by shortening the time period in which the proceeds of the sale are used to buy another stock, the trades which are based on information about the particular stock can be distinguished from trades made for liquidity or other reasons.

The question on why people engage in speculative trading remains unanswered. The same question was asked more than three decades ago by Milgrom and Stokey (1982). They state that the only motive to engage in speculative trading is a trader's belief that he can have a position in the market which yields the highest possible returns. Since public information is available to everybody, an investor should believe that he is capable of beating the market only if he has valuable private information and wants to benefit from it. In theory using private information is pointless, since at the moment a trader takes a position based on this private information it is not private anymore and becomes incorporated into prices. Based on this idea Milgrom and Stokey (1982) raise a question – "Why do traders bother to gather information if they cannot benefit from it?" Perhaps, it should be taken into account that questions like this are raised based on the assumption that investors are rational, which may not hold in real life. This could explain the presence of speculative trading.

Although in theory speculative trading should be pointless, there are many works in the field of behavioral finance explaining the underlying motives for investors to engage in speculative trading. For instance Barber and Odean (2002) state that the main reason for speculation is hope to enhance portfolio returns. Stoffmann (2011) suggests that the major underlying motivator of investors eager to speculate is private knowledge. Another reason why investors are willing to engage in speculative trading is presented by Mei, Scheinkman and Xiong (2009). They argue that in case arbitrage is limited by a constraint in short sales, (similar to Estonian stock market where short selling is prohibited) an incentive for speculative trading arises, since "an asset owner has the option to resell his shares to other more optimistic investors in the future for a profit".

2.2. Measures of speculative trading

Another challenge is to detect speculative trading. In several research papers academics have tried to distinguish between speculative and non-speculative trades. For instance, Dorn et al. (2008) used Barber and Odean (2002) definition of speculative trading employing a data set of randomly selected 37,000 brokerage clients in Germany including information on complete daily transactions. According to their study almost 60% of all purchases and sales in the market can be classified as speculative. However, it should be taken into account that their sample represents only a small fraction of 6.2 million investors in the market.

While Barber and Odean (2002) and Dorn et al. (2008) had actual data on all individual trades made by investors, this kind of data is rare and in many of the previous research papers speculative trading is distinguished using proxies. For instance, Mei et al. (2009), while investigating dual class shares in Chinese stock, decompose stock price into two parts - speculative and fundamental (stock price calculated using Gordon growth model). A recent paper by Gwilym, Hasan, Wand and Xie (2012) derived speculative demand using a novel proxy - Google statistics measuring investor interest in a particular stock.

2.3. Speculative trading and investor overconfidence

As mentioned before, the main reason for investors to engage in speculative trading is the belief that they can outperform the market and get higher returns, or access private information that is superior to the public information that has already been incorporated into prices. This is contrary to the Efficient Market Hypothesis, which states that in an efficient market all relevant information is incorporated into stock prices. This implies that it is not possible to “beat” the market and that the only trades that an investor should make are purchases of securities (a combination of the market portfolio and risk-free asset) when the investor wants to increase the size of the investment, and sales of these securities whenever the investor wants to decrease their investment, due to liquidity needs. This implies that most speculative traders suffer from investor overconfidence bias (belief that their knowledge of the market is superior to other market participants) by trying to employ private information. Furthermore, by trying to “outmatch” the market, speculators tend to trade too much, which, as illustrated by numerous papers (Barber and Odean, 2000; Barber and Odean, 2001) leads them to underperform the market, when adjusted for risk and transaction costs.

According to several research papers, e.g., Odean (1998; 1999), Glaser and Weber (2007) investor overconfidence leads investors to trade more, constantly shifting into stocks that the investor believes to outperform other stocks. In another work Barber and Odean (2001) examine the effect of overconfidence on trading volume, using gender as a proxy for different levels of overconfidence. They find that men, who have been found to be more overconfident than women, trade more. This characteristic is found to be more pronounced among single investors (as compared to married ones). They also find that this excessive trading causes men to underperform women (who both underperform the returns that would have been obtained by holding the initial portfolio). This negative effect on investor wealth is also recognized by Barber and Odean (2000), where they find that the households that trade the most also underperform the market the most. Their main conclusion is a bold statement: “trading is hazardous to your wealth”.

Lastly, evidence of overconfidence-driven excessive trading is also found by Chui et al. (2010). They use individualism as a proxy for overconfidence, which differs between countries due to cultural reasons. When using over 20 years of data from 55 countries, they find that the country specific level of individualism (measured by individualism index) has a strong positive relation with cross-country trading volume and stock volatility. They also note that as a result of this, European countries that were included in the sample showed the highest individualism index and had a more pronounced momentum effect, leading to higher profitability of momentum trading strategies. This establishes a link between overconfidence-driven trading and its effects on stock returns.

2.4. Return-volume relation

The return-volume relation is a phenomenon observed in stock markets where periods of significant positive returns are followed by increase in trading volume. Odean (1999), while examining excessive trading, spot a tendency for individual investors to be interested in buying "winners" or stocks with high historical returns over a longer time span comparing to the stock they sell. Opposite evidence is found by Kaniel, Saar and Titman (2008); they examine the relation between individual investor trading and returns on the NYSE and find that individual investors tend to buy stocks which have underperformed the market and sell stocks which have outperformed the market. Their found evidence is contrary to previous literature that finds individual investors to be prone to "buying winners".

This willingness of individual investors to increase their trading after significant returns (positive and negative) suggests a link between period returns and trading volume in the next period. This relation has been discussed by numerous research papers, whose findings are discussed below. Nevertheless, whilst the current literature acknowledges the existence of the phenomenon, it fails to decompose this increase in volume.

When examining the determinants of liquidity in NYSE, Chordia, Subrahmanyam and Anshuman (2001) find that market depth increases significantly in upwards moving markets, finding returns to be "by far the most significant predictor of turnover". Hiemstra and Jones (1994) find evidence of nonlinear bidirectional granger causality between returns and trading volume, using daily returns of the Dow Jones stock index. This relation between returns and subsequent market trading activity is also found to be present on NYSE/AMEX, in a paper by Statman et al. (2006), who find that the market wide turnover is significantly predicted by past returns, causing high market return periods to be followed by higher turnover. The extent of the strength of this relation in different countries is examined by Griffin et al. (2007), who examine 46 countries, finding that this relation is more persistent in developing markets. They also note that this relationship is more pronounced for individuals than for institutions. Gallant, Rossi and Sengmueller (1992) also find that the trading volume increases following large absolute prices changes, but they find that this relation is present both for positive and negative returns.

2.5. Reasons for return-volume relation

There are numerous explanations for return-volume relation with the majority being related to investor overconfidence and other individual investor biases. As proposed by Chordia et al. (2001), recent stock performance could change future expectations, likely causing investors to change the composition of their portfolio, investing into stocks whose expected future performance has improved. Moreover, they also argue that the recent price history is a direct cause for trades made by traders using “technical analysis”. However, according to the efficient market hypothesis, all available information is incorporated in prices. This implies that the change in expectations should also be incorporated into prices, suggesting that trades would only be made by those investors who believe that the information that they infer from the shift in prices is superior to the information inferred by others (and incorporated into prices). This in turn suggests that these investors are overconfident (believe they are better than the market) and are attempting to speculate on their information. The same can be applied to traders using technical analysis, believing that they can extrapolate superior information from past prices and beat the market.

Further reasons for return-volume relation, as noted by Griffin et al. (2007), stem from the inefficiencies of markets in incorporating new information into stock prices. If markets are inefficient (information is not incorporated into prices quickly), past returns, generated by informed traders who are trading based on private information, will drive the price towards its fundamental value. These changes will serve as a signal to uninformed speculative traders to shift into those stocks. In the case of short sale constraints, this return-volume relation will be more pronounced for positive returns. This explanation would also suggest that we should expect trades to be performed by speculative traders, who believe that information will be incorporated into prices slowly, allowing them to profit on these market inefficiencies.

Another reason for this relation, highlighted by Allen and Gale (1994), suggests that investor participation in trading is limited by transaction costs, leading to low trading volume as predicted by the efficient market hypothesis. When past returns are higher, investors see an increase in the likelihood that the profits will exceed their transaction costs, leading to increased trading. This suggests that investors, who are prone to other investor biases, such as overconfidence, may be susceptible to this bias as well.

Moreover, disposition effect serves as another possible explanation to the upwards-only return-volume relation. As argued by Shefrin and Statman (1985), investors seek actions that cause pride, and refrain from actions causing regret. Due to this, they tend to sell winners, to realize gains, and refrain from selling losers, to avoid realization of losses. This effect is also recognized by Griffin et al. (2007), finding that the return-volume relation is stronger for individual investors, who are thought to be more prone to individual biases (such as the disposition effect) than institutions. Chen, Kim, Nofsinger and Rui (2007) find that individual Chinese investors are prone to disposition effect.

Positive feedback traders are the basis for yet another explanation to the return-volume relation, proposed by Hiemstra and Jones (1994). Their trading strategies create a temporary component in the stock prices, which reverses out in the long run, causing stock returns to be positively autocorrelated in the short run, and negatively autocorrelated in the long run. This reasoning is also recognized by Griffin et al. (2007). Moreover, according to this theory, the volume generated by returns would cause positive feedback traders (speculative traders) to increase their positions in stocks which have exhibited high returns. This positive feedback trader phenomenon is also documented by Dorn et al. (2008). Whilst examining clients at a German retail broker, they find that due to these investors behaving as positive feedback traders, whose trades are correlated, the returns continue themselves in the short run and reverse out in the long run.

Lastly, Odean (1999) recognizes that investors buy securities which attract their attention. Since investors have limited time to choose securities they will invest in, they are unable to consider all available securities. This leads investors to consider only stocks which can attract their attention, either by being featured in the news or outperforming other stocks. Odean (1999) finds they find that investors purchase shares which have had higher relative price changes than the securities they sell. This effect is also found to be present by Barber and Odean (2008), who find that investors purchase stocks which have high trading volume, high daily returns and stocks that have been featured in the news. This would also suggest that stocks that have had higher returns would be more likely to be considered by speculative investors, as they are not only looking for stocks to invest in, but also looking for stocks that may outperform the stocks which they are currently holding.

The reasons for the return-volume relation suggested by previous works are all related to individual investor biases and suggest that investors, who are susceptible to such biases, would exhibit trades following periods of high returns, resulting in the return-volume relation.

3. Hypotheses

Based on the literature reviewed, several hypotheses have been proposed, both about the effect of speculative trading and the characteristics of speculative trading. Our first hypothesis is developed based on the findings of Odean (1999) about trader tendency towards buying "winning" stocks and Statman et al. (2006) findings on the return-volume relation. The first hypothesis is stated as follows:

H1: Level of speculative trading increases following periods of high stock returns.

If the hypothesis is confirmed we will prove that speculative traders are those who trigger the return-volume relation, by increasingly purchasing stocks that have performed well.

In our work we also look at the extent of speculative trading on the NASDAQ OMX Tallinn stock exchange. Based on Dorn et al. (2008) the following hypothesis has been proposed regarding speculative trades:

H2: Out of all trades in the market more than half can be considered as speculative.

