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ATTENTION EFFECT IN DECISION MAKING: THE CASE OF BALTIC INVESTORS

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Attention Effect in Decision Making: The Case of Baltic Investors

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Abstract

This research adopts a quasi-natural experimental method in a virtual market simulation to investigate the attention effect among Baltic investors. We define the attention effect as a deviation from rational trading behavior, caused by the allocation of scarce attention when solving a search problem. We expose the participants of the market simulation to an attention-grabbing element in the decision-making environment: a “Hot Stocks” box containing buy recommendations is displayed on the platform. We track whether there are any changes in trading behavior for the hot stocks. We find that on average participants initiated significantly more purchases per hot stock than per any stock, suggesting the presence of an attention effect. In addition, we employ three widely used proxies for investor attention – extreme previous day’s returns, abnormal trading volumes and appearance in news – and obtain results that confirm the main findings. We attempt to evaluate the relationship between an investor’s experience and their susceptibility to the attention effect and find weak evidence that more experience reduces the susceptibility. However, the results are mixed and better proxies for experience are needed.

Keywords: attention effect, Baltic investors, behavioral finance, quasi-natural experiment, decision making.

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Table of Contents

1 Introduction

For quite a long time the traditional discipline of finance has been based on the assumption that people are rational: all agents form correct beliefs about the information they receive, and that they all evaluate these beliefs in a consistent normative way. It has become apparent, however, that models based on such assumptions are not fit to explain how financial markets work in reality. Thus emerged the field of behavioral finance, putting to question the assumption of human rationality (Barberis & Thaler, 2003).

One branch of thought in this field has attempted to employ the knowledge of cognitive psychology in order to explain how exactly human irrationality manifests itself. A large amount of empirical evidence, mainly collected from experimental studies, is being built up to explain how humans form beliefs and preferences, and how they make decisions based on them. (Barberis & Thaler, 2003)

Research on decision making in the financial markets is highly concerned with recent societal changes: the *information age*, brought about by intense developments of technology. Easily accessible vast amounts of information have formed an *information overload* leading to a *search problem*, a phenomenon which encouraged behavioral economists to view *attention* as a scarce cognitive resource (Shapiro, 1998). The scarcity of attention is especially observable in the case of making investment decisions: there could be as many as 3 billion bits of information available to today's average technologically-savvy investor when she decides to invest her savings in common stock (Barber & Odean, 2001). Not surprisingly, such an amount of information cannot be processed by the human mind. The final investment decision is highly biased towards investing in stocks which grab the investor's attention by one way or another (Barber & Odean, 2007). We call such a deviation from rational trading behavior the *attention effect*.

An increasing amount of empirical research is attempting to define the factors which influence the allocation of investors' attention to certain competing bits of information. Most of this research is US- or globally-based, while little research has been done on the behavior of less experienced participants in less developed financial markets. Such knowledge is important if one seeks to understand the possible future course of development for these markets, and it could suggest what kind of policy might be required to protect individual investors who are under the influence of various environmental factors. Moreover, behavior in investment decision making can provide insights to the psychology of decision making on a more general basis (Slovic, 1972).

Thus, we are interested in the presence of the attention effect among investors coming from the transitional economies of the Baltic region, where trading in the stock market can still be classified as a novelty. We are also interested in the specific determinants of investors' attention allocation and how this allocation affects decision making. Therefore, we form the following research question:

To what extent are the investment decisions of Baltic investors influenced by the attention effect?

The setting of our empirical study was an 8-week-long virtual market simulation where we conducted a quasi-natural experiment. We displayed a highly visible box on the platform where participants logged in to place their orders, and we filled this box with a number of buy recommendations – "hot stocks".

The simulation is a unique setting to measure the attention effect. Firstly, the overall environment and the information overload closely resemble real life, which would be unachievable in any laboratory setting. Secondly, all participants have exactly the same choices and the same platform for making decisions, allowing us to expose them to exactly the same treatment ("Hot Stocks"), which would be unachievable in the real life setting.

In order to track whether attention grabbing stocks were traded more we employed the adjusted sorting methodology suggested by Barber and Odean (2007). Moreover, we collected additional information on the participants' preferences and decision-making behavior by means of a registration questionnaire and a survey. This provided us with a more general picture and suggested more interpretations to the results.

Based on the findings of other researchers, we expect the attention effect to be strongly present among the inexperienced Baltic investors. Since they are only starting to accumulate experience in trading, such a finding would support the idea that an individual's overconfidence (a behavioral bias that feeds the attention effect) is determined endogenously, and is only reduced when more experience and knowledge encourages more realistic self-assessment (Gervais & Odean, 2001).

Indeed, the experiment confirmed our expectations: buying activity for the "hot stocks" was relatively higher than the overall purchasing activity. The robustness check employing extreme previous day's returns, abnormal trading volume and appearance in news as attention proxies backed up our findings that on the days of high-attention the attention grabbing stocks are traded more. We obtained mixed indications about the relationship between an investor's experience and her susceptibility to the attention effect.

We begin by providing a theoretical background of the study and an overview of related literature. We continue by describing the methodology used. Subsequently, we discuss the data characteristics. Finally, we present the results, discuss them and conclude.

2 Background of the Study

In this section we show how behavioral finance can help to enhance the understanding of various financial phenomena and, most importantly, individual behavior. This, we believe, will help to grasp the wider context of our research and get an insight of how various psychological factors can affect stock markets.

2.1 Traditional Finance

The traditional finance paradigm rests on the theoretical foundations of the Efficient Market Hypothesis (EMH). The hypothesis has three basic assumptions behind it. Firstly, investors are rational and value securities according to their fundamental values. Secondly, even though there are some irrational investors, their trades cancel out without having effect on prices. Finally, if investors are irrational in similar ways, rational arbitrageurs will eliminate their influence on prices (Shleifer, 2000). Thus, according to EMH security prices in the market fully incorporate all available information and reflect their fundamental values (Shleifer, 2000). Yet, it has become clear that there are many anomalous results that cannot be explained by traditional finance paradigm (Bloomfield, 2006).

2.2 Behavioral Finance

At the end of the 20th century behavioral finance emerged as an alternative to traditional finance. The advocates of behavioral finance argue that adding human psychology and relaxing the assumption of fully rational agents might help to explain aggregate stock market movements, the cross section of average returns and individual trading behavior better (Barberis & Thaler, 2003).

According to Barberis and Thaler (2003) there are two main building blocks of behavioral finance. The first one concerns the "limits to arbitrage". It states that due to the fact that arbitrage is risky, changes in investor sentiment are not fully countered by arbitrageurs and can move security prices from their fundamental values (Shleifer &

Summers, 1990). The second building block of behavioral finance is psychology. It is concerned with people's preferences and deviations from rationality due to their beliefs.

2.3 Behavioral Biases of an Investor

The above mentioned beliefs and preferences can be especially valuable for explaining how individual investors make their portfolio choices (Barberis & Thaler, 2003). A large amount of literature provides evidence that investors diversify their portfolios less than it is optimal. Moreover, when they do diversify, they do this in a naïve way. There is also a bulk of evidence about excessive trading (Barberis & Thaler, 2003). Furthermore, Odean (1998), Grinblatt and Han (2005) and several other studies demonstrate that investors are reluctant to sell stocks that are losing value relative to their purchase price – the phenomenon called "disposition effect" by Shefrin and Statman (1985). Finally, one of the possible behavioralistic explanations for stock purchases might be the attention effect (Barber & Odean, 2007), which we discuss in detail later on.

Due to the fact that the Internet has significantly decreased the costs of investing, provided access to vast quantities of data and information as well as offered a possibility to trade without intermediaries, more people are encouraged to invest in stock markets (Barber & Odean, 2001). Therefore, the above mentioned studies that try to get insights in individual behavior become particularly important.

2.4 Internet Trading

As online trading has spread now so widely, we are particularly interested in behavioral biases caused by the Internet. One could claim that the presence of the Internet even strengthens the irrationality of investors. The possibility to place trades directly leads to an illusion of control over the outcomes of trades that might happen by chance. Moreover, easy access to plentiful information that justifies investors' beliefs and predictions causes an illusion of knowledge (Barber & Odean, 2001). Finally, investors who believe that additional information will help them make better investment decisions seek for evidence that only confirms their expectations and do not try to find contradicting opinions. This leads to overconfidence, which in turn encourages them to trade more actively and speculatively as well as poorly diversify. Such investors have lower expected utilities and make markets more volatile (Odean, 1998).

Indeed, after studying a sample of investors who switch from phone-based to online trading, Barber and Odean (2002) proved that they trade more actively and earn smaller profits not because of possible rational explanations (such as reduced costs or faster execution), but rather due to increased overconfidence boosted by self-attribution bias, the illusion of knowledge and the illusion of control.

2.5 Information Overload and the Search Problem

Plentiful information available to investors on the Internet and its extensive usage brings the problem of information overload. Due to the fact that people are not perfectly but boundedly rational, they have limited cognitive abilities to absorb loads of information accessible to them and cannot rightly asses all of their decisions (Simon, 1978). Therefore, in information rich situations human cognitive capabilities such as attention become scarce resources and allocation of them while making decisions becomes a problem.

A large amount of literature has been dedicated to describing the irrationality and behavioral biases of investors who are facing a search problem because of the information overload. They try to look at how and which information is processed during the problem solving activity before actually evaluating it. Such studies proved that when exposed to excess information people employ less complex decision making strategies that need less cognitive effort and, therefore, might make worse decisions (Keller & Staelin, 1987; Iselin, 1996). In addition, due to increased search and processing costs people might use less information and not necessarily the one that is most relevant for their analysis (Nisbett, Zukier, & Lemley, 1980; Tetlock & Boettger, 1989).

A branch of studies conclude that the way information is presented and accessed might determine which pieces of information will catch investors interest and will be considered further. This is where the attention and framing effects come in, along with the widely researched overconfidence phenomenon.

3 Literature Review

3.1 Defining and Measuring Attention

When researching decision making in the context of information overload, it is convenient to look at attention as a “scarce cognitive resource” (Kahneman, 1973). To figure out how decision makers solve the search problem, therefore, one needs to find out how they allocate their limited attention among the competing pieces of information. The actual attention allocation may result in deviations from rational trading behavior. We call this deviation the *attention effect*.

The presence of the attention effect indicates that investors are, in fact, overconfident. If they were rational, they would expect that the information they observe is also visible to other investors and therefore is already incorporated in the stock price (Barber & Odean, 2007). However, the fact that they do base their buying decisions on such information suggests that they believe this information is valuable, or they feel that they have more expertise solely because they possess such information (Da, Engelberg, & Gao, 2009).

A major issue for researchers of the attention effect is to decide how to detect attention itself, i.e. to determine which pieces of information received the investors' attention. It is convenient to distinguish two types of approach: indirect and direct attention measurement (Da, Engelberg, & Gao, 2009).

3.1.1 Direct measurements.

Little research has been carried out using direct attention measurements, which specifically record instances when an individual focuses on a piece of information. One possibility to employ such measurements is a laboratory setting, which provides the means to control for all the environmental factors. For example, an experimental study has been carried out where limited time was given to solve particular problems on the computer, and the researchers were able to see which and how many pieces of information the subjects chose to allocate their attention to (Gabaix, Laibson, Moloche, & Weinber, 2002). Outside the laboratory, however, tracking attention allocation is nearly impossible. An attempt to measure direct investor attention has been made by Da, Engelberg and Gao (2009) using trends of the Google search engine. They suggest to measure investor attention by the search volume index (SVI) on the Google trends service. This index can be a proxy for how interested investors are in a specific stock as it counts how many times Google users entered the name of this stock in the search engine (thus, allocated their attention) in order to retrieve information.

Yet, even though such a proxy is capable of measuring the intensity of attention, it has serious limitations. Only investors who are not familiar with a particular stock, which attracted their attention, use Google search engine to find information about it. More experienced traders check directly financial websites or other sources they are used to. In addition, there could be a significant amount of searchers who are googling the company for other purposes than investing in it. Therefore, it is very likely that Google SVI grasps the behavior of a sample which does not represent the population of investors.