Besides testing the return-volume relation and the extent of speculative trading, we also perform an analysis of the speculative traders on the Tallinn stock exchange. Based on our data set we can test the following hypothesis about characteristics of investors who are willing to engage in speculative trading. By looking at age, portfolio size and investor type we will be able to test following hypotheses:

H3: Younger investors tend to speculate more than older investors.

H4: Investors with large portfolios tend to speculate less than investors with smaller portfolios.

H5: Individual investors have a higher tendency to speculate than institutional investors.

H6: Domestic investors have a higher tendency to speculate than foreign investors.

4. Estonian stock market

NASDAQ OMX Tallinn is the only regulated stock exchange in Estonia established in 1995 and is part of the NASDAQ OMX exchanges. Similarly to the other two stock exchanges in the Baltics – Riga and Vilnius, the trading process is organized electronically. Trading hours are from 10:00 to 16:00 GMT +2. Currently there are only 16 companies listed in NASDAQ OMX Tallinn. They are listed in two lists – 13 are listed in the main list and 3 in the secondary list. The difference between the lists is that the latter one has looser requirements for disclosure, market capitalization and free float. The total market capitalization is around 1.5 EUR billion. In the analysis period between January 2004 and October 2010 the average transaction value is 4046 EUR, with half of the trades bellow 1050 EUR (NASDAQ OMX Group, 2012).

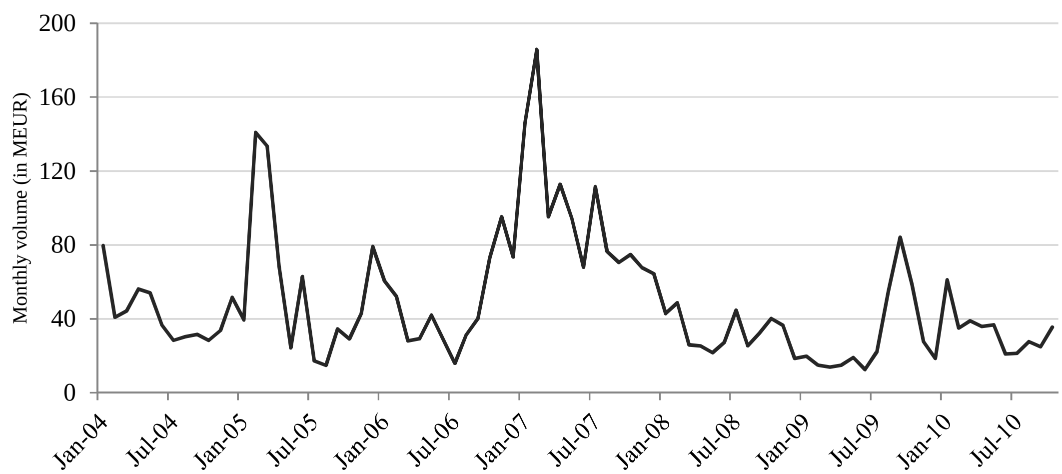

Figure 1. Monthly volume on Estonian stock market (measured in millions of euros). The graph shows trading volume development over time. Created by authors using NASDAQ OMX data.

Regarding trading volume and returns, a boom observed between 2006 and 2007 can be when both trading volume and returns increased significantly. Between July 2006 and February 2007 monthly trading volume increased from 160 MEUR to 186MEUR or by 16%. At the same time market index (1999=100) boomed from around 560 to 840 (an increase by almost 50%.

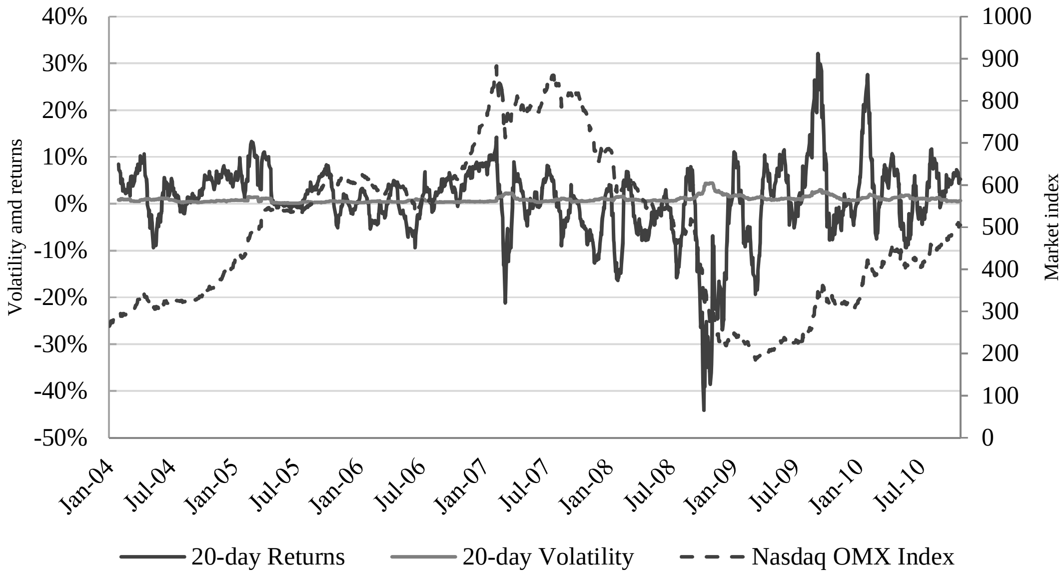

Figure 2. 20-day returns, volatility and market index (1999=100). The graph shows market return development and volatility development over time. Created by authors using NASDAQ OMX data.

5. Data description

The analysis will be based on a unique dataset consisting of three parts containing detailed individual trade/investor level data about all trades that have taken place on the Nasdaq OMX Tallinn stock exchange between January 2004 and December 2010. This unique dataset allows us to make inferences on a market-wide level.

The first part of our dataset lists all trades that have taken place in the respective period, with information about the investor ID, stock ID and name, trade and settlement dates, trade direction and volume (number of shares traded). This dataset will be used to calculate the degree to which each investor is speculative.

The second part contains information on 30,680 investors, with data covering the age and gender (if applicable), type (individual, institution, government or fund) and location (local or foreign) of each investor. Individual accounts are accounts that have been opened by a natural person who makes trades himself/herself. Institutions are accounts belonging to legal entities. Government accounts are those owned by government and fund accounts are accounts held by investment funds. This dataset will be used to investigate the characteristics of speculative traders.

The last part contains the positions of all investors on the Nasdaq OMX Tallinn stock exchange at the beginning of each month, with information on investor ID, stock ID, number of shares held and the date. In addition we use stock market returns. NASDAQ OMX Tallinn website.

For the purpose of calculating speculative trading ratios which were applied to each investor, we used all 35 stocks traded in NASDAQ OMX Tallinn between 2004 and 2010. For the regression specifications, we discard stocks with total trading period of less than a year, thus leaving us with 22 stocks (see Table 7).

6. Empirical methodology

In this section we describe empirical methodology used in order to answer our research question and proposed hypotheses. We start by explaining our measure of speculativeness, followed by calculation of individual speculative relation. Lastly we present our modified Vector autoregression model, based on the model used by Statman et al. (2006).

Measure of speculativeness

In order to measure the level of speculativeness in the Estonian stock market, we have to develop a measure of speculativeness and assign it to each investor from our data set. In order to do that, we have to distinguish all purchases of a stock that are financed by a sale of another stock and vice versa in a pre-defined trading window. Other academic papers measure the level speculativeness using several proxies (Mei et al., 2009; Gwilymet al., 2012). Due to the unique data set we are able to distinguish all speculative trades that occurred between 2004 and 2010 on Estonian stock exchange. This makes our measure a closer approximation to reality. It also makes our research the first one to measure speculative trading on market wide level, compared to previous works which estimate the level of speculative trading activity from a sample, e.g. Barber and Odean (2002).

As discussed before, purchases or sales of securities by an investor are considered to be speculative if that same investor makes a trade of opposite direction (purchase of a security is met by a sale of a security and vice versa) within a certain time period, denoted by *N - trading days (*according to Barber and Odean (2002) N=3-weeks or 15 days, however Stoffmann (2011) proposed to use a smaller N to get better approximate of speculative trading. For robustness purposes, we check for several trading windows (N=5;10;15;20;25).

To distinguish between these speculative trades and non-speculative trades, we select an investor j and a time t. For a given time window of N days, we look at all the trades that the investor has made in the period between days t and t-N, inclusive. Let $B(j,t,N)$ be the total purchases of securities of investor j between days t and t-N, and $S(j,t,N)$ be the total sales of securities within the same time period.

For a given period of time, the difference between the total purchases of securities made by an investor and the total sales of securities made by an investor is the net investment.

$$I(j,t,N) = B(j,t,N) - S(j,t,N)$$

The *I(j,t,N)* is the volume of trades that has been made for liquidity reasons or Net Investment. If *I(j,t,N)>0*, the investor is investing money into his portfolio; if *I(j,t,N)<0*, investor is divesting money from the portfolio.

In case the investor is investing money into his/her portfolio (*I(j,t,N)>0*), *S(j,t,N)* are classified as speculative. Therefore, the sales made were not liquidity motivated, suggesting that they are speculative.

$$IF\big(I(j,t,N)\big) > 0$$

$$NONSPEC(j,t,N) = B(j,t,N) - S(j,t,N) = I(j,t,N)$$

Moreover, the purchases of securities made that were financed by speculative sales of securities can also be considered as speculative, therefore:

$$SPEC(j,t,N) = B(j,t,N) - NONSPEC(j,t,N) + S(j,t,N) = 2 \times S(j,t,N)$$

If instead the investor is divesting funds from his/her portfolio (*I(j,t,N)<0*), the purchases can be classified as speculative.

$$IF(I(j,t,N)) < 0$$

$$NONSPEC(j,t,N) = S(j,t,N) - B(j,t,N) = (-I(j,t,N))$$

Similarly, the sales that were used to finance purchases (which are classified as speculative) can also be considered as speculative, as their proceeds were not used to satisfy liquidity needs.

$$SPEC(j,t,N) = S(j,t,N) - NONSPEC(j,t,N) + B(j,t,N) = 2 \times B(j,t,N)$$

In general terms, non-speculative trades are the absolute value of the difference between sales and purchases in a period, whereas the speculative trades are what remains, or 2 times the lowest of sales and purchases.

Since the data does not show the motivation behind each individual trade made by an investor (whether the security was sold due to pure liquidity concerns or due to an investor believing that it will underperform the market), allowing them to be separated into liquidity motivated trades and other trades (which we assume to be speculative or non-liquidity motivated), we assume that all trades that an investor makes on a given day are homogenous or have the same level of speculativeness. This implies that a given percentage of each trade can be considered speculative and a given percentage of each trade can be considered non-speculative.

Individual speculative trading ratio

It can be assumed that the speculativeness of an investor changes over time; either due to time constraints or changes in investor psychology. Due to this assumption two trades that are made within a single week are comparable; however two trades that are made in two separate years are not. An example could be an investor, who trades more actively when he is unemployed, speculating on market fluctuations, and invests in the market index when he is employed and has limited time for trading.

To account for this, the speculativeness of an investor will be evaluated over a time period of 3 months. This method, although allowing for variations in investor speculativeness, limits the effects of high volatility in daily speculativeness for an investor. The three month length of the period was chosen, as it was believed that taking a longer period would level out the speculativeness too much, limiting the ability to reflect the variance in investor trading habits.

For every trading day, the 3-month (or 63 trading day, under the assumption that a year has 252 trading days) speculative ratio will be obtained, by looking at the proportion of total trading volume that has been speculative.

$$ISTR_{j,t} = \frac{\sum_{t-31}^{t+31} SPEC(j,t,N)}{\sum_{t-31}^{t+31} SPEC(j,t,N) + \sum_{t-31}^{t+31} NONSPEC(j,t,N)} = \frac{\sum_{t-31}^{t+31} SPEC(j,t,N)}{\sum_{t-31}^{t+31} B(j,t,N) + \sum_{t-31}^{t+31} S(j,t,N)}$$

This obtained ratio, which varies over time, is a proxy for investors trading habits over a given period, and will be used to separate the trades made by investor in a given date into speculative and non-speculative, as on a given day, all trades made by an investor will be assumed to be homogenous.

Since in our analysis we use Statman et al. (2006) model to test the return-volume relation, all of the variables were transformed to 20-trading day frequency. This was done to avoid an excessive amount of coefficients, due to the long time horizon (10 months, or over 200 days). By calculating the 20-day variable for each date, we were able to retain the same number of observations as for daily frequency data.

Afterwards, the variables that reflect the aggregate speculative activity were calculated. To account for the long timeframe of the return-volume relation, they were calculated for 20-trading day frequency.

$P(j,i,t)$ – value of shares of company *i* purchased by investor *j* in period *t.*

$S(j,i,t)$ - value of shares of company *i* sold by investor *j* in period *t.*

$ISTR_{j,t}$ – individual speculative trading ratio of investor *j* at date *t*.

$$SP_t = \frac{\sum_{t-19}^{t} P(j,i,t) \times ISTR_{j,t}}{\sum_{t-19}^{t} P(j,i,t)}$$

$$SS_t = \frac{\sum_{t-19}^{t} S(j,i,t) \times ISTR_{j,t}}{\sum_{t-19}^{t} S(j,i,t)}$$

These show the relative speculative trading volume of a given day, which would allow us to analyze whether speculative purchases/sales increase more than non-speculative trades, following periods of high stock returns. This would provide evidence on the topic whether speculative traders react to return shocks more than non-speculative traders. Moreover, these variables could be combined to obtain the net speculative purchases, by subtracting the speculative sales from the speculative purchases, to obtain the net speculative purchases($NSP(i,t)$), which reflects the direction and magnitude of speculative trades at period *t*.

$$NSP_t = SP_t - SS_t$$

If $NSP_{i,t} > 0$, speculative purchases exceed speculative sales, whereas if $NSP_{i,t} < 0$, speculative sales exceed speculative purchases. The $NSP_{i,t}$ variable is a proxy for the actions of speculative traders, providing insight into the reactions of speculative traders to shocks in stock returns.

Vector autoregression model

The aim of this paper is to investigate the dynamic relation between security returns and trading volume on a market-wide level. To achieve this, a VAR model will be used. VAR is a version of the simple autoregression, which is used to investigate the dynamic interaction between two or more variables. A general form VAR can be written as follows

$$Y_t = \alpha + \sum_{k=1}^{K} A_k Y_{t-k} + \sum_{l=0}^{L} B_l X_{t-l} + e_t$$

where Y_t is a $n \times 1$ vector of endogenous variable observations at period t, X_t is a vector of period t exogenous (control) variables, and e_t is the period t model residual. The coefficient A_k estimates the relation between the current values of endogenous variables and the lagged values of endogenous variables and the coefficient B_l estimates the relation between current values of endogenous variables and the contemporaneous values of exogenous variables.

The regression which will be used to estimate the effects of speculative trades is based on the specification used by Statman et al. (2006) to estimate the presence of return-volume relation in stock markets. It was chosen as it could be adjusted to suit our data and the interactions between variables examined. The model specification for individual securities used by Statman et al. (2006) is as follows:

$$\begin{bmatrix} mturn_t \\ mret_t \end{bmatrix} = \begin{bmatrix} \alpha_{mturn} \\ \alpha_{mret} \end{bmatrix} + \sum_{k=1}^{10} A_k \begin{bmatrix} mturn_{t-k} \\ mret_{t-k} \end{bmatrix} + \sum_{l=0}^{2} B_l \begin{bmatrix} msig_{t-l} \\ disp_{t-l} \end{bmatrix} + \begin{bmatrix} e_{mturn} \\ e_{mret} \end{bmatrix}$$

The variables used in the model are as follows: $mret_t$ measures the return on market portfolio. The returns are expressed in natural logarithm form, measuring the 20-trading day returns. Market returns were calculated using the NASDAQ OMX Tallinn index. The individual security returns were also calculated, as they would later be required for the calculation of the dispersion variable. Individual security returns were calculated using adjusted stock prices.

$$ret_t = ln\left(\frac{Price_t}{Price_{t-20}}\right)$$

$$mret_t = ln\left(\frac{OMX\ Tallin\ Index_t}{OMX\ Tallinn\ Index_{t-20}}\right)$$

The next variable - $msig_i$ - measures the monthly volatility of market returns. It is calculated as the standard deviation of daily market returns over the past 20 days. The dispersion variable $(disp_{t-l})$ has been added to account for trades made in order to rebalance portfolio due to high differences between realized individual security returns. It is calculated as the cross sectional standard deviation of 20-trading day individual security returns.

$mturn_{i,t-l}$, used in the return-volume model by Statman et al. (2006) is the detrended log turnover. To compensate for the significant increase in the number of shares outstanding, they use the turnover.

$$turn_{i,t} = \frac{Shares\ Sold_{i,t}}{Shares\ Outstanding_{i,t}}$$

To account for the increasing fluctuations in turnover as it increases, they take the log of turnover. Afterwards, to account for a trend of growing turnover over the observation period, they use the Hordick and Prescott (1997) algorithm (from here referred to as HP algorithm) to detrend the stock turnover. This detrended log turnover has a mean value of 0, thus exhibiting both positive and negative values.

When examining the market-wide turnover on the Estonian stock exchange, a trend of growth or decline was not observed. Due to this, the relative trading volume measure will be used, which is the period *t* trading volume relative to the average trading volume for the market or individual security. The volume is also calculated for the 20-trading day frequency.

$$vol_{t,i} = \sum_{t-19}^{t} P(j,i,t)$$

$$r\_vol_{t,i} = \frac{vol_{t,i}}{avg\_vol_i}$$

This value, although not a perfect substitute for the HP algorithm, serves as a good approximation the relative changes in turnover that may be caused by speculative and non-speculative trading activity by traders.

The lag lengths were estimated by Statman et al. (2006) using the Schwarz Information Criteria, resulting in lag lengths of 10 for the endogenous variables, and 2 for the control variable. Since we wish to first test whether the return volume holds on the Estonian stock market, we use the same number of lags as Statman et al. (2006).

Since the reaction of speculative traders (instead of market as a whole) to shocks in stock returns is of interest to us, we will use a modified version of the model used by Statman et al. (2006), substituting the $turn_{i,t}$ variable with SS_t, SP_t and NSP_t variables in separate models. This will allow us to estimate whether returns are followed by increased speculative activity on both buy-side, sell-side and on market as a whole.

For the market wide regressions, estimating the dynamic interaction between speculative traders and market returns, the model specification is the following.

$$\begin{bmatrix} SP_t \\ mret_t \end{bmatrix} = \begin{bmatrix} \alpha_{SP} \\ \alpha_{mret} \end{bmatrix} + \sum_{k=1}^{10} A_k \begin{bmatrix} SP_{t-k} \\ mret_{t-k} \end{bmatrix} + \sum_{l=0}^{2} B_l \begin{bmatrix} msig_{t-l} \\ disp_{t-l} \end{bmatrix} + \begin{bmatrix} e_{SP} \\ e_{mret} \end{bmatrix}$$

$$\begin{bmatrix} SS_t \\ mret_t \end{bmatrix} = \begin{bmatrix} \alpha_{SS} \\ \alpha_{mret} \end{bmatrix} + \sum_{k=1}^{10} A_k \begin{bmatrix} SS_{t-k} \\ mret_{t-k} \end{bmatrix} + \sum_{l=0}^{2} B_l \begin{bmatrix} msig_{t-l} \\ disp_{t-l} \end{bmatrix} + \begin{bmatrix} e_{SS} \\ e_{mret} \end{bmatrix}$$

$$\begin{bmatrix} NSP_t \\ mret_t \end{bmatrix} = \begin{bmatrix} \alpha_{NSP} \\ \alpha_{mret} \end{bmatrix} + \sum_{k=1}^{10} A_k \begin{bmatrix} NSP_{t-k} \\ mret_{t-k} \end{bmatrix} + \sum_{l=0}^{2} B_l \begin{bmatrix} msig_{t-l} \\ disp_{t-l} \end{bmatrix} + \begin{bmatrix} e_{NSP} \\ e_{mret} \end{bmatrix}$$

Since the data transformation to 20-day interval creates overlapping observations, serial autocorrelation is likely to be an issue. To compensate for this, we use the Prais-Winsten estimation, including the Cochrane-Orcutt option.

7. Results

In this section we will discuss the results of our analysis. We start with descriptive statistics of our dataset; we first look at the market wide level of speculative trading on the Estonian stock market. Then we describe the main characteristics of speculative traders, and how the level of speculativeness changes among investor type, gender, age and portfolio size. Then we present the results of Vector autoregressive model which was used to test the return volume relation, afterwards arriving at the results for our model.

7.1. Descriptive statistics

In our data set we observe 30, 680 accounts – 4,211 institutions, 26,411 individuals, 34 government owned accounts and 24 funds. In the observed time span 57% of all trades were made by institutions, 42% by individuals and the remaining 1% are divided between funds and government owned accounts. In terms of value, institutions account for 81% and individuals only for almost 18% of total trade value between 2004 and 2010 (see Table 3). The results show that average value of a single trade for institutions is much larger than for individuals. The largest average trade size is for funds – around 46,000 Euros, followed by government owned accounts and institutions with average trade size of approximately 6,900 and 5,700 Euros respectively. The smallest average trade size is observed for individual investors – around 1,700 Euros.

Market wide level of speculativeness

In order to examine the total level of speculative trading in the Estonian stock market, we look at the total level of speculativeness in the market. To describe the extent of speculative activity, we used Barber and Odean (2002) proposed definition, therefore we choose 3 week or 15 day (N=15) speculative trading window. The results show that between 2004 and 2010 on average 58% of all trades happening in Estonian stock market can be classified as speculative (see Table 1).

In order to check the robustness of our results, we account for different trading day windows (we use N=5, N=10, N=15, N=20 and N=25). For instance, if we take one week trading window (N=5) almost half or 49.3% of total trade volume appear to be speculative. Not surprisingly, the level of speculativeness increases with N or trading windows. If we calculate for 5 week trading period (N=25) – almost 62 % of all trades can be classified as speculative (see Figure 3).