3.1.2 Indirect measurements.

Given the difficulty of tracking attention allocation directly, we turn to the conventional indirect proxies, which have been widely used among researchers. The indirect measurement is based on logical assumptions of which pieces of information are more likely to be noticed in the financial market setting. For example, scanning such information channels which investors are most likely to use: newspapers, online news services and market trading data.

Several different indirect measurements have proven to be effective. Counting a company's appearance in news, newspaper front pages, or on information channels such as the Dow Jones News Service (Gadarowski, 2002; Barber & Odean, 2007; Yuan, 2009) can predict which pieces of information investors come across while reading the news. Absolute or abnormal trading volume (Barber & Odean, 2007; Hou, Peng, & Xiong, 2008) can be seen as an indirect measurement because high trading activity captures the attention of investors who are merely searching for information. It can also be seen as a direct measurement because it means that investors are already paying attention to the stock. Extremely high or low returns of the previous day can also be attention grabbing (Barber & Odean, 2007) since the "extremes" are often noticed by investors and reported in trading session overviews. Advertising expenditure is another popular proxy which possibly encompasses a much broader part of the environment in which the investor lives (Grullon, Kanatas, & Weston, 2004; Lou, 2009; Chemmanur & Yan, 2009).

3.2 The Attention Effect

The precision of the widely used attention proxies can be debated; nevertheless, empirical research has resulted in rather homogenous insights on the attention effect, no matter which proxies were used. Researchers agree that limited attention has certain implications on investor decision making: investors are more likely to trade stocks which grab their attention. (Barberis & Thaler, 2003).

Most researchers are concerned with how decision making with limited attention can affect stock prices. The problem here is that in many cases high attention can be correlated with a release of economically important information, which indeed implies a change in stock price. Yet, there have been instances of "nothing new" news, or attempts to control for economically important effects of information, leading to the conclusion that information-free attention grabbing events succeed to change investor trading patterns (Yuan, 2009).

Huberman and Regev (2001) analyze a case where a front page New York Times article on the development of possibly cancer curing drugs creates extreme returns for the company's stock, even though the same news had been made public five months ago. What is more, the attention effect spilled over to other stocks in the biotechnology sector despite the fact that the article did not bring any economically significant information about any of these companies.

Advertising effects have been found to have a somewhat similar effect on investor activity. Grullon, Kanatas, Weston (2004) find that product market advertising spills over to the stock market and increases liquidity as well as the number of investors who hold the stock. Chemmanur and Yan (2009) detect that increased advertising expenses lead to a larger return the same year yet smaller return in the subsequent year, due to the fact that advertising increases visibility of the stock in the market. Lou (2009) finds similar effects and adds that in fact marketing managers deliberately increase advertising expenses to influence short-term stock prices.

If advertising has such effects, it is only natural that other means of increasing the visibility of a company should influence trading behavior as well. Gadarowski (2002) finds that a high level of news coverage in financial press for a particular firm can explain overpricing of its stocks. Another attention grabber is stock picking by the so-called ”momentum websites” that release buy recommendations in order to coordinate investor activity. Antunovich and Sarkar (2006) show that indeed such activities may push the stocks into a new liquidity equilibrium. The stocks in question experienced liquidity gains and excess returns on the pick day. Barber and Odean (2007) use three different proxies for attention (extreme returns on the previous day, abnormal trading volume and appearance in news) and find that by every measurement individual investors purchase the high attention stocks more than the low attention stocks.

3.2.1 Individual versus institutional investors.

It is not surprising that the attention effect has more weight for the decisions of individual, less sophisticated investors. Compared to institutional investors who possess better tools and allocate more resources for processing all the available bits of information, individual investors have high search costs and therefore are prone to exhibit rather different behaviour (Barber & Odean, 2007). In other words, investors are not a homogenous group when it comes to making decisions based on information. In the event of firm earnings announcement news, small trades (individual investors) react slower and weaker and they are net buyers (Lee, 1992).

There are certain characteristics about the small individual traders that can explain such behavior. In the event of earnings announcements, small traders buy the stock because the news caught their attention (Lee, 1992), yet they do not short sell as much as institutional investors because they face higher financial and psychological costs.

This notion is supported by Barber and Odean (2007) who find that the search problem has more profound effects on the decisions of individual investors and, even more so, on their buying decisions per se. The reason is that since an individual investor normally makes a sell decision only for the stocks she already owns in her portfolio (and it does not include that many), she does not face a big search problem. When, in contrast, an investor is making a buy decision, she needs to choose from an enormous amount of possibilities and is more likely to settle with a stock that catches her attention.

Even though the attention effect is visible for individual investors and not so much for the institutional ones, empirical evidence suggests that it is strong enough to translate to the aggregate level and affect market prices. Hou, Peng and Xiong (2008) find that in case of earnings announcements, pre-announcement level of overall investor attention to the stock can predict how fast the earnings news will be incorporated into the stock price in the market. Little attention predicts initial underreaction to the news and gradual information incorporation later on, whereas a high level of attention predicts that the price will overreact and reverse afterwards. There is consensus among research findings that in the case of information-free high attention, the attention effect on prices and liquidity wears off in the longer period.

4 Hypotheses

Given the findings of previous research, we post several hypotheses that enable us to structure our study and help answer the question of interest: *to what extent are the investment decisions of Baltic investors influenced by the attention effect?*

As presented in the literature review section, many researchers have proven that individual investors tend to more actively trade stocks that catch their attention. Therefore, we want to test this same hypothesis for our sample:

1) *H_0: investors initiate trades for attention-grabbing stocks as much as for other stocks.*

Barber and Odean (2007) found that individual investors do not make all kinds of trades on the days of high attention, but instead are net buyers. Also, they are net sellers on the days of low attention. Thus, we are interested in testing the following alternative hypotheses:

2) *H_0: investors are equally buyers and sellers during the periods of high attention.*
3) *H_0: investors are equally buyers and sellers during the periods of low attention.*

The same research of Barber and Odean (2007) provided insights into susceptibility to attention effect by different investor groups. They found that the attention effect has less impact on the buying decisions of professional (institutional) investors. Thus, we anticipate similar results for our sample and aim to test the subsequent hypothesis:

4) *H_0: the attention effect does not depend on how experienced the investor is.*

Given the findings of previous research and expecting our proxies for attention to be effective we expect to reject all the above mentioned hypothesis.

5 Methodology

5.1 Quasi-natural Experiment Using Stock Picks

5.1.1 Manipulating investor attention in a quasi-natural experiment.

The environment of the widely used laboratory experiments is highly unrealistic since it can by no means resemble the complex information overload that individuals face in the real life setting. However, the conventional indirect attention proxies offer rather imperfect coverage of the investor's environment and rely on risky assumptions on how and where investors access information. Therefore, we opt to contribute to the research on the attention effect by introducing a quasi-natural experiment in a partly controlled decision-making environment.

Setting our empirical study in a virtual simulation guarantees that all subjects who are about to make a portfolio decision are actually exposed to the attention grabbing event which we deliberately simulate. At the same time, however, participants are surrounded by the same information overload as real stock market investors. In addition, their trades do not influence the prices, therefore, we are able to observe an isolated decision-making action – a convenient simplification which eliminates any ambiguous causality.

5.1.2 Experiment setting: the Investment Game.

The Investment Game 2010 (www.invest-game.com) was used as the main source of data for our research. The game is a real-time stock market simulation organized by the Investment Fund, a student organization of the Stockholm School of Economics in Riga.

During the game participants can create three virtual portfolios (each initially worth 100 000 EUR) and trade with 121 most liquid securities from 6 stock exchanges: Riga, Tallinn, Vilnius, Stockholm and Helsinki Stock Exchanges as well as Russian Trading System. Shares are traded using real-time quotes on the stock exchange; however, orders are executed with approximately 15-minute lag. The players are able to maintain both long and short positions, place both market and limit orders.

The game consists of two rounds, each lasting for four weeks. After the first round 500 players, who have achieved the highest return on their portfolios, advance to the second round. They continue competing for the main monetary prizes, while the rest are able to obtain only weekly prizes. All the players start the second round with new 100 000 EUR worth portfolios. The winners are determined by the value of their portfolios at the end of the second round.

The Investment Game provides a unique means of studying the decisions of individual investors for several reasons. Firstly, it allows us to access the daily portfolio holdings of all the players throughout the game as well as all of their personal information obtained through the use of online questionnaires. Secondly, the game is based on real life data and offers prizes to the best performers; thus, the setting is closer to reality than a laboratory simulation. Third, the number of players is close to 3000 – a conveniently large sample which would not be obtainable in a laboratory experiment.

In addition, due to the fact that externally determined price quotes are used in the game, investor decisions do not have an impact on prices. This allows us to avoid causality biases. Finally, unlike in a real market, we have an opportunity to control certain circumstances of the game.

Nevertheless, the Investment Game does not fully reflect the real life investing process. The rules of the game put some restrictions on transactions that would not be present in a real life setting. For instance, a player cannot buy or sell a single stock at more than 20% of portfolio value or cannot short sell more than 30% of portfolio's initial value. Moreover, there is a limit of 100 orders per day. Also, only the most liquid stocks are traded.

5.1.3 Experiment.

Conventional measures for investor attention are based on certain assumptions on what kind of information the investors are exposed to. In order to capture investors' attention better, we conducted a quasi-natural experiment in the Investment Game, by constructing a tool which exposes the participants to certain attention grabbing pieces of information. This tool has a high probability to be noticed by all the participants who make decisions for their portfolios.

The experiment involved weekly buy recommendations ("stock picks"). In order to simplify the design and due to the fact that Investment Game traders in general tend to buy more than sell, we do not include sell recommendations and focus on tracking solely buying behavior. The tickers of recommended stocks were listed in a visible table entitled "Hot Stocks" on the Investment Game's website, which must be accessed in order to make a trade (see Appendix A). Clicking on the ticker automatically took the players to the page where orders were made, already pre-filled to execute a buy of the recommended stock. Players were able to check the reasoning behind each pick. The advice was given for 6-8 stocks each week.

New recommendations were published each Sunday night, suggesting that some particular stocks would be a worthy purchase in the upcoming week, based mostly on technical analysis. Such weekly-based event allows us to measure the aggregated attention effect over a longer period of time, and to capture the attention of investors who do not access their portfolios every day. In order to have an uncontaminated period which could be used for robustness checks, the stock picks were introduced only during the second four-week round of the game.

We take into account that only 500 best performing players compete in the second round for the main award and the rest of the participants continue playing just for educational purposes and minor prizes. This could cause changes in motivation or activeness of the rest of the players, biasing our results. Therefore, we carry out our calculations only for the subsample of the 500 top players.

5.1.4 Sorting and measuring trading behavior.

By introducing "stock picks" we want to test whether the investors in our sample are susceptible to the attention effect, i.e. whether they are more likely to buy stocks during the week when they are recommended ("hot stocks") and therefore are attention-catching. We adapt the sorting method from Barber and Odean (2007) to sort stocks by their attention grabbing level - in this case, our own "Hot Stocks" proxy.

To analyze the results of the experiment, we aggregate weekly in-game trading data for each stock, i.e. sum up all the buys (B), buy-to-cover deals (BC), sells (S), and short sells (SS) for each stock that appeared during the week following the recommendations' release:

$$WNB_{wi} = \sum_{d=1}^{5} NB_{di} \qquad (1)$$

Here WNB_{wi} is the weekly number of buys for stock i on week w. Weekly number of sells, short sells, and buy to cover deals is calculated in the same way. We also carry out the calculations for trades aggregated on a daily basis.

Subsequently, for each week (or day) we split the stocks according to their noticeability into two partitions: the ones that were recommended in the stock-picking experiment ("hot stocks") and those that were not. We further calculate the buys (B), buy-to-cover deals (BC), sells (S) and short sells (SS) of each stock in each partition on time period *t.*

Barber and Odean (2007) construct their measure of the attention effect based on the idea that some types of decisions involve a search problem (buy decisions), while others don't (sell decisions, due to high costs of short-selling). We follow the same logic to determine which types of decisions in our setting might result in an attention effect. Obviously, buy decisions fall into this category. Unlike in the real life setting, short selling in the simulation has roughly the same financial costs as buying, therefore, if we do not take into account psychological constraints, short selling might also be classified to involve a search problem.