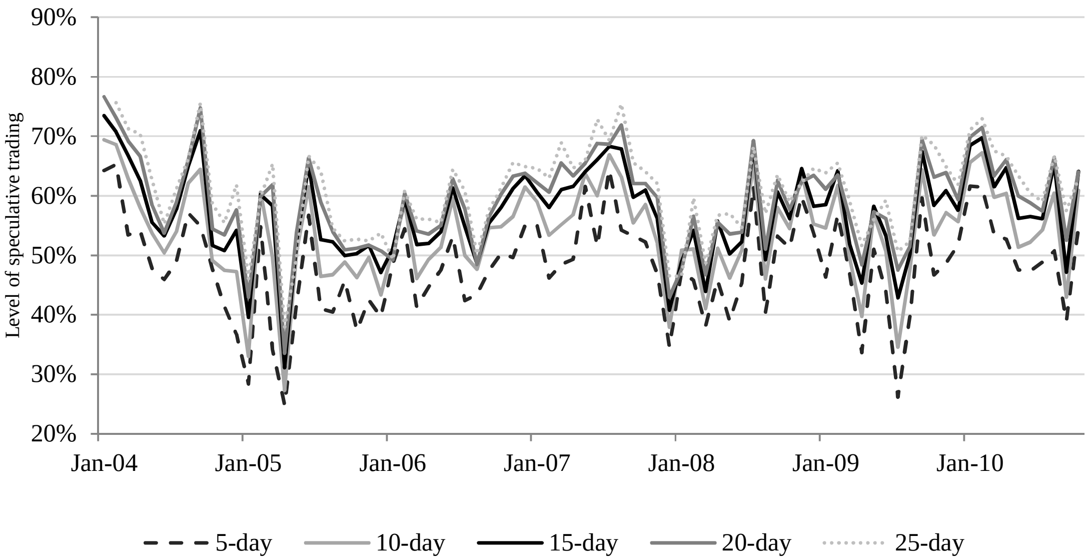

Figure 3. Level of speculative trading development over time. The graph shows market wide speculative trading activity between 2004 and 2010. Lines represents different trading windows (for N=5; 10; 15; 20; 25). Created by authors based on NASDAQ OMX Tallinn trade-level data.

If we take look at the speculative trading development over time, we can observe that speculative trading, both in terms of volume and a proportion of total trades, spiked in the middle of 2007 (see Figure 3). In 2007 the level of speculative trading (for N=15) hit 68%, meaning that on average 68% of trades are classified to be motivated by speculation. The lowest level of speculativeness was observed in April 2005, when speculative trades accounted for only 31% of total market turnover (for N=15).

Based on the results we can also observe that the speculative trading activity tends to be higher when economic conditions are improving. For instance, between December 2005 and August 2007 when the economy was booming during the real estate market bubble market index increased by around 40%. In the same period the average level of speculative trading (for N=15) gradually increased from 47% to almost 70% (see Figure 3). At the same time the monthly value of speculative trading increased from 37 MEUR to 52 MEUR (with a spike in February 2007 when value of speculative trading exceeded 100MEUR) (see Figure 4). Similar trend can be observed from July 2009 to September 2009.

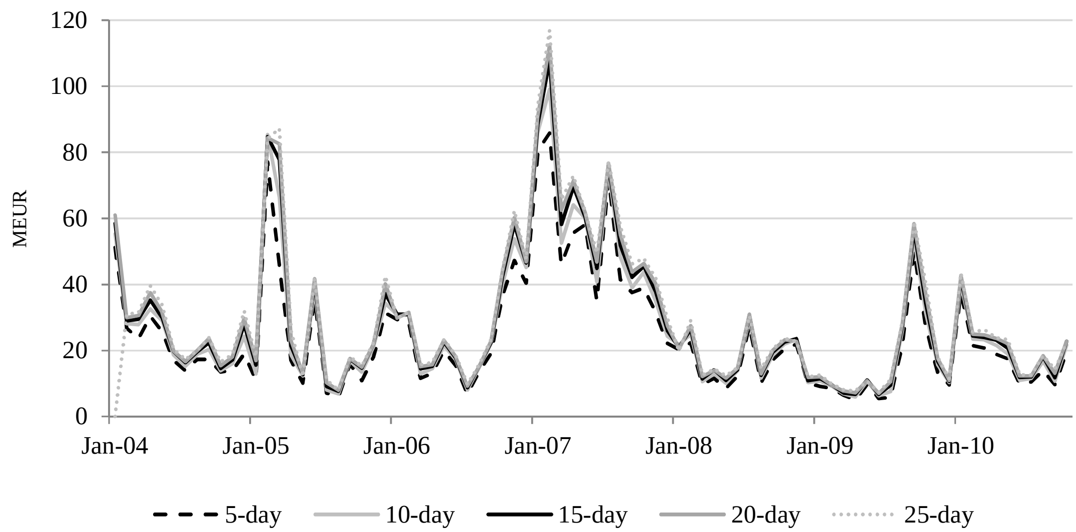

Figure 4. Value of speculative trading (in millions euros). The graph shows speculative trading development over time in terms of value. Lines represents different trading windows (for N=5; 10; 15; 20; 25). Created by authors based on NASDAQ OMX Tallinn trade-level data.

Individual stocks and speculative trading

We also look at speculative trading (N=15) on individual security level between 2004 and 2010 (see Table 2). For 22 stocks included in our data set, the average level of speculativeness among individual stocks varies between 38% and 62%. This percentage represents the share out of total trading volume for a given stock that can be classified as of speculative nature.

The results indicate a trend that speculative traders are interested in companies with higher betas. In our sample these companies represent industries which are more correlated with economic cycles such as real estate, construction and retail. Stocks which are of less interest from investors engaging in speculative trading are the ones with lower betas. In our sample these companies are from food manufacturing and pharmaceutical industries.

A simplified regression analysis is performed to approximate the relation between beta and the level of speculative trading. According to our simplified approach, beta turns out to be a significant predictor of speculative trading levels. When removing a single outlier, we found that beta of a stock is able to explain 56% of variation in the level of speculative trading between individual stocks (however, these results are strictly for illustrative purposes). The abovementioned relationship can be assessed from the graph below (see Figure 5). We plot the average level of speculative trading (N=15) and stock beta. The size of a bubble represents the total trading volume between 2004 and 2010.

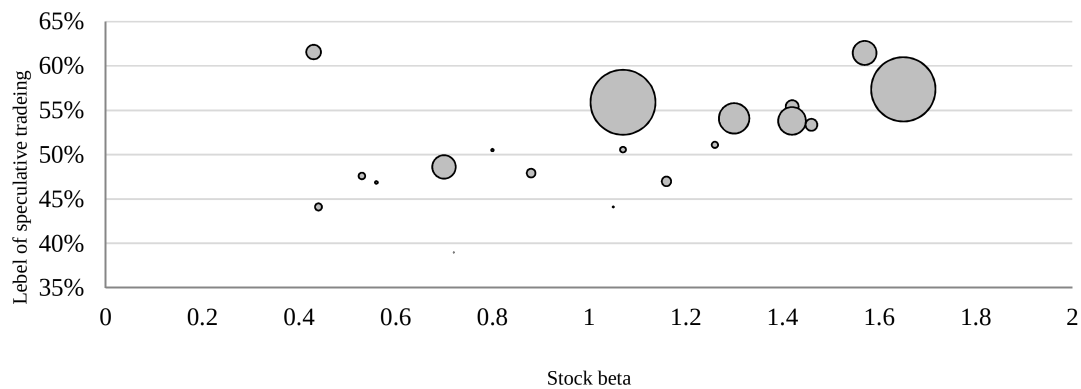

Figure 5. Speculative trading (for N=15) and stock betas. The graph illustrates the relationship between level of speculative trading (for N=15) and stock beta. For the illustrative purposes the average level of speculative trading between 2004 and 2010 was used. Bubbles represent trading volume. Created by authors based on NASDAQ OMX Tallinn trade-level data.

Characteristics of speculative traders

We also examine what types of traders tend to engage in speculative trading (see Table 4). Institutions appear to be the most speculative– for 3-week trading window 63% of all trades on average can be classified as speculative. If the trading window is reduced to one week, the speculative trades account for 54% of the total trades. Individual traders seem to be less speculative than institutions – for 3-week trading period only 42% of all trades can be considered as speculative. However, if the trading window is reduced to one-week only 29% of all trades can be accounted as speculative. The least speculative appeared to be government owned accounts and funds – for 3-week trading window speculative trades out of all trades are only 8.75% and 16.20% respectively. However, if the time span is shortened to one week, meaning that there is a bigger chance to capture speculative trading the speculativeness level is considerably lower – 5.36% for government owned accounts and 6.63% for funds.

The breakdown of speculative trading volume by investor type has not remained constant over time. The share of individual investors in the speculative trading portfolio is increasing over time (see Figure 6) from less than 0.8% of total speculative trading volume in 2004 to 14.4% of total speculative trading volume. This large increase can be explained with two factors: trades by individual investors as a percentage of total trades increased from 9.8% in 2004 to 28.1% in 2010 and speculativeness of individual investors increased significantly over time.

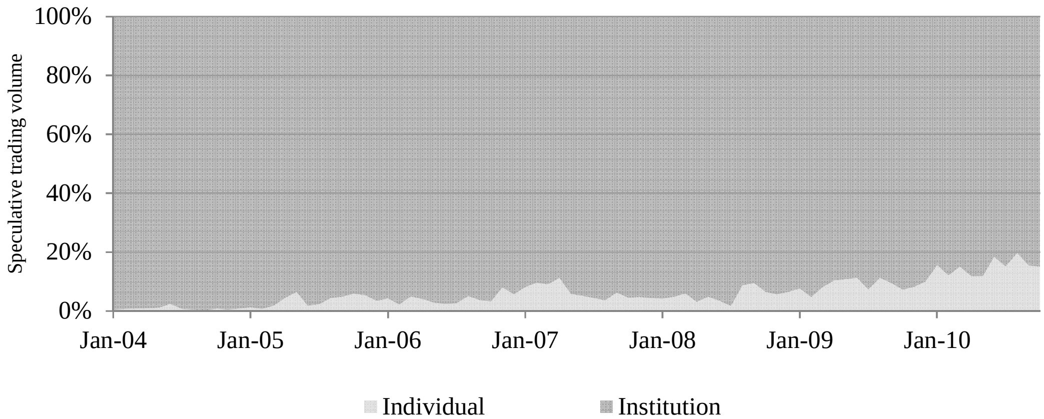

Figure 6. Breakdown of speculative trading volume (for N=15) by investor type. The graph shows speculative trading volume development (for N=15) over time by investor type. Fund and government accounts were disregarded as they account for an insignificant share of total trade volume. Created by authors based on NASDAQ OMX Tallinn trade-level data.

If we look at the speculative trading development over time by investor type, it can be observed that in the beginning of our data set individual investors are less speculative than institutional investors (N=15) (see Figure 7). In September 2004 only 16% of all trades by individual investors were classified as speculative comparing to 84% for institutional investors. According to our results, starting from 2004 individual investors are constantly becoming more speculative – reaching peak in March 2007 when out of all trades around 75% were classified as speculative.

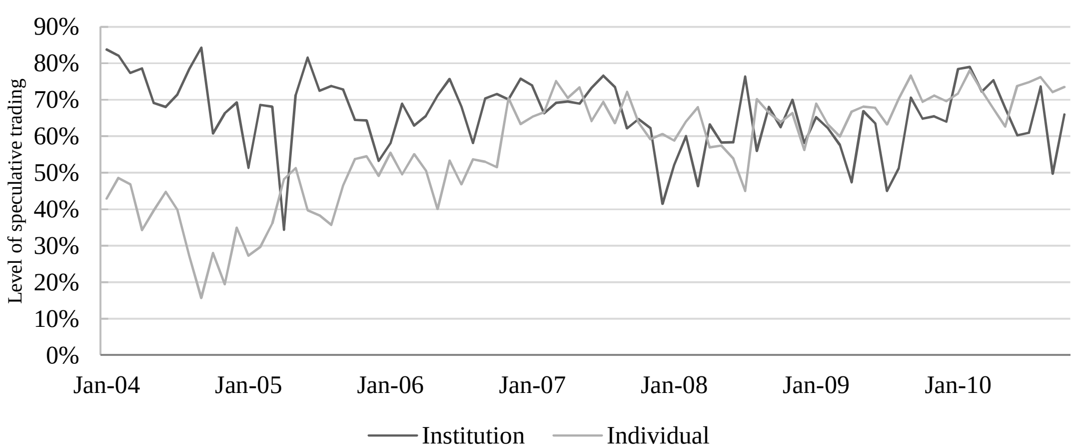

Figure 7. Speculative trading (for N=15) by investor type. The graph shows speculative trading volume development (for N=15) over time by investor type. Created by authors based on NASDAQ OMX Tallinn trade-level data.

Regarding how speculativeness differs between genders our results suggest that men tend to engage in speculative trading more than women (see Table 5). For 3-week trading window around 31% of all trades by men appear to be speculative. Only 26% of all trades by females are speculative. When we distinguish between foreign and domestic investors, we find evidence that domestic investors tend to engage in speculative trading more – for three week trading window almost 50% of trades made by domestic investors seems to be speculative. The proportion of the speculative trades out of total trades is lower for foreign investors, namely almost 41%.

Regarding the investor age, the data suggests that younger investors tend to speculate more than older investors (see Table 5). For instance the average speculativeness for investors between 21 and 40 is 33% (N=15). The average speculativeness of investors between 61 and 80 is only 29%. The highest speculative proportion of total trades appears to have investors between 81 and 100. In our sample this age group represents 1% or 254 accounts. The average speculative ratio for this age group is 51% (N=15), which is considerably higher compared to other groups.

Finally, we also look at average portfolio size and how speculativeness changes across investors with different portfolio size (see Table 6). We only account for the investors which have been active in the observed period and had non-zero number of trades between 2004 and 2010. The data set was divided in percentiles and we the results indicate that the most speculative are the investors in the first percentile with an average portfolio size of 0.45 MEUR. Their average speculative ratio in the observed period was almost 61%. We also observe a tendency that average speculativeness gradually decreases together with decreasing portfolio. Only exception is for 10th percentile or accounts with average portfolio size of 82 Euros. For those accounts the average speculativeness is 42%.

7.2. Return volume relation

The first step of the empirical research is to establish the presence of the return-volume relation on the Estonian stock market. For this we use the same model specification as used by Statman et al. (2006) to estimate the presence of the phenomenon on the NYSE/AMEX stock exchanges.

Table 9 summarizes the results for the market wide bivariate VAR model, which estimates the presence of return-volume relation on a market level. It shows the coefficients on the lagged endogenous (Relative market turnover and Market returns) and contemporaneous and lagged exogenous variables (Volatility of market returns and Dispersion of individual security returns).

The results suggest a significant negative autocorrelation in both of the endogenous variables. When examining the determinants of Relative market turnover, coefficients on lagged values of turnover are all highly significant and negative, indicating strong negative autocorrelation. Moreover, the coefficient is of the highest magnitude on the 2nd lag (-0.5265, with a standard error of 0.0262) and declining afterwards. This suggests that the adjustment in the first month after a turnover shock will not be severe (coefficient of -0.0713); however in the 2nd month after the turnover shock, the adjustment will be the most significant.

Relative market turnover is also significantly predicted by lagged monthly returns; following periods of high returns, turnover is expected to increase (and vice versa), with the coefficients on the first 6 lags being significant at 1% significance level, and coefficient on the 7th lag being significant at the 5% significance level. A noteworthy observation is that the coefficients tend to increase, being the highest at for the 5th lagged value of market returns (0.6205), and declining afterwards.

Market returns also exhibit significant negative autocorrelation, with highly negative and highly significant coefficients. Here the effect is not lagged, with the largest adjustment taking place in the first month after the shock (coefficient on the first lagged value of

-0.9667), and declining afterwards. The coefficients on lagged values of Relative market turnover are not significant, suggesting that the return-volume relation is not bidirectional on the Estonian stock market; returns influence turnover, but not vice versa. The coefficients on the exogenous control variables are statistically insignificant, suggesting that neither returns, nor turnover are dependent on the level of volatility or the dispersion of security returns.

7.3. Return volume relation

Market wide models

The second step of our empirical research is estimating the dynamic interaction between variables measuring speculativeness and market returns, aiming to understand whether speculative trading can explain the return-volume relation. For this three models will be used, estimating the interaction between returns and speculative purchases, sales or net purchases.

Speculative purchases

The first model to be tested is the market-wide speculative purchases and its interaction with lagged market returns (see Table 10). Again, dispersion and monthly volatility are used as control variables. The results, as for the return-volume relation, suggest a significant negative autocorrelation for both market returns and speculative purchases. The negative autocorrelation effect for speculative purchases is significant for the first four lags, with the highest adjustment taking place in the first month (-0.4957) and declining afterwards, but for the market returns the adjustment is longer (all of the 10 lagged coefficients are highly significant), with the magnitude of the re-adjustment being strongest in the first month (coefficient of -0.9680, standard error of 0.0266), and fading off afterwards.

Speculative purchases are positively affected by market returns, with coefficients on 3rd to 7th lag being significant at the 5% level, and coefficient on 4th lag being significant at the 1% level. These coefficients are all positive, with the highest coefficient for the 4th lag, suggesting that the speculative purchases, as a share of total trades, increase following periods of high returns, and decline following periods of low and negative returns. The coefficients on the lags reach their peak on the 4th lag (coefficient of 0.1159, standard error of 0.0383), declining afterwards. Although the coefficients on the first two lags are also positive, they are not significant, suggesting that the reaction of speculative traders, in the form of increased purchases, picks up three months after the return shock, reaching its peak 4 months after the purchase.

Speculative sales

The second model examines the interaction between speculative sales and market returns (see Table 11). As before, dispersion and market volatility are added as control variables. As in previous models, both endogenous variables exhibit significant negative autocorrelation and the time horizon for this negative autocorrelation is longer for market returns (all of the coefficients are negative and significant) than for speculative sales (only the first three coefficients are significant at 1% level, with the 4th being significant at the 5% level). After the 4th lag, the coefficients for lagged Speculative sales become insignificant (p-values in excess of 20%). The negative autocorrelation for Market returns remains present in coefficients for all 10 lags, being the most pronounced in the 1st lag (coefficient of -0.9665), and fading off afterwards.

The interaction between the two endogenous variables is not significant, with none of the variable being significant at 10% level. This suggests that the level of speculative sales is not predicted by past market returns, and vice versa. Control variables, as with the previous regressions, are not significant.

Net speculative purchases

The third model estimates the relation between net speculative purchases (speculative purchases less speculative sales) and market returns (see Table 12). As before, both of the endogenous variables exhibit negative autocorrelation, and as in other models, the horizon for this negative autocorrelation is longer for market returns than for speculativeness variable (net speculative purchases). The adjustment of net speculative sales is also the highest in the first month (coefficient of -0.4896), and declining afterwards, becoming insignificant in 5th month. The adjustment for market returns is also the most pronounced in 1st month, declining afterwards. As in the remaining models, the control variables are insignificant.

8. Analysis and discussion

Level of speculative trading

By introducing speculative trading measure, we find supportive evidence to our hypothesis that more than half of all trades in the market are speculative. According to our measure 58% of all trades in the Estonian stock market were classified as speculative, which is in line with Dorn et al. (2008) findings.

The phenomenon that investors tend to speculate more in times of high market returns can be linked with investor overconfidence as documented in previous works of Odean (1998; 1999). This is also consistent with Shi and Wand (2011) findings that in bull markets individual investors falsely believe that their success is attributable to their talent and skills, not the overall conditions. Our findings suggest that similar phenomenon may be present in Estonian stock market as well, since the overall level of speculative trading increases in the period of high market returns between 2005 and 2007.

If we take a look at the level of speculativeness by stock, there is a trend that speculative traders tend to choose stocks with higher betas. This can be explained with the higher fluctuation (by definition) that high beta stocks exhibit, thus giving traders and illusion of higher potential gains. The findings are consistent with Ferson and Schadt (1996) that in time of high market returns investors prefer stocks with high betas.

Characteristics of speculative investors

Regarding the characteristics of investors which engage in speculative trading, we find that on average institutional investors are more speculative than individual investors. Despite this, the results differ significantly, depending on whether we compare institutions and individuals in 2004 or in 2010; if in 2004 the level of speculativeness of institutions is significantly higher than that of individuals (75.3% compared to 36.9%, with N=15), then in 2010 these levels are similar, with individual investors even being more speculative (70.9% compared to 71.9%). This significant increase could be attributed to the significant improvement in availability of individual trading platforms (also accounting for the large increase in overall trading volume of individual investors). As investors shift from using brokerage services provided by large financial institutions to using their own, personal accounts, individual trading volume is likely to increase. Moreover, due to the ease of making trades, it would be reasonable to see speculativeness (shifting between stocks) go up, which is in line with our results.

Consistent with the findings of Barber and Odean (2001) we also observe that men tend to speculate more than women. However, the difference is relatively small – the difference in the average speculative ratios between men and women is only 5% (comparing to Barber and Odean (2001), who find that men trade 45% more than women, thus being significantly more speculative).

Regarding investor age, we find evidence that investors which are younger are more speculative. This is in line with our proposed hypothesis, with the exception for investors which are older than 80. On one hand our findings can be explained by the idea that older investors have more experience, thus they tend suffer less from investor biases, such as excessive trading (also documented by Korniotis and Kumar (2011)). However, the fact that elderly investors (older than 80) trade more is in line with an idea by Feng and Seasholes (2005) that neither sophistication, nor experience reduces investor biases. Another explanation to this phenomenon could be the fact that older investors have a shorter investment horizon, thus they are willing to actively manage their assets and prefer short term gains over long term stable portfolio growth, attainable by investing in market portfolio.

Considering foreign and domestic investors, our findings suggest that domestic investors on average tend to speculate more than foreign investors, which is in line with the proposed hypothesis. This might be explained by the idea that investors feel more confident to buy and sell stock which they are familiar with. This can be linked with the idea documented by Graham, Harvey and Huang (2009). In their work they find evidence that, when investors feel more competent of their knowledge about their investment decisions, they are willing to trade more actively. Moreover, domestic investors might have more information about traded stocks, thus they can benefit from speculation more than foreign investors (Dvorak, 2001; Hyuk, Kho and Stulz, 2005; Baik, Kang and Kim, 2010). Another explanation for foreign investors being less speculative is introduced by Hamao and Mei (2001) where they found evidence that foreign investors are more interested in long-term investment rather than short term gains by speculation. Finally, perhaps investors choose to invest in foreign markets for the sake of international diversification (also documented by Obstfeld (1994)), not active trading and therefore foreign investors on average tend to speculate less than domestic investors.