To evaluate the attention effect in the decisions which we classify as affected by the search problem, we construct the following measure which we call the Relative Initiated Trades. It tests the first hypothesis that investors initiate trades for attention grabbing stocks as much as for other stocks. The calculation is adapted from that of Barber and Odean (2007), taking into account the different search problem.

$$RIT_{pt} = \frac{\frac{\sum_{i=1}^{n_{pt}} NIT_{it}}{n_{pt}}}{\frac{NIT_{it}}{n_t}} = \frac{\left(\sum_{i=1}^{n_{pt}} NIT_{it}\right) * n_t}{NIT_{it} * n_{pt}} \qquad (2)$$

Here n_{pt} is the number of stocks in partition *p* at the period of calculation (*t*). NIT_{it} is the number of initiated trades of stock *i* on period *t*. This measure reveals the relative number of initiated trades in each partition on each time period. "Initiated trades" refers to such trades for which decisions are made under the search problem, i.e. buys and short sells. Due to the specification of the experiment (we attempt to influence buying behavior only), *RIT* measure in this case includes only buys. Additionally, we calculate several other specifications of the measurement in order to test the effect of the box on other types of trades.

We repeat all the calculations using the values of trades instead of the numbers, i.e. inserting the money value of stock *i* that was bought (sold, etc.) on day *t*, instead of NIT_{it}.

To draw conclusions, we calculate the mean *RIT* for each partition over the weeks (days) of measurement, excluding the periods where there were less than 5 trades in a particular partition. We also calculate the standard deviation of the daily time series, adjusted for serial dependence using the Newey-West correction.

Under the null hypothesis that investors initiate the same number of trades for attention-grabbing stocks as for other stocks the *RIT* average should be equal to 1. Therefore, if our reasoning is true and the attention effect is present, the mean *RIT* will be higher for the "hot stocks" partition.

5.1.5 Susceptibility to the attention effect by different investor types.

In addition, we are interested in what characterizes the investors who are more susceptible to the attention effect. To do this, we collect descriptive background information on the players by two means: first and most important, the registration questionnaire of the game, and second, a short survey distributed during the game. See the registration questionnaire in Appendix B and the survey in Appendix C.

We are particularly interested in the questions about the characteristics of the players that help to capture their experience and knowledge. Measuring investor experience is rather tricky. Some measurements used in research have been linked to the individual investor's number of securities ever held (Feng & Seasholes, 2005) or the length of owning an account for investment purposes (Chen, Kim, Nofsinger, & Rui, 2007). We do not have access to reliable history of the participants' trading experiences. Instead, we construct several proxies for experience using their data from the registration form and answers in the survey.

Our proxies used are: knowledge of investments (Appendix B, Question 8), possession of a real investment portfolio (Appendix C, Question 2), browsing patterns (Appendix C, Question 4). We also take a closer look at personal information about the participants, such as occupation and gender. Even though not directly related to experience, these characteristics split the sample to distinctive social groups. In light of existing literature on behavioural biases by such social groups (such as gender differences in overconfidence), this may provide interesting insights.

With the help of characteristics' proxies we are able to test our fourth hypothesis that more experienced investors should be as much likely to be affected by the attention effect. We do that in two ways.

First of all, following Barber and Odean (2007), who compared their results for different investor groups, we split the dataset according to the above mentioned characteristics and calculate *RIT* averages for each investor type separately. In order to draw conclusions, we test for the difference between obtained *RIT* means and calculate the standard deviation of the time series.

Second of all, we try to identify possible causalities between the same investor characteristics and the extent to which she is likely to be distracted by the attention effect. In order to do that, we construct a measurement of players' susceptibility to the attention effect in the following way. We count the number of trades each player has executed over the duration of the experiment, and the trades which were executed for stocks classified as attention-grabbing by our buy recommendations. Susceptibility to the attention effect of player *i* is defined as:

$$S_i = \frac{TAT_i}{TT_i} \tag{6}$$

Where TAT_i is the total attention-affected trades by player *i* and TT_i is the total trades by the same player. We calculate the measurement firstly for only purchases of "hot stocks" and then for all the trades made with the recommended stock.

Due to the fact that quite a substantial part of Investment Game players traded rarely in the second round (i.e. approximately one third of all investors made less than five transactions), we include in the sample only those investors who made more than five trades.

We run regressions with S_i as the dependent variable, and the above mentioned descriptive variables as the independent variables.

$$S_i = \alpha + \beta_j\theta_j + \beta_k\pi_k + \varepsilon_i \tag{7}$$

Here α is the intercept, θ_j are the independent variables of interest such as knowledge; π_k are the control variables such as age, gender, experience in investing, etc; and ε_i is the error term.

5.2 Robustness Check: Other Proxies for Attention

We perform a robustness check of our results by additionally measuring investor attention employing three proxies as in Barber and Odean (2007): extreme trading volume, extreme returns and appearance in news. These proxies allow us to examine the attention phenomenon caused by natural external factors.

5.2.1 Extreme returns.

Extreme daily returns gained by some stocks may catch the attention of investors the following day. In some cases such returns are driven by news, yet it is not uncommon that the returns themselves would become news, since many analysts on media channels tend to report such returns in their market overviews. Thus, if investors are influenced by attention, they will be more likely to initiate trades for these extreme winners or losers the following day. The proxy is constructed from daily returns as reported in NASDAQ OMX.

5.2.2 Trading volume.

Of the three, abnormal trading volume is the most direct measure of investor attention since, obviously, in order to trade a stock investors need to pay attention to it. However, there is also an indirect effect – whatever the reasons why some investors trade actively, others may start paying attention to this stock simply because they noticed that it is being highly traded.

We calculate a stock's average trading volume over the previous year. Then, we define abnormal daily trading volume as the daily trading volume over the average figure:

$$AV_{it} = \frac{V_{it}}{\bar{V}_{it}} \qquad (8)$$

$$\bar{V}_{it} = \sum_{d=t-252}^{t-1} \frac{V_{id}}{252} \qquad (9)$$

We measure only the indirect attention effect, where the V_{it} is the volume of stock i traded on day t, as reported by NASDAQ OMX.

5.2.3 Appearance in news.

Appearance of a listed company in the news is a vigorous attention catcher. Any investor who at least opens the morning newspaper or web news portal will come across such news and will thus be possibly influenced when making investment decisions that day.

To measure news coverage, we compile a binary measurement for each day during the period of the study, marking each stock that appeared in the news on that day. We distinguish between different levels of news: news that are specifically about company-related events, news that are related to the subsidiaries, parent companies or other company-related events, and finally news which mention the company in a more general context (such as stock market overviews).

Since our sample is individual investors from the Baltics, many of them having little or no experience, we take into account only those sources which are accessible to them. In order to make sure that we cover all the news sources that our sample reads, we include a question in our short survey asking them to name their most read news sources. The responses indicate that the general news portals such as Delfi are the most common source of news. In the end, our measurement includes Delfi of all three Baltic countries and specialized business news sites vz.lt, aripaev.ee, and db.lv. We also check the Russian versions of these websites because a significant number of residents in the Baltics are Russian-speaking.

5.2.4 Sorting and measuring trading behaviour.

In order to test whether the investors are more likely to buy stocks on the days when they are classified as high attention by the above proxies, we employ similar methodology as for the experiment.

Only the first round data is used for the analysis of the conventional attention proxies so that their attention grabbing abilities would not be overlap with the "hot stocks". We carry out calculations not only for the sub-sample of 500 top performers but also for the whole sample of investors, because during the first part of the game even those who did not transfer to the second round were still motivated by the possibility to win the main prizes.

We start by aggregating daily trading data for each stock by summing up all the different trades for each stock that were added during a particular day. For each day we make independent sorts of the stocks depending on their visibility:

1) We sort the stocks into deciles based on their returns on the previous day.
2) We sort the stocks into deciles based on their abnormal trading volume on that day.
3) For the news proxy, we split the stocks into two partitions: news, and no news.

For each type of sort or split, we calculate the number of all types of trades of each stock in each partition on time period *t* and calculate the Buy-Sell Imbalance for that period as suggested by Barber and Odean (2007):

$$\sum_{i=1}^{n_{pt}} NB_{it} + \sum_{i=1}^{n_{pt}} NBC_{it} + \sum_{i=1}^{n_{pt}} NS_{it} + \sum_{i=1} \square) \qquad (10)$$

Here n_{pt} is the number of stocks in partition *p* at the period of calculation (*t*). NB_{it} (NBC_{it}, NS_{it}, NSS_{it}) is the number of buys (buy-to-cover deals, sells, short sells) of stock *i* on day *t*. This measurement indicates the composition (buying versus selling activities) of trading across partitions.

We make calculations using the values of trades as well. Similarly to the *RIT* measure, we calculate the mean *BSI* over the days of measurement, excluding the days where there were less than 5 trades in a particular partition and the standard deviation of the time series using the Newey-West correction.

Barber and Odean (2007) find that in the case of individual investors the *BSI* is larger for the partitions which include stocks that catch attention, that is, for the highest abnormal volume partition, the lowest and highest return partitions, and for the appearance in news partition. Therefore, under the null hypothesis (2nd and 3rd hypotheses) that investors are equally buyers and sellers during the periods of both high and low attention the BSI measure should be equal to 0.

Due to the specifics of the Investment Game (participants face a search problem not only when buying), we believe that the *RIT* measure should provide more interpretable results. Therefore, we calculate the *RIT* measure for each type of sort or split as well, and test the 1st hypothesis.

Finally, we compute both *RIT* and *BSI* averages separately for different investor groups to once again check what type of investors are susceptible to the attention effect the most. In order to do that we split them according to the same characteristics as for the experiment. We use the whole Baltic sample of investors for these calculations.

6 Data Description

6.1 Trading Characteristics

Out of the total of 3,064 Investment Game 2010 participants, 2,632 players came from the Baltic States and were included in our sample. In total, they possessed 4,478 portfolios, which is 1.7 portfolios per player. They executed 28,049 trades during the first and 9,062 trades during the second round of the game. This amounts to about 14 trades per player. Most of the transactions (72%) were buy orders. Sell orders, short sells or buy to cover deals accounted for 19%, 6% and 3%, respectively. We take into account only executed trades and remove waiting or cancelled orders.

Out of the top 500 players who after the first round proceeded to compete for prizes in the second round, 456 came from the Baltic States and therefore qualified for our sample for the quasi-natural experiment. These players executed 18,229 trades during the two rounds, which is about 40 trades per player, significantly more than the average of all players. 13,427 of these trades were executed during the first round and 4,802 during the second round. Of the top 500 players, only 307 continued trading during the second round.

6.2 Player Characteristics

More detailed information on the players' background, knowledge and experience was obtained from the short registration questionnaire that appeared on the Investment Game 2010 platform (see Appendix B) and the survey which was distributed at the end of the first round (see Appendix C). Each player had to fill in the form before being able to play the game.

The results of the questionnaire revealed that of the Baltic players, 52% came from Lithuania, 38% from Latvia and 10% from Estonia. About the same proportions were kept in the top 500 subsample.

In the whole Baltic sample, the majority of the players were high-school students (36% of the total players), young professionals (27%) or undergraduate students (21%). Among the top 500 players, the majority was working people (30%), 28% were in high school and 25% undergraduate students (see Appendix C, Chart 1). Slightly more than half of all the participants were aged from 20 to 25 (see Appendix C, Chart 2).

The sample consists mostly of inexperienced investors. Almost half of the players had no experience in trading in stock markets, while 29% considered having experience of a year or less (see Appendix C, Chart 3). The most common sources of experience in investing were indicated as hobby and studies. Only 6% and 10% of the persons told to have experience in trading from their job and savings management, respectively (see Appendix C, Chart 4). Only 13% of the players claimed to have good or excellent knowledge in the field, while 51% of them considered their knowledge as basic (see Appendix C, Chart 5).

The subsample of the top 500 players exhibited a somewhat similar distribution of characteristics. Some notable differences were that the percentage of high-school students was smaller, and more participants described their experience in investing coming from a hobby and investment simulation games.

Most players noted that they were participating in the simulation in order to try investing in the stock markets (see Appendix C, Chart 6) and most did not own an investment portfolio (see Appendix C, Chart 7). Almost 60% of the survey respondents answered that they check the state of their portfolio as often as daily or even several times a day. Their main sources of information for making decisions were the stock exchange website and media, of which online news portals were the most popular. The majority, 39% of the participants, stated that when making investment decisions they prefer technical analysis, while 30% preferred their “gut feeling” and 25% fundamental analysis.

As much as 62% of the respondents stated that they sometimes browse the game website, whereas a quarter did not browse at all and 14% followed every publication (see Appendix C, Chart 8). This estimates that about 86% of the participants were very likely to notice the “Hot Stocks” box. The rest 14% were still likely to be distracted by the box when entering the website to place orders, even if they did not deliberately look for information.

6.3 Possible Data Shortcomings

The dataset has several shortcomings. First of all, we had to deal with the problem that due to this being a game with virtual money, a certain share of players were inactive and/or did not take their decisions as seriously as they would have in real life. Alternatively, some players might have followed more active strategies and sought more volatile portfolios than in real life in order to obtain higher returns and win a prize.

It is also important to note that there were some players who registered several times, which is not against the rules. Some of these players might also have created “trial” portfolios for learning or other purposes, which might also create a bias. However, the number of such instances is too small to have any effect on our results.

Secondly, the sample of Investment Game players is not random and truly representative for studying the behaviour of investors from the Baltics: students tend to most actively participate in the game and they constitute the majority of the players. Similarly, the sample is subject to selection bias: although we would like to know the investment behavior of individual Baltic investors, our sample might consist of investors who are more amateur and younger than the average member of the population. Moreover, the reasons why they choose to play the game might be different from the ones why an investor chooses to put her money in the stock markets: they want to try out their skills of investing; they do not have a real portfolio to manage but want to gain experience anyway; they want to test and evaluate their skills compared to other market participants, etc. These weaknesses delimit the possibility of generalizing conclusions inferred from empirical findings to the whole population of the Baltic investors.

7 Results and Discussion

7.1 Quasi-Natural Experiment

7.1.1 Attention effect on the buying behavior.

The “Hot Stocks” box which was inserted in the game platform was a highly visible piece of information, likely to catch the attention of any player accessing the platform to make portfolio decisions. To have a clearly defined measurement of the attention effect, we simplified the purpose of the box to convey only buy recommendations, not sell or hold. Therefore, the attention effect should be present in the participants’ buying decisions only.

If the investors were rational, we should fail to reject the first null hypothesis, which states that investors initiate as many trades for the attention-grabbing stocks as they do for the rest of the stocks. To test this, we calculate the weekly averages of the *RIT* measure for the buy orders in the “hot” and “not hot” partitions (see Table 1 for the detailed results). The results suggest that, in fact, buying activity for the “hot stocks” was relatively higher than the overall buying activity: for the “hot” partition, *RIT*=2.006, which means that there were twice as many purchases per hot stock than there were purchases per any stock. The result is even more extreme when calculating the values rather than the number of trades (*RIT*=2.212), which suggests that these “hot” purchases had even more weight in value.

Table 1*: Weekly and daily averages of trades in “hot” and “not hot” partitions*

	Weekly Averages				**Daily Averages**			
	Hot		**Not Hot**		**Hot**		**Not Hot**	
	Number	*Value*	*Number*	*Value*	*Number*	*Value*	*Number*	*Value*
RIT (B)	2.006	2.212	0.943	0.928	1.979	2.100	0.946	0.935
					(0.294)	(0.270)	(0.015)	(0.0166)
RIT (S & SS)	0.978	0.829	0.999	1.008	0.960	0.798	1.0004	1.011
					(0.168)	(0.159)	(0.008)	(0.008)
RIT (All trades)	1.605	1.562	0.965	0.964	1.621	1.612	0.964	0.962
					(0.191)	(0.242)	(0.0101)	(0.0136)

Note. Compiled by the authors. The table reports the Relative Initiated Trades (RIT) averages during the second round of the simulation. The RIT was calculated for the recommended stocks (“hot”) and all other stocks (“not hot”), using number of trades and value of trades. The rows display calculations using only buy (B) orders, only sell and short-sell (S & SS), and finally all trades. Only orders by the players who qualified as top 500 in the first round were included in the calculations. Under the null hypothesis that the behavior of participants is not affected by the attention-grabbing piece of information, RIT should be equal to 1. An RIT larger than 1 signifies that on average, there were more trades per stock in the particular partition than there were trades per any stock. The standard errors of the time series, as reported in the parenthesis, were computed using the Newey-West adjustment for serial correlation.

Although the weekly aggregate allows us to capture the trading behavior of investors who might not be active every day, daily calculations might be better at showing a more detailed view of how the attention effect manifested during the course of each week. Moreover, our survey revealed that almost 60% of the players access the platform to check the state of their portfolio on a daily basis, justifying daily measurement of the phenomenon.

The average measure of the daily *RIT* for the number of buy orders is estimated at 1.979, which is economically the same result as in the weekly calculations. In addition, we test the time series and find that the measure is statistically significantly higher than 1 at all conventional significance levels. Similarly, the average of the value measure is larger – 2.100.

Considering that new content is placed in the “Hot Stocks” box each Sunday night and kept there throughout the week, we are interested whether the attention effect that it creates changes during the week, i.e. whether participants become indifferent about the displayed information when it becomes stale. To check this, we calculate the average *RIT* buys measure for each weekday. It turns out that on Mondays the average *RIT* measure is 3.538 whereas for the other weekdays – 1.451, 1.799, 2.078 and 1.634 chronologically. These results imply that the attention effect is strongest right after new information has been posted – on Monday. The effect keeps working during the rest of the week as well, but not to the same extent.

7.1.2 Other observations.

Another issue to consider when observing the trading behavior of participants during the experiment is whether the “Hot Stocks” box conveyed the intended message. The purpose of the box was to try to influence buying behavior; yet, on the front page there was no directly visible explanation that these stocks are recommended for buying (rather than selling). A detailed explanation was provided only in the “Detailed Overview” page, which one had to open on purpose. Therefore, we calculate the *RIT* measure for other types of trades as well, in order to determine what effect the box had on them.

The selling and short selling behavior seems to have not been affected by the “Hot Stocks” box. We calculate *RIT* for these two types of trades (in fact, most of the trades were short sells, as selling decisions are very rare due to the specifics of the game). We find that the measure is less than 1 in the “hot” partition and slightly more than 1 for the rest of the stocks, suggesting that there were less selling orders per hot stock than per any stock. However, the results are neither economically nor statistically significant; therefore, little or no attention effect is observed for these types of trades. This supports the idea that the “Hot Stocks” box succeeded in affecting only the targeted type of trades - buys.

We also calculate the RIT measurement for all types of trades at once, checking whether overall trading activity was more intensive in the "hot" partition. Unsurprisingly, both the weekly and daily *RIT* average is around 1.6, meaning that overall there were 60% more trades per hot stock than trades per any stock. The results are statistically significantly different from 1 and similar for number and value measures.

In conclusion, the results of the quasi-natural experiment are consistent across different ways of calculation. The attention-grabbing event created an attention effect i.e. caused the participants' trading choices to be biased towards the stocks which were deliberately placed to catch the decision makers' attention. On the other hand, the interpretation of these results should be careful: it could be argued that buying the recommended stocks is not a behavioral bias but a rational choice of an inexperienced investor to follow advice which she perceives as expert's.

7.2 Attention Effect and Investor Characteristics

We have identified that participants of the simulation were susceptible to the attention effect. Our further interest lies in how certain characteristics of the participants can make them more or less susceptible to our manipulation of their attention. More precisely, the main personal characteristic of our interest is experience.

7.2.1 Knowledge.

Participants were asked to choose the best fitting description of their knowledge on investing: none, basic, good or excellent. The level of understanding investment tools and concepts could be what distinguishes investors who are susceptible to the attention effect from those who are not. To test this we split the sample of investors according to their answer to this question. Very few participants claimed having excellent knowledge; therefore, we cannot draw conclusions from that particular partition. The results of the other three partitions are reported in Appendix E, Table 2. We report only daily results due to the fact that the weekly results do not bring any different conclusions.

The results suggest that on average individuals who had no knowledge on investing along with those who claimed to have good knowledge have been more affected by the attention effect (the *RIT* buys measure in these partitions is above 2), while those with basic knowledge were affected less. However, testing the differences between these measures did not reject the null hypothesis of equal means.

7.2.2 Possession of a real investment portfolio.

Possessing a real investment portfolio outside the simulation game could be a vigorous proxy for whether the participant's trading behavior in-game is determined by their experience, or if it is shaky and can be easily affected by such tools as our "Hot Stocks" box. Therefore, we split the sample according to their answer to the second question of the survey.

The resulting *RIT* measures are higher and statistically significantly larger than 1 for the participants who do not own an investment portfolio or plan to own one in the future. The other participants, who have a certain amount of their wealth invested, have lower *RIT* measures, i.e. their trading behavior was affected less by the "Hot Stocks" box. The *RIT* measures for such players are not statistically significantly different from 1.

We test the difference of the *RIT* means of the "significant amount invested" and "not invested" subsamples and find that this difference is statistically significantly different from 0 at 99% confidence level (t=3.078). This means that participants who do not own a real investment portfolio (thus might be less experienced) were more affected by the "Hot Stocks" box.

7.2.3 Browsing patterns.

Apart from experience, how often and to what extent a player browses the Investment Game website is an important dimension when determining how much their attention was being attracted to the "Hot Stocks" box. More thorough browsing should mean more likeliness to be affected by the box. There are too few observations of players who read all the available information, therefore, we report the results only for those who do not browse at all and those who browse some of the content.

The results imply that both types of players on average were affected by the attention effect, but to a different extent: those who browse the website record a high *RIT* (for hot buys) of 2.3, whereas those who do not browse have an *RIT* of hot buys of 1.6 (see Appendix E, Table 4). The former is statistically significantly different from 1, whereas the latter is not. With a t-statistic of 1.388 we cannot reject the hypothesis of no difference between the samples.

7.2.4 Occupation and gender.

Although not directly related to trading experience, occupation and gender are interesting characteristics to look at as they split the sample to rather distinctive social groups. However, the gender split does not render any significant results: women appear to be as likely as men to trade "hot" stocks relatively more (see Appendix E, Table 6). Splitting by occupation reveals that compared to high-school students and university students, working people have lower *RIT* buy measures calculated both by value and by number (see Appendix E, Table 5). However, this difference is not statistically significantly different from 0.

Overall, we find some evidence that more experience could reduce an investor's susceptibility to the attention effect. However, the results of our proxies are inconsistent and lack significance, suggesting that better proxies for experience are needed in order to investigate this relationship.

7.3 Determinants of Susceptibility to the Attention Effect

To further investigate the relationship between certain investor characteristics and their likeliness to trade with a bias towards attention grabbing stocks, we construct a measure which we call the "susceptibility to the attention effect": the proportion of a player's attention-affected trades to all of her trades. First, the measure is calculated for buys only, then the same is repeated using all types of trades. The calculations are done for the whole top performing sample, but we drop the players who executed 5 trades or less. This leaves us with 214 participants in the sample.

We run regressions with the susceptibility measure as our dependent variable. See Appendix E, Table 7 for a summary of the results. The main variable of interest is knowledge, which has four levels: none (0), basic (1), good (2) and excellent (3). The results imply that each level of knowledge reduces the proportion of attention-affected trades by 11% of total trades, and this result is statistically significantly different from 0 at a 99% confidence interval. Both types of measures – using only buy orders (equation 1 in the table) and all orders (equation 2) – provide the same outcome. Subsequently, from here on we report only the results as calculated with buy orders.