Lastly, we find evidence that investors with large portfolios tend to speculate more than those with smaller portfolios. This is consistent with our proposed hypothesis with the exception for portfolios with average size below 350 Euros. The high level of speculative trading by investors with large portfolios can be partly explained by lower transaction costs relatively to the trade size. Regarding investors with small portfolios, one explanation of their high level of speculativeness is the underlying motive to trade. As they have relatively small portfolios it might be that their motive to trade is to explore stock market rather to invest.

Another explanation for the phenomenon, where large investors tend to speculate more than investors with smaller portfolios, is that they feel superior in terms of knowledge and skills comparing to other investors, therefore they speculate more in order to get higher returns. Our findings are highly linked with a paper by Ekholm and Pasternack (2007). In their study they find evidence that larger portfolio holders are more overconfident. Thus our findings suggest that there might be a strong linkage between overconfidence and speculative trading and overconfidence might be a strong driver of speculative trading in Estonian stock market.

Return-volume relation and speculative trading

Using the model of Statman et al. (2006) we confirm the presence of return-volume relation on the Estonian stock market. Our findings are similar to those of Statman et al. (2006) and Griffin et al. (2007), confirming that past market returns predict total trading volume. The effect that returns have on total trading volume lasts for 7 months, fading out afterwards. When analyzing the relation between speculative trading activity and market returns, only speculative purchases (as a share of total trading volume) are found to respond to shocks in market return, showing an economically and statistically significant increase in levels of speculative purchases 3 – 6 months after a positive return shock; speculative sales and net speculative purchases did not exhibit a significant relation with the lagged market returns. This implies that, although the initial effect (first two months) cannot be fully explained with speculative trading theories, speculative trading does explain a large part of return-volume relation through a significant increase in the share of speculative purchases out of all market-wide purchases. These findings are robust to changes in speculative trading window. This confirms our proposed hypothesis that level of speculative trading increases following periods of high stock returns.

Our findings that speculative trading drives the return-volume relation in the Nasdaq OMX Tallinn stock exchange can be explained using the various theories on investor biases. The observed increase in share of purchases that are speculative can be explained with the existence of positive feedback traders, who purchase stocks following periods of high returns. Existence of transaction costs could explain this increase in share of purchases that are speculative – after periods of positive returns investors believe that the likelihood that their gains exceeding the transaction costs has improved, leading to increased market participation.

Another possible explanation, suggested by Griffin et al. (2007), hints that the relation may stem from market inefficiencies; since new information is not incorporated into prices immediately, seeing a rise in prices, traders, expecting that the price adjustment process may not be immediate, invest in the stock, hoping to profit from the slow adjustment process. The presence of these effects is confirmed by the following observations: the magnitude of the relation increases during the 6 months after an increase in returns and the first two months of increased trading volume cannot be explained with increase in speculative purchases. As more speculative traders succumb to beliefs, they increase their purchases, continuing the return-volume relation. The effect of trading costs is particularly relevant for a small and relatively illiquid (by US standards) market as Tallinn stock exchange. Lastly, our findings support the work of Gwilym et al. (2012), who suggest that high recent past returns increase speculative demand.

Our findings also suggest that speculative traders are not prone to disposition effect, as speculative trades do not increase after periods of significant positive stock returns. As total trading volume increases (implying that sales increase as well), the increase in level of sales is likely to be equally caused by speculative and non-speculative traders. If speculative traders close their positions to obtain funds for shifting into profitable stocks, non-speculative traders are likely to close their positions in order to realize gains. This suggests that non-speculative traders are more prone to disposition effect than speculative traders.

Contradictory to a work by Hiemstra and Jones (1994), we do not find the return-volume relation to be bidirectional; trading volume does not have an effect on future market returns. We also find that speculative trading volume does not have an effect on stork returns in following periods. This is somewhat surprising, considering the illiquid nature of Tallinn stock exchange. Also, our findings contradict those of Chordia et al. (2001), who find that trading volume increases in both up and down markets; when testing the model using absolute returns, the relation proved to be highly insignificant. This suggests that trading volume in the Estonian stock market decreases in down markets and increases in up markets.

9. Concluding remarks

The purpose of the thesis is to examine speculative trading on Estonian stock market. We examine both speculative trading on a market wide level, analyze the characteristics of investors who engage in speculative trading and assess the effects that speculative traders have on the market.

We find that more than half of all the trades that take place on the NASDAQ OMX Tallinn stock exchange can be classified as speculative. We also find that this level of speculativeness exhibits significant fluctuations over time. The market wide level of speculativeness increases during bull markets, suggesting that traders are subject to various investor biases. The level of speculativeness does not exhibit a trend of growth over time. We also find strong evidence that speculative traders are interested in high beta stocks.

When examining the characteristics of investors we arrive at several noteworthy findings. Contrary to previous literature and our expectations, institutional investors are found to be more speculative than individual investors. It is worth noting that speculativeness of individual investors has increased significantly over the sample period, reaching the same levels of speculativeness as institutions. It would be interesting to obtain more current data and examine how speculativeness of investors has developed in the past years, comparing speculativeness of individual investors and institution in 2012. Men, as expected, are found to be more speculative than women. We also find that speculativeness of individual investors decreases as investors get older, with the exception of elderly investors, who are found to be the most speculative, and that speculativeness increases with investor portfolio size, with the exception of investors with very small portfolios. Lastly, domestic investors were found to be more prone to engaging in speculative trading than foreign investors.

We confirm the presence of a unidirectional return-volume relation in the Estonian stock market; past returns on the market portfolio are a significant predictor of trading volume in following periods. Our findings suggest that this relation is driven by increased level of purchases made by speculative investors.

Our research provides valuable insights into the characteristics of speculative traders, filling gaps in existing literature on investor biases. It also provides an overview of the market wide level and volume of speculative trading. We decompose the return-volume relation, providing an explanation to this phenomenon by creating a unique link to speculative trading. We find that, although speculative traders react to returns, their actions do not impact future stock returns, questioning grounds for the negative emotions associated with speculative trading. This also provides the regulatory bodies, concerned with market stability, with valuable information for further policies.

The findings of our paper also outline several further lines of research. First, a detailed study on whether speculative obtain superior returns and the characteristics of speculative traders that obtain higher returns. Secondly, although our research examines how speculative traders react to returns, further research could examine the impact that speculative traders have on the liquidity. Third, a further study on commonality of speculative traders on individual security level would bring valuable insights about speculative trading.

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Appendix A. Descriptive statistics tables

Table 1. Level of speculative trading in the Estonian stock market.
This table summarizes market-wide levels of speculative trading, both in relative terms and in absolute terms for different time windows and for different years.

Year		Total turnover, millions EUR	Trading window 5	10	15	20	25
2004	Volume	516.00	268.68	296.91	314.54	325.24	336.76
	%		52.1%	57.5%	61.0%	63.0%	65.3%
2005	Volume	686.91	283.51	324.42	347.36	361.09	375.23
	%		41.3%	47.2%	50.6%	52.6%	54.6%
2006	Volume	570.46	281.48	312.33	326.85	332.39	339.46
	%		49.3%	54.8%	57.3%	58.3%	59.5%
2007	Volume	1167.45	605.98	668.07	709.71	738.58	768.19
	%		51.9%	57.2%	60.8%	63.3%	65.8%
2008	Volume	389.50	191.83	208.42	216.05	220.18	224.31
	%		49.2%	53.5%	55.5%	56.5%	57.6%
2009	Volume	361.18	173.83	197.38	211.43	221.14	229.63
	%		48.1%	54.6%	58.5%	61.2%	63.6%
2010	Volume	338.29	180.04	199.08	210.36	216.83	222.87
	%		53.2%	58.8%	62.2%	64.1%	65.9%
Average	**Volume**	**576**	**284**	**315**	**334**	**345**	**357**
	%		**49.3%**	**54.8%**	**58.0%**	**59.9%**	**61.9%**

Source: created by authors based on NASDAQ OMX Tallinn trade-level data.

Table 2. Descriptive statistics of stocks used in empirical analysis.

This table provides statistics for stocks used in the empirical analysis for the period from 01.01.2004 –26.10.2010. The table provides information on the total number of trades that were made with that stock; the total value of all trades; the percentage of all trades that can be considered speculative (using the 15-day window); 20-day volatility of daily log-returns; industry the company operates in; company market capitalization for year 2010; company Beta, calculated using 20-day returns.

ISIN	Stock	Number of trades	Turnover, MEUR	Speculative trading (N=15), %	Volatility of daily returns %	Industry	Capitalisation, MEUR*	20-day beta**
EE3100026436	Tallinna Vesi A-	39434	332.40	61.56%	1.57%	Utilities	157.80	0.43
EE3100034653	Arco Vara	65347	112.73	61.46%	4.32%	Real estate	26.13	1.57
EE3100039496	EESTI EHITUS liht	48079	139.11	58.19%	2.99%	Construction	-	-
EE3100084021	OLYMPIC ENTERTAINMENT GROUP	174940	512.90	57.37%	3.53%	Gambling	224.72	1.65
EE3100004466	Tallink Grupp	176633	666.53	55.90%	2.73%	Transport	532.32	1.07
EE3100001751	Silvano Fashion Group A-	35098	79.57	55.42%	3.96%	Retail/Manufacturing	108.13	1.42
EE3100003609	Baltika	82874	226.99	54.10%	3.40%	Retail	31.32	1.3
EE0000001105	Tallinna Kaubamaja	75665	204.45	53.80%	2.83%	Retail	252.93	1.42
EE3100016965	Ekspress Grupp	32283	70.18	53.37%	3.70%	Printing house	45.53	1.46
EE3100003559	Merko Ehituse	32759	173.37	51.81%	3.39%	Construction	-	-
EE3100098328	MERKO EHITUS	17438	35.42	51.12%	3.38%	Construction	160.19	1.26
EE3100003443	Trigon Property Development	15891	15.87	50.56%	4.34%	Property development	2.25	1.07
EE3100092503	Viisnurk	6940	4.50	50.52%	4.02%	Wood processing	-	0.8
EE3100007220	Eesti Telekomi	63747	544.66	48.61%	1.42%	Telecomunication	-	0.7
EE3100004250	Harju Elektri	23738	52.45	47.93%	2.61%	Utilities	50.74	0.88
EE3100001850	Norma	18537	95.35	47.61%	2.03%	Manufacturing	-	0.53
EE0000001063	Hansapanga	25790	607.68	47.00%	1.21%	Banking	-	1.16
EE3100008830	Starman	8007	33.67	46.88%	3.36%	Telecomunication	-	0.56
EE3100002486	Rakvere Lihakombinaadi	2868	4.84	44.11%	2.29%	Food manufacturing	-	1.05
EE0000001287	Saku Õlletehase	19313	44.93	44.11%	2.06%	Food manufacturing	-	0.44
EE3100001744	Tallinna Farmaatsiatehase	1466	0.74	38.98%	6.24%	Pharmacy	-	0.72
EE3100002460	Kalevi	17439	41.76	37.84%	4.26%	Food manufacturing	-	-

Source: created by authors using data from NASDAQ OMX

Table 3. Speculative trading proportion and volume 2004-2010.
This table reports trading and portfolio statistics for different investor types.