The low R^2 result shows that the equation has little explanatory power. Some other characteristics could be driving the difference in the players' behavior. We argue that age could be correlated with knowledge and could also be another proxy for a participant's experience. Indeed, adding age to the regression increases the explanatory power. Elder participants appear to have been less susceptible to the experiment. Yet this effect is not economically significant (even though it is significant statistically at the 10% significance level).

Adding dummies for occupation (undergraduate student, graduate student and working) to the regression (equation 4) did not bring any significant conclusions. We run a joint test to check if the three dummies together have any explanatory power and find that they do not. We then include the male dummy to check for gender effects and find none (equation 5).

Finally, as suggested by the results of sample splits, we reason that possession of a real investment portfolio might have an effect on the susceptibility to the attention effect. We add the dummies for having a significant investment, an insignificant investment, and planning to invest in the future, but none of them provide any insights (equation 6).

In conclusion, we find that more knowledge about investing decreases the attention-affected trading behavior of individuals, all other things held constant. We do not succeed to find more explanations for the individual's susceptibility to the attention effect, perhaps because of the need for better measures of investor experience. For example, the knowledge characteristic could be inaccurate because the players were not assessing themselves consistently when answering the question. In addition, the period of the quasi-natural experiment could be too short to accumulate observable behavioral tendencies.

7.4 Other Proxies for Attention

In order to check the robustness of the results obtained by the experiment, we employ extreme previous day's returns, abnormal trading volume and appearance in news as other proxies for attention suggested by Barber and Odean (2007). As described in the methodology part, for each proxy we calculate Buy-Sell Imbalance and Relative Initiated Trades measures.

Differently from the *RIT* calculations in the quasi-natural experiment where we intentionally took only buy orders as our interest, for these proxies we calculate the measure using buy and short-sell orders simultaneously. We argue that such a specification of the measurement is reflective of the idea that, given the lack of short-selling constraints in the game, participants face an almost identical search problem for both types of trades.

In order to reject our hypothesis that investors are equally buyers and sellers on the days of high attention, we should obtain positive Buy-Sell imbalances for high-attention partitions and negative ones for low-attention partitions. *RIT* measure higher than 1 would reject the hypothesis that investors initiate the same number of trades for attention grabbing stocks as for other stocks: it would indicate that more trades per an attention-grabbing stock are done as compared to any other stock.

We perform calculations only for the first round data so that the behavior of investors would not be affected by the experimental buy-recommendations.

7.4.1 Returns.

If extreme returns of the previous day are attention grabbing and investors are susceptible to the attention bias, the stocks which experienced such returns should be more likely to enter investors' minds when they are solving a search problem in decision making. Therefore, stocks that had extreme returns should be traded more on the subsequent day. We expect to obtain different measures in the high attention partitions (extremely high returns and extremely low returns) as compared to the middle partitions.

The results generated using the extreme returns proxy for attention are reported in Appendix F, Table 8. The Buy-Sell Imbalance calculated using the return proxy does not provide any insights. The time-series mean is slightly positive in all partitions, meaning that the players of Investment Game are net buyers of stocks regardless whether these stocks experienced relatively high or low returns as compared to other stocks. The result is similar when calculating by the number or value of trades. Therefore, no attention effect is detected. The positive *BSI* measure suggests that the players still face minor non-financial short selling constraints and prefer long positions over short. Yet, such a conclusion should also be tested taking into account the overall movements of the market (for example, in a fastly growing market it is natural that more long than short positions are opened) and the specific trading dynamics of the simulation.

The *RIT* average across the partitions suggests that the investors of our sample on average initiate more trades for the stocks in high attention partitions. The measure is 1.642 for the extremely high and 1.089 for the extremely low returns partitions – on average there were more initiated buys and short sales per attention grabbing stock as compared to other stocks. Yet, testing time-series reveals that only the mean of the extremely high returns is statistically higher than 1 (at 1% significance level), while the measure for extremely low returns is insignificant. Therefore, the effect is stronger for the positive end of the sort, suggesting that on average investors pay attention to positive previous day gains more than to negative. We obtain analogous results calculating the values rather than the number of trades. The difference between the means of the first and last partitions as compared to middle partitions is also statistically significant at least at 5% significance level.

We find evidence of an attention effect in the *RIT* but not in the *BSI* measurement. The difference between these two calculations is that the first one indicates trading activity per stock across partitions, whereas the second one indicates the composition of trading activity (i.e. buying versus selling). Therefore, we find that there is an attention effect for the level of trading activity across partitions (more trades per stock are done in high-attention partitions), but the composition of this activity is not affected (the proportion of buying and selling remains the same).

7.4.2 Volume.

Trading volume is another proxy for when investors pay attention to a particular stock. Therefore, we would expect that on the days when a stock experienced an abnormal trading volume, e.g. it appeared in the highest partition, the value of our measures is higher.

Table 9 in Appendix F presents *BSI* and *RIT* measures for stocks sorted on the current day‘s abnormal trading volume. Similarly to the case of return sorts, *BSI* does not support the idea that investors are net buyers on high attention days: the values of *BSI* are positive in all the partitions and do not differ significantly neither for the number nor value of trades. This once again supports the inference that participants of the game in general buy more and no search problem changes that.

The *RIT* measure, though, proves that on high attention days, investors put relatively more buy and short sell orders: *RIT* average for the first partition, where the trading volume is highest, is statistically significantly higher than 1 (at 1% significance level) and amounts to 1.639. This shows that on average around 60% more trades per a high-attention stock were initiated as compared to all stocks. As expected, the measure for the lowest partition is 0.671, which at 1% significance level is less than 1. The attention effect has less strength, but is still present in the second and third partitions as well. Calculations using the value of trades provide the same results.

7.4.3 News.

Firms that are mentioned in the news are more likely to grab investors’ attention than those that are not; therefore, we again expect to get higher values of our measurements in the partitions of stocks with news..

Table 10 in Appendix F reports the results of our calculations for “news” and “no news” partitions. They are also reported in separate panels according to what type of news is considered to be attention grabbing. Panel A includes only the news that is specifically about company-related events. Panel B additionally incorporates the news that is related to the subsidiaries, parent companies or similar events. Panel C adds news that mentions the company in a more general context (such as stock market overviews). Finally, for a robustness check in Panel D we take into account the fact that news which was published after the stock markets close might be read by the participants only on the subsequent day, and thus affect their trading on that day. However, it is also likely that the participants read the evening news and place trading orders on the same day it was published; therefore, the results of Panel D should be interpreted with care.

We find no support for the idea that investors are net buyers on the days of high attention and sellers on the low attention days as there is no significant difference between the Buy-Sell Imbalance for the two partitions in all the panels. All the imbalances are positive, which supports the fact that investors in general prefer long positions over short.

Nevertheless, the prediction that investors are more likely to buy or short sell on high attention days is confirmed by the *RIT* measure. In Panel A, *RIT* average using number of trades is 0.938 for the stocks without news and 1.918 for those stocks that appeared in the news. Including less significant company-related news in Panel B on average improves the measures: the *RIT* measures are 0.912 and 2.409 for no news and news respectively. However, the difference between the *RIT* means for the “news” partition for these two panels is not statistically significantly different from 0 at 99% confidence level. Therefore, it is hard to say whether news where the company is not the central issue still captures investors’ attention.

Panel C provides interesting results. The *RIT* measure here reaches 7.105 in the partition “news” and decreases to 0.720 for the partition “no news”. Nevertheless, such extreme outcomes might be caused by the fact that this proxy might be wide enough to include simply all actively traded stocks instead of attention grabbing stocks. Thus, economic significance of the measures is questionable.

As expected, Panel D reports economically and statistically similar results to Panel A and does not bring new insights.

Very similar results were obtained using the value of trades instead of the number of trades while calculating both of the measures.

The news proxy was calculated during a relatively short period and in rather small and inactive markets with infrequent newsworthy events: during four weeks of measurement we detected approximately 3.5 company related news per day. Therefore, a longer study period might be needed to increase the reliability of our results.

7.4.4 Susceptibility to the attention effect by different investor groups.

The calculation of both *RIT* and *BSI* measures for different investor groups, which we identified according to the same characteristics as for the sample of top performers used in the experiment, serves us as a robustness check to verify what type of investors are susceptible to the attention effect the most. Yet again we expect more experienced players to be less prone to be biased by the attention effect.

Due to the fact that the *BSI* measure did not provide meaningful and significant results, we calculate only *RIT* measures in this section. Also, because measures calculated according to the value of trades do not bring economically different results, we look only at measures computed using the number of trades. The values of the highest partitions are of particular interest to us, because they indicate the trading activity for attention grabbing stocks.

We first of all look at how the level of knowledge about investments influences a player's susceptibility to the attention effect. The splits for extreme returns and volume proxies provide the same results: investors that have the deepest knowledge are most likely to be affected by the attention effect. This is indicated by the *RIT* measures of the first partition that amount to 1.887 and 2.017 for the positive abnormal returns and abnormal trading volume proxies respectively (see Appendix F, Table 11). The differences between the *RIT* means for investors who have good knowledge of investment and the ones that are less or not knowledgeable at all is significant at 5% and 10% significance levels respectively for both proxies. Such findings might imply that people who understand investment principles employ trading strategies that involve the analysis of stock returns and trading volumes, while those who do not know much about it might simply not examine them. Conversely, the splits for the news proxy do not reveal any significant difference between investors having diverse level of knowledge (see Appendix F, Table 12).

By splitting investors according to their occupation we get opposite results. For working individuals, the *RIT* average in the positive abnormal returns partition is 1.402, which is significantly lower (at 5% significance level) than the measures for high-school, graduate or undergraduate students (that are equal to 1.815 and 1.726 respectively) (see Appendix F, Table 13). Similarly, the *RIT* measure of abnormal trading volume for working individuals is 1.553, while for the other participant groups 1.721 and 1.663 respectively. This might imply that along with increasing "sophistication" of occupation investors tend to be less affected by high-attention events. Again, calculations with the news proxy do not bring any economically and statistically significant results (see Appendix F, Table 14).

We also try to capture participants' experience and the extent to which it strengthens or reduces the attention effect by looking at whether they own a real investment portfolio. The differences between the measurements are statistically and economically insignificant for return and volume proxies, while the news proxy calculations suggest that players who plan to invest in the future are significantly less affected by the attention effect than those who have a significant amount invested (see Appendix F, Tables 15 and 16).

Finally, we split investors according to gender. Extreme returns and abnormal volume proxies indicate that on average women are less susceptible to the attention effect (see Appendix F, Table 17). This is in line with the reasoning that males are more overconfident than females (Barber & Odean, 2001); therefore, they might be too assured when interpreting the implications of extreme returns or trading volume. Yet, testing the differences between measures for females and males did not reject the null hypothesis that the means are equal. The news proxy does not provide any significant insights either (see Appendix F, Table 18).

To summarize, we find that participants who have more knowledge about investing are most likely to be affected by the attention effect. On the contrary a more advanced level of occupation links to lower susceptibility. Finally, men are found to be more affected by the attention effect. Overall, the evidence is mixed and the explanatory power of the differences between measures calculated for different investor splits is not very high. One of the reasons might be that the players answered the questions carelessly. Also, we cannot draw any meaningful conclusions from splits according to the news proxy. Most probably it is because of the relatively short study period and inactive markets.

8 Conclusion

To what extent are the investment decisions of Baltic investors influenced by the attention effect?

In order to answer the proposed research question, we have conducted an empirical study in a unique setting: an online stock market simulation game, played mainly by young inexperienced investors from the Baltic States. We attempted to measure how the participants allocate their attention – a scarce cognitive resource – when they face a search problem, and track how such attention allocation affects their trading decisions. We tried to grab the participants' attention by exposing them to a few visible stock tickers. Knowing that any player who accessed the platform to make decisions would notice these tickers, we were able to measure whether the resulting attention allocation had an impact on their trading behavior.

The results confirm the presence of an attention effect among our sample. On average, players executed purchases of the exposed stocks approximately twice as much as they purchased any stocks. These aggregate results are not only economically, but also statistically significant. In addition, we followed Barber and Odean (2007) to check how the same players are affected by other attention-grabbing pieces of information: extreme previous day's returns, abnormal trading volume and appearance in news. The results are consistent across all attention proxies: players tended to initiate more trades for the stocks which grab their attention in one way or another. Thus, our results are in line with the theory and existing empirical findings.

We checked the extent of the attention effect across different investor groups by splitting the participants according to their characteristics that we obtained with the help of in-game questionnaire. This allowed us to check for a relationship between being susceptible to the attention effect and being experienced in investing. Although there is some evidence that more experienced participants are less susceptible to the attention effect, most of the results of these calculations are mixed. Many of our splits do not provide meaningful results, either because there are not enough observations or because the questionnaire answers are not adequate proxies for the true investor characteristics.

Our study contributes to the existing research in two ways. First of all, it is the first such type of study for relatively young financial markets in the Baltic States. Second of all, we employ a unique setting of an investment simulation game that has more advantages as compared to laboratory and real life settings, due to the possibility to track the daily portfolio holdings and personal information of investors. Most importantly, such a setting allows us to expose them to the same experimental treatment due to exactly the same trading environment.

This paper is a pioneering work measuring attention effect using a virtual investment simulation; therefore, additional research should be done to better understand the issue. The study could be extended by manipulating the simulation environment to affect the investors' behavior in other ways. In addition, to encourage more realistic trading behavior a better motivation system could be applied. This could be done, for instance, by rewarding all participants with monetary prizes proportional to their portfolio return, rather than giving a prize to one best winner. Finally, prolonging the length of the experiment and constructing better proxies for investor's experience should improve the reliability of the results and bring new insights on the phenomenon. With such improvements, the simulation environment could become a practical setting for researching a variety behavioural biases of investors.

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Appendix A: "Hot Stocks"

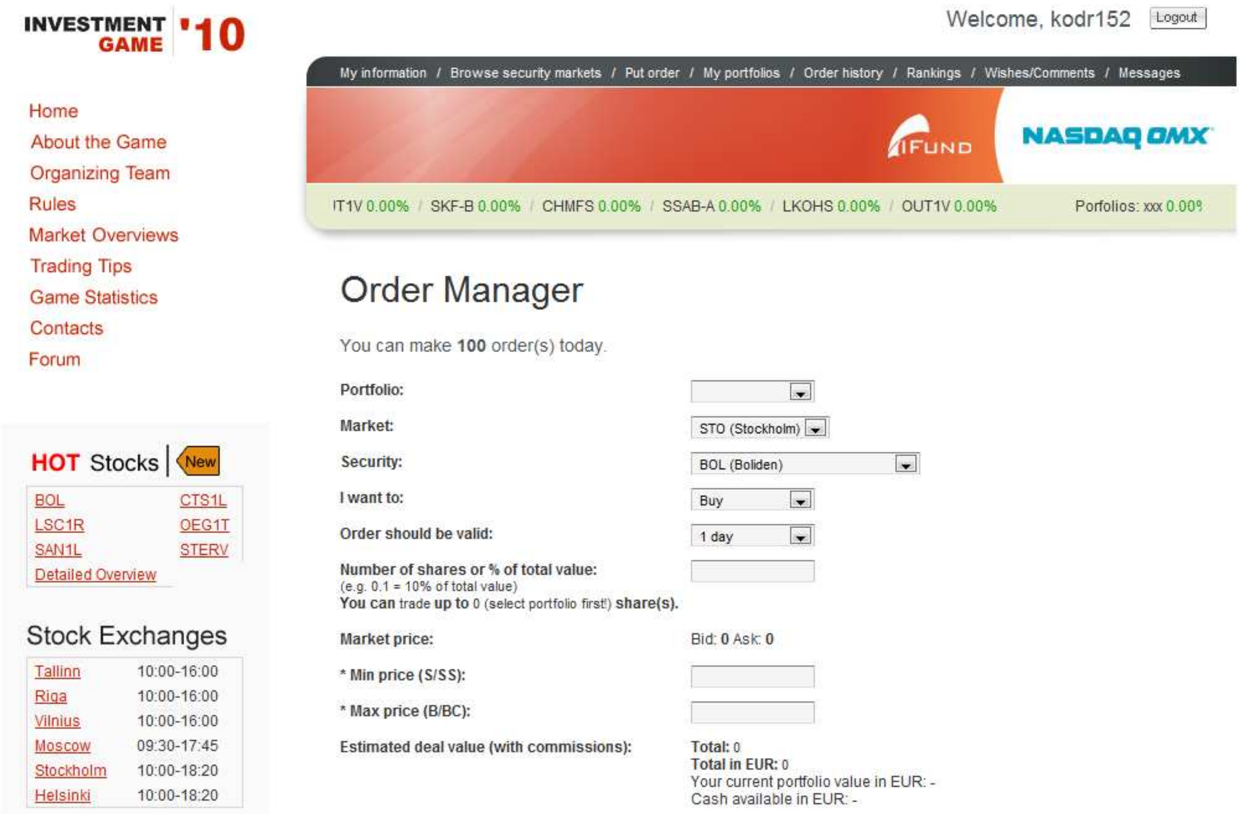

Figure 1. Screenshot of the Investment Game platform. The "Hot Stocks" box is visible on the left-hand side of the website. The whole panel was static while browsing the platform. The heading of the box was colored in red to attract more attention. In addition, the flag "New" was added to even further ensure that the box would be noticed. Clicking on one of the "hot" stocks took the player to the "Order Manager" page (as seen in the screenshot) with an automatically prefilled order to buy the particular stock.

Appendix B: Registration Questionnaire of Investment Game 2010

Below are the registration form questions as they appeared in Investment Game 2010. Each player had to fill in the form before being able to play the game. All the questions were obligatory.

1) Gender:
   - Male
   - Female

2) Year of Birth: *drop-down menu with years from 1900 to 2000*

3) Name

4) Surname

5) Main occupation:
   - High-school student
   - Undergraduate student
   - Graduate student
   - Working
   - Other

6) Your experience in investing: *(multiple answers possible)*
   - None
   - Job
   - Studies
   - Savings management
   - Hobby
   - Investment simulation games
   - Other

7) Length of your experience trading in stock markets:
   - None
   - <1 year
   - 1-3 years
   - 4-6 years
   - 6 and more years

8) Which of the following statements best describes your knowledge of investments?
   - None
   - Basic: I know the basic features of stocks and bonds markets.
   - Good: I am confident with my knowledge of the main capital markets and am familiar with more advanced concepts, such as derivative instruments.
   - Excellent: I have excellent knowledge of all kinds of financial markets and investment theories.

9) From a scale 1 to 7, rate how ready you are to accept risk in order to earn higher returns:
   no risk 1 - 2 - 3 - 4 - 5 - 6 - 7 high risk

10) Institution/Organization:

11) Email:

12) Country: *drop-down menu with all the countries in the world*

Appendix C: Survey as Distributed to the Participants

1) Which of the following statements best describes your purpose of playing Investment Game?
   - You want to win the prizes
   - You want to try investing in the stock markets
   - You want to compete with other players to compare your skills
   - Other

2) Do you also have a real investment portfolio?
   - Yes, I have a significant amount of money invested in stocks, bonds and/or other instruments
   - Yes, but the value of this portfolio is not a significant part of my income
   - No, but I plan to invest in the near future
   - No

If you answered No, please move to question 4.

3) Rate how similar are your investment decisions made for the virtual portfolios as compared to your real ones (1 – completely different, 7 – exactly the same):
   1 - 2 - 3 - 4 - 5 - 6 - 7

4) How often do you check the state of your portfolio on Investment Game?
   - Several times a day
   - Once a day
   - Several times a week
   - Once a week
   - Once a month or less frequently

5) How likely are you to make changes in your portfolio under the following circumstances (1 - very unlikely, 7 - very likely)

Whenever there are news that change my opinion about a stock I own or want to own
1 - 2 - 3 - 4 - 5 - 6 - 7
Whenever there are (un)favourable price changes of the stocks I own or want to own
1 - 2 - 3 - 4 - 5 - 6 - 7

6) Which of these sources are you most likely to use to make your investment decisions? (*Check all applicable answers.)*
   - Company website
   - Stock exchange website
   - Your broker or investment consultant
   - Analysts' evaluations
   - Media (newspapers, radio, etc)
   - Friends', relatives', co-workers' opinions
   - Other (specify:)

7) Which media channels are your most common sources of daily news:
- Newspapers
- TV
- Radio
- Online news portals (such as Delfi.lt / Delfi.lv / Delfi.ee)
- Specialized news portals (such as vz.lt / db.lv / aripaev.ee)
- spekuliantai.lt, traders.lt, treideri.lv, lhv.ee, tarkinvestor.ee and similar websites dedicated to trading
- Others (specify:)

8) How often do you browse for information related to your investment decisions?
- Several times a day
- Once a day
- Several times a week
- Once a week
- A few times a month or less
- Irregularly - whenever I want to make a change to the portfolio

9) Which do you prefer most:
- Fundamental analysis (e.g. company performance indicators)
- Technical analysis (e.g. stock price movement trends)
- Your gut feeling
- Other (specify:)

10) How likely are you to follow publicly available analysts' advice when making portfolio decisions? (1 – very unlikely, 7 – very likely)
1 - 2 - 3 - 4 - 5 - 6 - 7

11) How often do you read market overviews and other information or tips published on invest-game.com?
- I follow every publication
- I sometimes browse the published materials
- I never read this information

•

Appendix D: Player Characteristics

Below we present visual charts describing player characteristics, compiled using their answers to questions in the registration questionnaire (see Appendix A) and survey (see Appendix B).

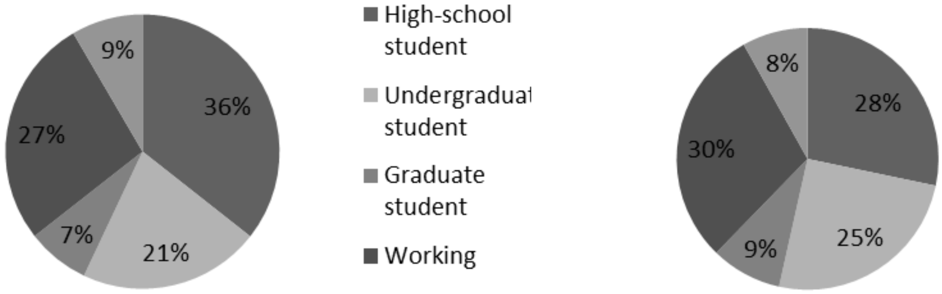

Chart 1 Occupation of the Baltic players: all (left) and top 500 (right)

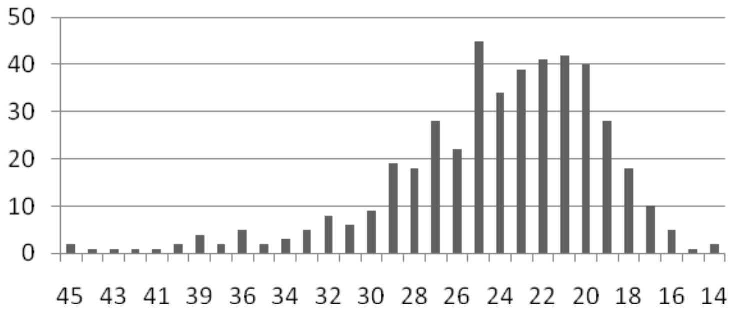

Chart 2 Age distribution of the top 500 players

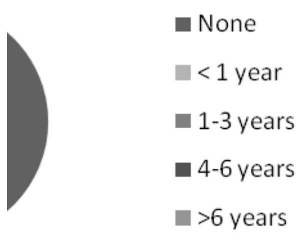

Chart 3 Length of experience in investing of the top 500 players

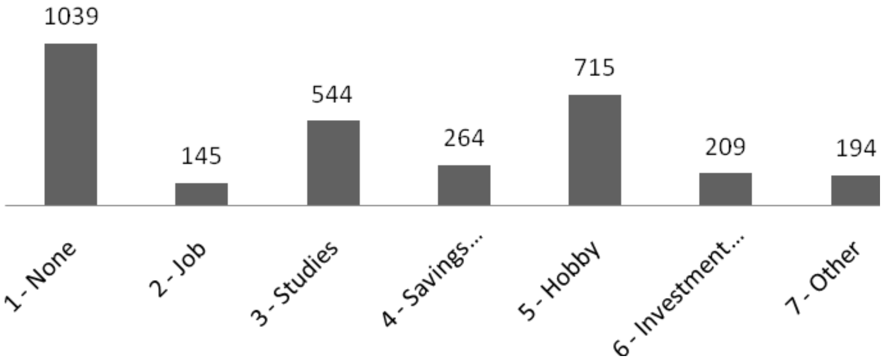

Chart 4 Sources of experience in investing of the Baltic sample

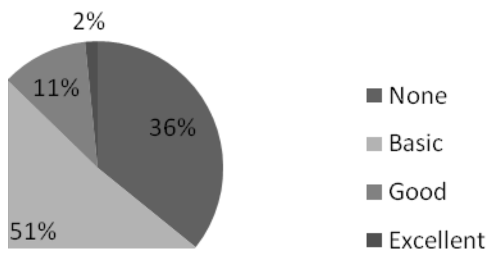

Chart 5 Knowledge on investing (Baltic sample)