Investor type	Number of accounts	Number of trades		Value of trades (EUR mil)		Portfolio value (2004/01) (EUR mil)		Portfolio value (2004/01) (EUR mil)	
Institution	4,211	572,285	57.44%	3,266	81.02%	2,749	96.30%	1,246	89.14%
Individual	26,411	422,793	42.43%	717	17.79%	94	3.28%	142	10.19%
Government	34	329	0.03%	2	0.06%	-	-	-	-
Fund	24	982	0.10%	46	1.14%	12	0.42%	9	0.68%
Total	30,680	996,389	100.00%	4,032	100.00%	2,854	100.00%	1,397	100.00%

Source: created by authors based on NASDAQ OMX Tallinn trade-level data.

Table 4. Proportion of speculative trades by investor type.
This table reports levels of speculative trading of different investor groups by speculative trading window.

N	Institution	Individual	Fund	Government	Total
5	54.00%	29.04%	6.63%	5.36%	49.27%
10	58.84%	37.34%	11.24%	7.43%	54.74%
15	61.66%	42.22%	16.20%	8.75%	57.94%
20	63.51%	44.65%	18.34%	9.62%	59.90%
25	65.35%	47.32%	20.25%	10.61%	61.89%

Source: created by authors based on NASDAQ OMX Tallinn trade-level data.

Table 5. Level of speculativeness by investor characteristics.
This table reports levels of speculative trading by individual investor characteristics (gender, age and country) for different speculative trading windows.

		Trading window				
Investor gender	# of Accounts	5	10	15	20	25
Female	15,012	15.62%	22.28%	25.79%	26.10%	18.41%
Male	24,410	19.37%	26.76%	30.79%	32.08%	27.10%
Investor location						
Foreign	46,262	30.74%	37.60%	40.99%	41.38%	32.49%
Domestic	2,249	42.77%	47.16%	49.92%	51.12%	49.22%
Investor age group						
0-20	1,291	20.13%	29.59%	34.98%	37.94%	41.03%
21-40	13,298	31.94%	40.51%	45.54%	47.93%	50.53%
41-60	6,410	21.83%	28.96%	33.42%	35.80%	38.38%
61-80	3,665	16.75%	24.19%	28.87%	31.32%	33.95%
81-100	254	39.08%	47.03%	50.87%	52.73%	54.95%

Source: created by authors based on NASDAQ OMX Tallinn trade-level data.

Table 6. Level of speculative trading by portfolio size.

This table reports statistics for portfolios, broken down by percentiles. The table reports number of accounts included in each of the percentiles, average portfolio size as at 01.01.2004, average portfolio size as at 01.10.2010, average portfolio size of these two dates and the weighted average level of speculativeness, using the 15-day trading window. Only accounts that were active during this period were included in the table.

Percentile	Number of accounts	Average portfolio size 2004 (EUR)	Average portfolio size 2010 (EUR)	Average	Average speculativeness
1	1527	571332	476672	450733	60.90%
2	1527	15034	14111	14408	47.37%
3	1527	7427	7386	7379	34.32%
4	1527	4501	4378	4413	39.60%
5	1527	2924	2673	2737	28.75%
6	1527	1769	1714	1727	33.38%
7	1527	1159	1099	1118	25.80%
8	1527	695	693	692	19.36%
9	1527	362	345	347	27.23%
10	1531	91	81	82	42.35%

Source: created by authors based on NASDAQ OMX Tallinn trade-level data.

Table 7. Data on individual listed securities used in the model.
This table reports the number of days the security was traded and whether the security was included in the regression analysis.

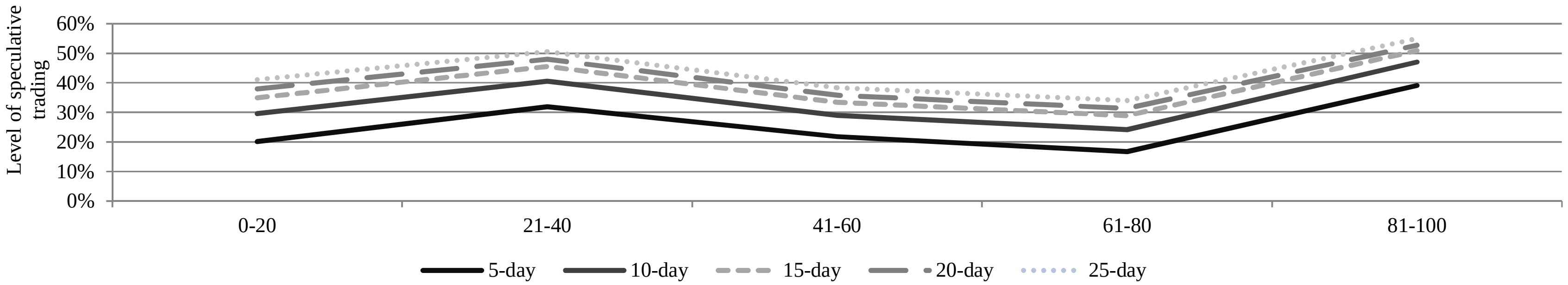
Stock Name	Days traded	
Hansapanga aktsia	378	Keep
Tallinna Kaubamaja aktsia	1723	Keep
Saku Õlletehase aktsia	1191	Keep
Estiko E-aktsia	123	Discard
Tallinna Farmaatsiatehase aktsia	744	Keep
Silvano Fashion Group A-aktsia	1724	Keep
Norma aktsia	1638	Keep
Kalevi aktsia	1437	Keep
Rakvere Lihakombinaadi aktsia	674	Keep
Trigon Property Development aktsia	1724	Keep
Merko Ehituse aktsia	1724	Keep
Baltika aktsia	1720	Keep
Harju Elektri aktsia	1724	Keep
Tallink Grupp aktsia	1229	Keep
Eesti Telekomi aktsia	1520	Keep
Starman aktsia	944	Keep
Ekspress Grupp aktsia	894	Keep
Tallinna Vesi A-aktsia	1363	Keep
Arco Vara aktsia	843	Keep
EESTI EHITUS lihtaktsia	1119	Keep
OLYMPIC ENTERTAINMENT GROUP aktsia	1009	Keep
Viisnurk aktsia	776	Keep
MERKO EHITUS aktsia	556	Keep
Premia Foods aktsia	122	Discard
Ekspress Grupp aktsia märkimisõigus 1	8	Discard
Tallinna Kaubamaja aktsia täiendav 2	8	Discard
Kalevi täiendav aktsia 2	33	Discard
Eesti Telekom täiendav aktsia 2	37	Discard
Harju Elekter täiendav aktsia 3	6	Discard
Hansapanga täiendav aktsia 2	30	Discard
Merko Ehitus täiendav aktsia 4	5	Discard
EESTI EHITUS lihtaktsia täiendav 4	2	Discard
OLYMPIC ENTERTAINMENT GROUP aktsia täien	1	Discard
Tallink Grupp aktsia täiendav 8	96	Discard
Tallink Grupp aktsia täiendav 9	8	Discard

Source: created by authors based on NASDAQ OMX data.

Appendix B. Figures

Figure 8. Level of speculativeness by investor age.

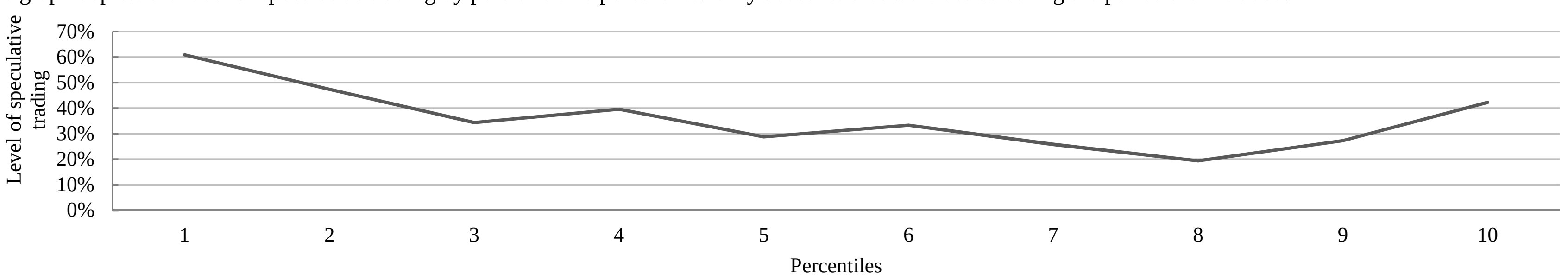
This graph depicts the weighted average level of speculativeness of individual investors for different age groups and for different speculative trading windows.



Source: created by authors based on NASDAQ OMX Tallinn trade-level data.

Figure 9. Level of speculative trading by portfolio size.

This graph depicts the level of speculative trading by portfolio size percentiles. Only accounts that were active during the period are included.



Source: created by authors based on NASDAQ OMX Tallinn trade-level data.

Appendix C. Regression output tables

Table 8. Descriptive statistics for market level model

This table reports descriptive statistics for variables used in the regression analysis. Monthly market return is the 20-day log-return of market index. Dispersion of individual returns is the cross sectional standard deviation of 20-day individual security log-returns. Volatility of market returns is the 20-day standard deviation of daily log-returns of market index. Relative market turnover is the past 20-day cumulative turnover over the sample average 20-day cumulative turnover. 3 week speculative purchases is the relative share of purchases that are speculative, using the 3-week trading window, expressed as the value of purchases that are speculative over the total value of trades during that period. 3 week speculative sales is the relative share of sales that are speculative. 3 week net speculative purchases are the 3 week speculative purchases less the 3 week speculative sales for that period.

Variable		Observations	Mean	St.Dev.	Min	Max
Monthly market return	month_mret	1704	0.0068	0.0851	-0.4719	0.3135
Dispersion of individual returns	month_disp	564	0.0961	0.0508	0.0086	0.3098
Volatility of market returns	mrkt_sdev	1705	0.0117	0.0051	0.0035	0.0343
Relative market turnover	rel_mrkt_turn	1705	1.0000	0.6844	0.1899	3.9524
3 week speculative purchase	3m_buy	1660	0.0541	0.0940	0.0000	0.7518
3 week speculative sales	3m_sell	1660	0.5408	0.0976	0.0000	0.6927
3 week net speculative purchases	3m_net	1660	0.0001	0.0839	-0.1752	0.2965

Source: created by the authors using output STATA.