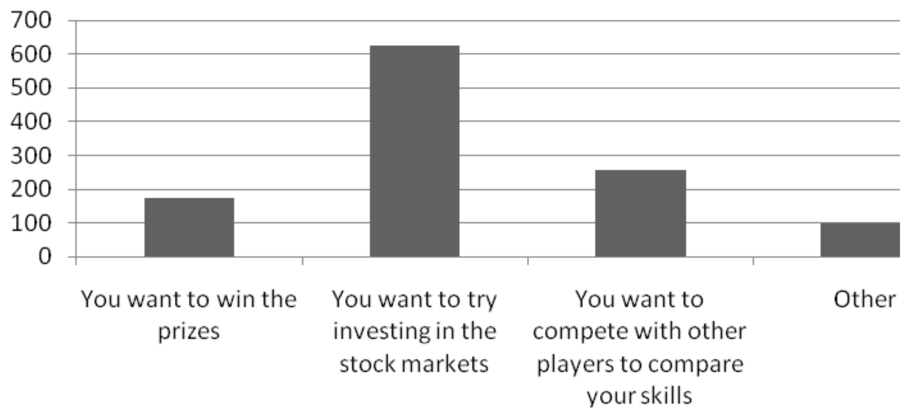

Chart 6 Purpose of playing the Investment Game (Baltic sample)

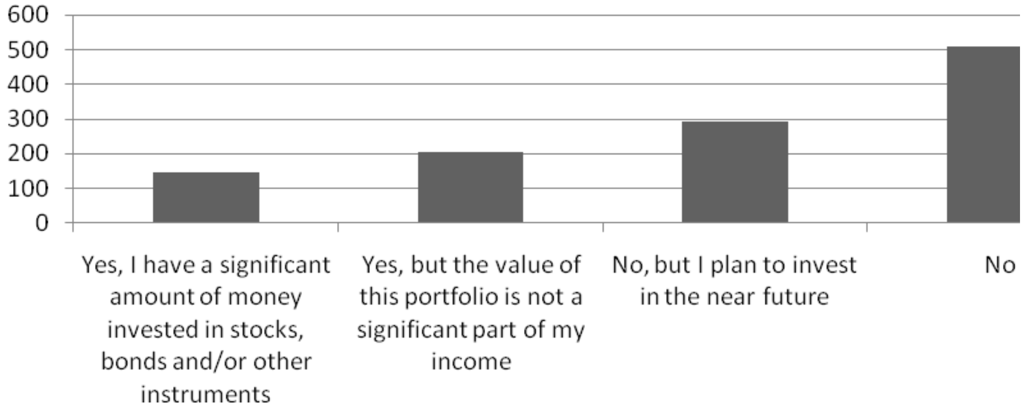

Chart 7. Do you also have a real investment portfolio?

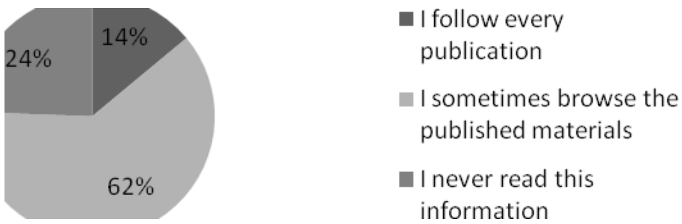

Chart 8. How often do you read market overviews and other information or tips published on invest-game.com?

Appendix E: Results of the Quasi-Natural Experiment

Table 2: *Trades Split According to Knowledge, as Specified by the Participants in the Registration Questionnaire*

	Knowledge: "None"				Knowledge: "Basic"				Knowledge: "Good"			
	Hot		**Not Hot**		**Hot**		**Not Hot**		**Hot**		**Not Hot**	
	Number	*Value*	*Number*	*Value*	*Number*	*Value*	*Number*	*Value*	*Number*	*Value*	*Number*	*Value*
RIT (B)	2.413	2.617	0.920	0.906	1.487	1.850	0.969	0.946	2.370	1.738	0.935	0.964
	(0.551)	(0.660)	(0.0230)	(0.0381)	(0.260)	(0.372)	(0.0149)	(0.0232)	(0.787)	(0.551)	(0.0410)	(0.0296)
RIT (S & SS)	1.423	1.439	0.971	0.971	0.776	0.766	1.0120	1.0126	0.798	0.869	1.009	1.008
	(0.461)	(0.515)	(0.0266)	(0.0305)	(0.191)	(0.262)	(0.0096)	(0.0136)	(0.287)	(0.391)	(0.0158)	(0.0209)
RIT (All trades)	2.204	2.506	0.929	0.912	1.244	1.486	0.983	0.968	1.915	1.310	0.956	0.986
	(0.417)	(0.536)	(0.0229)	(0.0296)	(0.227)	(0.300)	(0.0122)	(0.0177)	(0.498)	(0.402)	(0.0258)	(0.0216)

Note. Compiled by the authors. The table reports the Relative Initiated Trades (RIT) averages during the second round of the simulation. The daily RIT was calculated for the recommended stocks ("hot") and all other stocks ("not hot"), using number of trades and value of trades. The rows display calculations using only buy (B) orders, only sell and short-sell (S & SS), and finally all trades. Only orders by the players who qualified as top 500 in the first round were included in the calculations. Under the null hypothesis that the behavior of participants is not affected by the attention-grabbing piece of information, RIT should be equal to 1. An RIT larger than 1 signifies that on average, there were more trades per stock in the particular partition than there were trades per any stock. The standard errors of the time series, as reported in the parenthesis, were computed using the Newey West adjustment for serial correlation.

Table 3: *Trades Split According to Possession of a Real Investment Portfolio, as Specified by the Participants in the Survey*

	Invest: significant amount				Invest: insignificant amount				Invest: in the future				Invest: no			
	Hot		**Not Hot**		**Hot**		**Not Hot**		**Hot**		**Not Hot**		**Hot**		**Not Hot**	
	Number	*Value*	*Number*	*Value*	*Number*	*Value*	*Number*	*Value*	*Number*	*Value*	*Number*	*Value*	*Number*	*Value*	*Number*	*Value*
RIT (B)	1.134	1.177	0.989	0.985	1.37	0.977	0.977	0.995	2.808	2.896	0.909	0.898	2.196	2.474	0.931	0.914
	(0.348)	(0.39)	(0.0195)	(0.0231)	(0.485)	(0.307)	(0.0256)	(0.0192)	(0.796)	(0.69)	(0.0402)	(0.0372)	(0.354)	(0.408)	(0.0214)	(0.0247)
RIT (All)	1.196	1.299	0.986	0.979	0.817	0.706	1.032	1.015	2.012	2.065	0.946	0.94	1.844	1.93	0.95	0.944
	(0.399)	(0.406)	(0.0201)	(0.0227)	(0.182)	(0.204)	(0.0079)	(0.0298)	(0.276)	(0.39)	(0.0147)	(0.0221)	(0.269)	(0.312)	(0.015)	(0.0176)

Note. Compiled by the authors. The table reports the Relative Initiated Trades (RIT) averages during the second round of the simulation. The daily RIT was calculated for the recommended stocks ("hot") and all other stocks ("not hot"), using number of trades and value of trades. The rows display calculations using only buy (B) orders, only sell and short-sell (S & SS), and finally all trades. Only orders by the players who qualified as top 500 in the first round were included in the calculations. Under the null hypothesis that the behavior of participants is not affected by the attention-grabbing piece of information, RIT should be equal to 1. An RIT larger than 1 signifies that on average, there were more trades per stock in the particular partition than there were trades per any stock. The standard errors of the time series, as reported in the parenthesis, were computed using the Newey West adjustment for serial correlation.

***Table 4**: Trades Split According to the Frequency of Browsing the Investment Game Content, as Specified by the Participants in the Survey*

	Browse sometimes				**Browse never**			
	Hot		**Not Hot**		**Hot**		**Not Hot**	
	Number	*Value*	*Number*	*Value*	*Number*	*Value*	*Number*	*Value*
RIT (B)	2.297	2.292	0.932	0.927	1.582	1.720	0.960	0.951
	(0.369)	(0.274)	(0.0180)	(0.0166)	(0.397)	(0.442)	(0.0245)	(0.0280)
RIT (S&SS)	1.169	1.130	0.988	0.993	0.225	0.360	1.042	1.035
	(0.226)	(0.293)	(0.0114)	(0.0153)	(0.127)	(0.217)	(0.00716)	(0.0118)
RIT (All)	1.779	1.786	0.956	0.953	1.279	1.462	0.980	0.968
	(0.184)	(0.267)	(0.0101)	(0.0154)	(0.284)	(0.345)	(0.0157)	(0.0199)

Note. Compiled by the authors. The table reports the Relative Initiated Trades (RIT) averages during the second round of the simulation. The daily RIT was calculated for the recommended stocks ("hot") and all other stocks ("not hot"), using number of trades and value of trades. The rows display calculations using only buy (B) orders, only sell and short-sell (S & SS), and finally all trades. Only orders by the players who qualified as top 500 in the first round were included in the calculations. Under the null hypothesis that the behavior of participants is not affected by the attention-grabbing piece of information, RIT should be equal to 1. An RIT larger than 1 signifies that on average, there were more trades per stock in the particular partition than there were trades per any stock. The standard errors of the time series, as reported in the parenthesis, were computed using the Newey West adjustment for serial correlation.

***Table 5:** Trades Split According to Occupation, as Specified by the Participants in the Registration Questionnaire*

	High-school students				**Undergraduate and Graduate students**				**Working**			
	Hot		**Not Hot**		**Hot**		**Not Hot**		**Hot**		**Not Hot**	
	Number	*Value*	*Number*	*Value*	*Number*	*Value*	*Number*	*Value*	*Number*	*Value*	*Number*	*Value*
RIT (B)	2.395	2.275	0.923	0.921	2.460	2.674	0.919	0.906	1.657	1.355	0.969	0.978
	(0.407)	(0.501)	(0.0223)	(0.033)	(0.604)	(0.613)	(0.0315)	(0.0333)	(0.464)	(0.318)	(0.020)	(0.0182)
RIT (S & SS)	1.0871	1.127	0.990	0.992	1.070	1.510	0.996	0.973	0.809	0.643	1.012	1.019
	(0.342)	(0.356)	(0.0188)	(0.018)	(0.273)	(0.686)	(0.014)	(0.0353)	(0.288)	(0.271)	(0.0149)	(0.0148)
RIT (All trades)	1.942	1.908	0.946	0.943	1.950	2.104	0.946	0.935	1.304	1.094	0.985	0.993
	(0.267)	(0.371)	(0.0160)	(0.0231)	(0.357)	(0.411)	(0.0188)	(0.0236)	(0.221)	(0.236)	(0.0105)	(0.0134)

Note. Compiled by the authors. The table reports the Relative Initiated Trades (RIT) averages during the second round of the simulation. The daily RIT was calculated for the recommended stocks ("hot") and all other stocks ("not hot"), using number of trades and value of trades. The rows display calculations using only buy (B) orders, only sell and short-sell (S & SS), and finally all trades. Only orders by the players who qualified as top 500 in the first round were included in the calculations. Under the null hypothesis that the behavior of participants is not affected by the attention-grabbing piece of information, RIT should be equal to 1. An RIT larger than 1 signifies that on average, there were more trades per stock in the particular partition than there were trades per any stock. The standard errors of the time series, as reported in the parenthesis, were computed using the Newey West adjustment for serial correlation.