		Lagged market turnover									
		rm_turn t-1	rm_turn t-2	rm_turn t-3	rm_turn t-4	rm_turn t-5	rm_turn t-6	rm_turn t-7	rm_turn t-8	rm_turn t-9	rm_turn t-10
rm_turn	Coefficient	-0.0713	-0.5265	-0.3827	-0.3473	-0.2931	-0.2846	-0.2748	-0.2514	-0.1730	-0.0925
	SE	0.0262	0.0318	0.0340	0.0347	0.0349	0.0348	0.0342	0.0336	0.0315	0.0257
	P-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
month_mret	Coefficient	0.0070	0.0070	0.0054	0.0010	-0.0005	0.0034	0.0096	0.0141	0.0044	-0.0047
	SE	0.0060	0.0073	0.0078	0.0079	0.0079	0.0079	0.0078	0.0077	0.0072	0.0059
	P-value	0.245	0.333	0.490	0.903	0.955	0.671	0.220	0.066	0.538	0.422
		Lagged market return									
rm_turn	Coefficient	0.3074	0.4083	0.4772	0.5239	0.6205	0.6092	0.4678	0.2745	0.3387	0.1518
	SE	0.1147	0.1582	0.1819	0.1946	0.2053	0.2072	0.2007	0.1871	0.1638	0.1187
	P-value	0.007	0.010	0.009	0.008	0.003	0.003	0.020	0.143	0.039	0.201
month_mret	Coefficient	-0.9667	-0.8286	-0.7527	-0.6592	-0.5011	-0.4608	-0.4065	-0.3146	-0.2224	-0.1166
	SE	0.0262	0.0361	0.0415	0.0448	0.0468	0.0473	0.0458	0.0427	0.0374	0.0271
	P-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

		Exogenous variables						
		Constant	mrkt_sdev t	mrkt_sdev t-1	mrkt_sdev t-2	month_disp t	month_disp t-1	month_disp t-2
rm_turn	Coefficient	3.7526	1.5196	1.0853	0.7742	-0.0163	-0.0376	-0.0180
	SE	5.2008	1.0847	1.2243	1.0896	0.0463	0.0463	0.0462
	P-value	0.471	0.161	0.375	0.478	0.725	0.416	0.697
month_mret	Coefficient	0.0134	-0.0978	-0.2673	-0.2627	-0.0082	-0.0033	-0.0112
	SE	0.4195	0.2475	0.2794	0.2487	0.0106	0.0106	0.0106
	P-value	0.975	0.693	0.339	0.291	0.436	0.752	0.290

Table 9. *The table reports coefficient (coefficient), standard errors (SE) and t-statistics significance levels (p-value) from a VAR of relative monthly turnover (rm_turn) and market return (month_mrett) with 10 lags. The VAR also includes two exogenous variables with two lags for volatility of market returns (mrkt_sdev) and dispersion of individual security returns (month_disp). The regressions were performed using Prais-Winsten estimation.*

Source: created by the authors using output from STATA regressions.

		3m_buy t-1	3m_buy t-2	3m_buy t-3	3m_buy t-4	3m_buy t-5	3m_buy t-6	3m_buy t-7	3m_buy t-8	3m_buy t-9	3m_buy t-10
Lagged speculative purchases											
3m_buy	Coefficient	-0.4957	-0.2444	-0.1706	-0.1258	-0.0536	-0.0290	0.0026	0.0080	-0.0233	-0.0295
	SE	0.0269	0.0310	0.0319	0.0320	0.0321	0.0315	0.0306	0.0304	0.0294	0.0260
	P-value	0.000	0.000	0.000	0.000	0.095	0.357	0.939	0.792	0.428	0.257
month_mret	Coefficient	-0.0275	-0.0457	-0.0219	-0.0453	-0.0842	-0.0573	-0.0165	-0.0295	-0.0134	-0.0349
	SE	0.0380	0.0355	0.0367	0.0369	0.0370	0.0363	0.0352	0.0349	0.0337	0.0298
	P-value	0.372	0.199	0.551	0.221	0.023	0.114	0.639	0.399	0.629	0.241
Lagged market return											
3m_buy	Coefficient	0.0228	0.0069	0.0895	0.1159	0.0935	0.0987	0.0800	0.0872	0.0371	0.0357
	SE	0.0230	0.0312	0.0356	0.0383	0.0399	0.0403	0.0391	0.0368	0.0327	0.0239
	P-value	0.320	0.824	0.012	0.003	0.019	0.014	0.041	0.039	0.256	0.136
month_mret	Coefficient	-0.9680	-0.8326	-0.7619	-0.7633	-0.5096	-0.4679	-0.4075	-0.3056	-0.2132	-0.1154
	SE	0.0266	0.0365	0.0420	0.0454	0.0474	0.0478	0.0463	0.0433	0.0381	0.0276
	P-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

		Constant	mrkt_sdev t	mrkt_sdev t-1	mrkt_sdev t-2	month_disp t	month_disp t-1	month_disp t-2
Exogenous variables								
3m_buy	Coefficient	1.2203	0.1691	-0.0196	-0.1236	0.0062	-0.0082	0.0024
	SE	0.0960	0.2198	0.2479	0.2201	0.0095	0.0095	0.0095
	P-value	0.000	0.442	0.937	0.574	0.511	0.385	0.803
month_mret	Coefficient	0.1889	-0.0666	-0.2132	-0.2566	-0.0117	-0.0041	-0.0116
	SE	0.3822	0.2508	0.2832	0.2513	0.0108	0.0108	0.0108
	P-value	0.621	0.794	0.794	0.307	0.277	0.706	0.282

Table 10. *The table reports coefficient (coefficient), standard errors (SE) and t-statistics significance levels (p-value) from a VAR of three week speculative buy (3m_buy) and market return (month_mrett) with 10 lags. The VAR also includes two exogenous variables with two lags volatility of market returns (mrkt_sdev) and dispersion of individual security returns (month_disp). The regressions were performed using Prais-Winsten estimation.*

Source: created by the authors using output from STATA regressions.

		Lagged speculative sales									
		3m_sellt-1	3m_sellt-2	3m_sellt-3	3m_sellt-4	3m_sellt-5	3m_sellt-6	3m_sellt-7	3m_sellt-8	3m_sellt-9	3m_sellt-10
3m_sell	Coefficient	-0.5022	-0.3255	-0.1588	-0.0736	-0.0328	-0.0097	-0.0375	-0.0006	-0.0032	0.0240
	SE	0.0267	0.0307	0.0322	0.0323	0.0324	0.0139	0.0318	0.0315	0.0300	0.0261
	P-value	0.000	0.000	0.000	0.023	0.311	0.761	0.238	0.984	0.915	0.357
month_mret	Coefficient	0.0191	0.0329	0.0430	-0.0072	-0.0145	-0.0057	0.0037	-0.0205	-0.0429	-0.0298
	SE	0.0272	0.0313	0.0328	0.0330	0.0330	0.0325	0.0323	0.0320	0.0305	0.0265
	P-value	0.484	0.294	0.190	0.827	0.661	0.861	0.908	0.521	0.160	0.262
		Lagged market return									
3m_sell	Coefficient	-0.0185	-0.0321	0.0180	0.0550	0.0815	0.0603	0.0199	0.0260	-0.0104	-0.0137
	SE	0.0261	0.0358	0.0410	0.0442	0.0460	0.0465	0.0451	0.0423	0.0373	0.0271
	P-value	0.479	0.369	0.661	0.213	0.077	0.195	0.659	0.539	0.779	0.612
month_mret	Coefficient	-0.9665	-0.8269	-0.7510	-0.6632	-0.5074	-0.4675	-0.4061	-0.3061	-0.2155	-0.1136
	SE	0.0266	0.0365	0.0419	0.0452	0.0472	0.0476	0.0462	0.0433	0.0381	0.0276
	P-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

		Exogenous variables						
		Constant	mrkt_sdev t	mrkt_sdev t-1	mrkt_sdev t-2	month_disp t	month_disp t-1	month_disp t-2
3m_sell	Coefficient	1.2391	-0.0900	-0.2420	-0.1205	0.0224	-0.0118	0.0067
	SE	0.1245	0.2474	0.2790	0.2481	0.0106	0.0106	0.0106
	P-value	0.000	0.716	0.386	0.627	0.035	0.268	0.529
month_mret	Coefficient	0.0274	-0.0815	-0.2347	-0.2519	-0.0125	-0.0051	-0.0097
	SE	0.4066	0.2514	0.2837	0.2522	0.0108	0.0108	0.0108
	P-value	0.946	0.749	0.408	0.318	0.246	0.634	0.369

Table 11. *The table reports coefficient (coefficient), standard errors (SE) and t-statistics significance levels (p-value) from a VAR of three week speculative sales (3m_sell) and market return (month_mrett) with 10 lags. The VAR also includes two exogenous variables with two lags volatility of market returns (mrkt_sdev) and dispersion of individual security returns (month_disp). The regressions were performed using Prais-Winsten estimation.*

Source: created by the authors using output from STATA regressions.

		Lagged net speculative purchases									
		3m_net t-1	3m_net t-2	3m_net t-3	3m_net t-4	3m_net t-5	3m_net t-6	3m_net t-7	3m_net t-8	3m_net t-9	3m_net t-10
3m_net	Coefficient	-0.4896	-0.2902	-0.1663	-0.1125	-0.0332	-0.0447	-0.0507	-0.0194	0.0019	0.0218
	SE	0.0262	0.0290	0.0298	0.0298	0.0297	0.0289	0.0285	0.0283	0.0271	0.0240
	P-value	0.000	0.000	0.000	0.000	0.263	0.122	0.076	0.494	0.944	0.365
month_mret	Coefficient	-0.0375	-0.0649	-0.0602	-0.0274	-0.0450	-0.0373	-0.0182	-0.0052	0.0291	0.0014
	SE	0.0279	0.0309	0.0319	0.0318	0.0317	0.0319	0.0305	0.0302	0.0289	0.0256
	P-value	0.178	0.037	0.058	0.389	0.152	0.227	0.551	0.864	0.315	0.955
		Lagged market return									
3m_net	Coefficient	0.0353	0.0274	0.0519	0.0517	0.0094	0.0346	0.0490	0.0401	0.0352	0.4410
	SE	0.0248	0.0338	0.0386	0.0415	0.0431	0.0435	0.0422	0.0396	0.0351	0.0256
	P-value	0.154	0.417	0.126	0.213	0.826	0.426	0.246	0.311	0.316	0.086
month_mret	Coefficient	-0.9678	-0.8298	-0.7557	-0.6649	-0.5046	-0.4618	-0.4033	-0.3045	-0.2138	-0.1140
	SE	0.0266	0.0366	0.0420	0.0453	0.0472	0.0476	0.0461	0.0431	0.0379	0.0275
	P-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

		Exogenous variable						
		Constant	mrkt_sdevt	mrkt_sdev t-1	mrkt_sdev t-2	month_disp t	month_disp t-1	month_disp t-2
3m_net								
	Coefficient	-0.0374	0.3258	0.2217	-0.0126	-0.0161	0.0051	-0.0019
	SE	0.0475	0.2357	0.2657	0.2365	0.0101	0.0102	0.0101
	P-value	0.432	0.167	0.404	0.958	0.112	0.615	0.853
month_mret	Coefficient	-0.0077	-0.0774	-0.2570	-0.2622	-0.0131	-0.0033	-0.0104
	SE	0.3701	0.2503	0.2823	0.2511	0.0108	0.0108	0.0108
	P-value	0.983	0.757	0.368	0.297	0.225	0.757	0.335

Table 12. *The table reports coefficient (coefficient), standard errors (SE) and t-statistics significance levels (p-value) from a VAR of three week net speculative trades (3m_net) and market return (month_mrett) with 10 lags. The VAR also includes two exogenous variables with two lags volatility of market returns (mrkt_sdev) and dispersion of individual security returns (month_disp). The regressions were performed using Prais-Winsten estimation.*
Source: created by the authors using output from STATA regressions