Table 6: *Trades Split According to Gender, as Specified by the Participants in the Registration Questionnaire*

	Males				Females			
	Hot		Not Hot		Hot		Not Hot	
	Number	*Value*	*Number*	*Value*	*Number*	*Value*	*Number*	*Value*
RIT (B)	2.044	2.143	0.943	0.933	2.056	2.433	0.934	0.905
	0.29	0.265	0.0151	0.0161	0.547	0.823	0.0338	0.0551
RIT (S & SS)	0.762	0.774	1.013	1.012	2.524	2.109	0.912	0.94
	0.153	0.201	0.00783	0.0103	0.921	0.958	0.0484	0.05
RIT (All trades)	1.611	1.62	0.966	0.962	1.968	1.981	0.938	0.935
	0.196	0.26	0.0102	0.0144	0.411	0.502	0.0267	0.0344

Note. Compiled by the authors. The table reports the Relative Initiated Trades (RIT) averages during the second round of the simulation. The daily RIT was calculated for the recommended stocks ("hot") and all other stocks ("not hot"), using number of trades and value of trades. The rows display calculations using only buy (B) orders, only sell and short-sell (S & SS), and finally all trades. Only orders by the players who qualified as top 500 in the first round were included in the calculations. Under the null hypothesis that the behavior of participants is not affected by the attention-grabbing piece of information, RIT should be equal to 1. An RIT larger than 1 signifies that on average, there were more trades per stock in the particular partition than there were trades per any stock. The standard errors of the time series, as reported in the parenthesis, were computed using the Newey West adjustment for serial correlation.

Table 7: *Determinants of Susceptibility to the Attention Effect (Regression Analysis)*

	(1) SusB	(2) SusT	(3) SusB	(4) SusB	(5) SusB	(6) SusB
Knowledge	-0.109**	-0.107**	-0.111**	-0.106**	-0.109**	-0.101**
	(0.029)	(0.029)	(0.0288)	(0.0293)	(0.029)	(0.0305)
Age			-0.00375	-0.00349	-0.00368	-0.00453*
			(0.00226)	(0.00245)	(0.00227)	(0.00217)
Undergrad				-0.0442		
				(0.0549)		
Grad				-0.0317		
				(0.0834)		
Working				-0.0544		
				(0.0535)		
Male					-0.0512	
					(0.0633)	
InvestBig						-0.042
						(0.0660)
InvestSmall						-0.0443
						(0.0611)
InvestFuture						-0.0006
						(0.0571)
_cons	0.498**	0.487**	0.597**	0.616**	0.639**	0.599**
	(0.0333)	(0.0333)	(0.0657)	(0.0741)	(0.0821)	(0.0662)
R^2	0.0398	0.0389	0.0498	0.0512	0.388	0.0566

Note. The table reports results of regressions with "Susceptibility to the attention effect" as the dependent variable. SusB stands for the susceptibility measurement using only buy orders, and SusT – all trades. The control variables were constructed from the participants' answers to the respective questions in the registration questionnaire and survey. ** stands for 99%, and * - for 95% level of statistical significance. Heteroscedasticisty robust standard errors are reported in parenthesis below the coefficients.

Appendix F: Results of Other Proxies

Table 8: *Averages of Daily Measurements Calculated Using Previous Day's Returns as a Proxy for Attention*

All Baltic Investors				
	RIT		**BSI**	
	Number	*Value*	*Number*	*Value*
1	1.642	1.675	0.323	0.307
	(0.108)	(0.124)	(0.078)	(0.085)
2	1.030	1.020	0.330	0.333
	(0.055)	(0.064)	(0.079)	(0.091)
3	0.828	0.823	0.324	0.322
	(0.033)	(0.048)	(0.095)	(0.095)
4	0.981	0.994	0.385	0.376
	(0.119)	(0.122)	(0.086)	(0.094)
5	0.889	0.891	0.406	0.375
	(0.073)	(0.078)	(0.068)	(0.088)
6	0.842	0.836	0.369	0.347
	(0.089)	(0.100)	(0.106)	(0.111)
7	0.905	0.892	0.433	0.412
	(0.067)	(0.074)	(0.084)	(0.099)
8	0.837	0.815	0.420	0.392
	(0.043)	(0.047)	(0.083)	(0.097)
9	0.954	0.954	0.456	0.447
	(0.094)	(0.105)	(0.073)	(0.078)
10	1.089	1.096	0.411	0.386
	(0.080)	(0.094)	(0.075)	(0.083)

Note. Compiled by the authors. The table reports the Buy-Sell Imbalance (BSI) and Relative Initiated Trades (RIT) averages for the stocks sorted on the basis of the previous day's returns. The rows represent the measures for the different partitions of stocks where partition 1 includes stocks that had the highest previous day's return. The measures were calculated using both the value and number of trades. The calculations were done only for the first round of the simulation and included all the sample of Baltic participants. Under the null hypothesis that investors are equally buyers and sellers on the days of high and low attention, BSI should be equal to 0. Positive BSI would indicate that on average on the days of high attention participants purchase more then sell. Under the null hypothesis that the behavior of participants is not affected by the attention, RIT should be equal to 1. An RIT larger than 1 would indicate that, on average, there were more trades per stock in a particular partition than there were trades per any stock. The standard errors of the time series, as reported in the parenthesis, were computed using the Newey West adjustment for serial correlation.

Table 9. *Averages of Daily Measurements Calculated Using Abnormal Trading Volume as a Proxy for Attention*

	All Baltic investors			
	RIT		**BSI**	
	Number	*Value*	*Number*	*Value*
1	1.639	1.701	0.351	0.334
	(0.115)	(0.133)	(0.079)	(0.085)
2	1.449	1.489	0.394	0.380
	(0.095)	(0.114)	(0.062)	(0.085)
3	1.269	1.286	0.341	0.296
	(0.065)	(0.061)	(0.085)	(0.096)
4	1.002	1.024	0.377	0.365
	(0.085)	(0.075)	(0.090)	(0.091)
5	0.814	0.787	0.370	0.356
	(0.058)	(0.061)	(0.090)	(0.089)
6	0.797	0.782	0.382	0.379
	(0.081)	(0.100)	(0.087)	(0.088)
7	0.751	0.712	0.384	0.314
	(0.040)	(0.044)	(0.067)	(0.081)
8	0.815	0.786	0.351	0.301
	(0.080)	(0.082)	(0.091)	(0.094)
9	0.821	0.811	0.298	0.277
	(0.059)	(0.066)	(0.107)	(0.115)
10	0.671	0.650	0.305	0.303
	(0.064)	(0.060)	(0.099)	(0.112)

Note. Compiled by the authors. The table reports the Buy-Sell Imbalance (BSI) and Relative Initiated Trades (RIT) averages for the stocks sorted on the basis of the abnormal trading volume. The rows represent the measures for the different partitions of stocks where partition 1 includes stocks that had the biggest abnormal trading volume. The measures were calculated using both the value and number of trades. The calculations were done only for the first round of the simulation and included all the sample of Baltic participants. Under the null hypothesis that investors are equally buyers and sellers on the days of high and low attention, BSI should be equal to 0. Positive BSI would indicate that on average on the days of high attention participants purchase more then sell. Under the null hypothesis that the behavior of participants is not affected by the attention, RIT should be equal to 1. An RIT larger than 1 would indicate that, on average, there were more trades per stock in a particular partition than there were trades per any stock. The standard errors of the time series, as reported in the parenthesis, were computed using the Newey West adjustment for serial correlation.

Table 10:

All Baltic investors				
	RIT		**BSI**	
	Number	*Value*	*Number*	*Value*
Panel A: only news that are specifically about company-related events				
News	1.918	1.882	0.285	0.272
	(0.192)	(0.174)	(0.092)	(0.105)
No News	0.938	0.938	0.312	0.293
	(0.016)	(0.015)	(0.088)	(0.092)
Panel B: news related to the company, to its subsidiaries or parent company				
News	2.409	2.350	0.307	0.294
	(0.271)	(0.250)	(0.085)	(0.099)
No News	0.912	0.915	0.310	0.293
	(0.019)	(0.017)	(0.089)	(0.092)
Panel C: all company related news and market overviews				
News	7.105	7.330	0.295	0.272
	(1.011)	(1.136)	(0.080)	(0.089)
No News	0.720	0.716	0.313	0.299
	(0.033)	(0.030)	(0.095)	(0.098)
Panel D: taking into account the time of news				
News	1.976	1.956	0.301	0.259
	(0.186)	(0.183)	(0.093)	(0.111)
No News	0.934	0.934	0.311	0.293
	(0.014)	(0.014)	(0.089)	(0.094)

Averages of Daily Measurements Calculated Using Appearance in News as a Proxy for Attention

Note. Compiled by the authors. The table reports the Buy-Sell Imbalance (BSI) and Relative Initiated Trades (RIT) averages for the stocks sorted into two partitions according to their presence in news. The rows represent the measures for the stocks that appeared in the news and those that did not. The results are divided into four panels distinguishing between different levels of news. The measures were calculated using both the value and number of trades. The calculations were done only for the first round of the simulation and included all the sample of Baltic participants. Under the null hypothesis that investors are equally buyers and sellers on the days of high and low attention, BSI should be equal to 0. Positive BSI would indicate that on average on the days of high attention participants purchase more then sell. Under the null hypothesis that the behavior of participants is not affected by the attention, RIT should be equal to 1. An RIT larger than 1 would indicate that, on average, there were more trades per stock in a particular partition than there were trades per any stock. The standard errors of the time series, as reported in the parenthesis, were computed using the Newey West adjustment for serial correlation.

***Table 11**: Averages of Relative Initiated Trades (RIT) Calculated Using Returns and Abnormal Trading Volume as Proxies for Attention and Split According to Players' Knowledge, as Specified in the Registration Questionnaire*

	Knowledge: "None"				**Knowledge: "Basic"**				**Knowledge: "Good"**			
	Returns		**Volumes**		**Returns**		**Volumes**		**Returns**		**Volumes**	
	Number	*Value*	*Number*	*Value*	*Number*	*Value*	*Number*	*Value*	*Number*	*Value*	*Number*	*Value*
1	1.584	1.608	1.518	1.636	1.643	1.698	1.674	1.719	1.887	1.823	2.017	1.972
	(0.099)	(0.110)	(0.127)	(0.147)	(0.119)	(0.137)	(0.134)	(0.148)	(0.160)	(0.188)	(0.217)	(0.278)
2	1.059	1.046	1.398	1.448	1.018	1.033	1.419	1.431	0.989	0.911	1.603	1.656
	(0.056)	(0.070)	(0.075)	(0.104)	(0.061)	(0.073)	(0.108)	(0.121)	(0.096)	(0.095)	(0.193)	(0.218)
3	0.764	0.807	1.236	1.284	0.869	0.817	1.294	1.267	0.842	0.869	1.256	1.308
	(0.065)	(0.082)	(0.082)	(0.100)	(0.033)	(0.062)	(0.087)	(0.072)	(0.094)	(0.062)	(0.094)	(0.095)
4	0.904	0.921	1.009	1.016	1.029	1.056	1.003	1.060	0.909	0.849	0.923	0.889
	(0.071)	(0.095)	(0.073)	(0.084)	(0.172)	(0.179)	(0.100)	(0.085)	(0.088)	(0.079)	(0.096)	(0.105)
5	0.834	0.843	0.852	0.793	0.947	0.926	0.826	0.829	0.822	0.896	0.635	0.588
	(0.074)	(0.081)	(0.081)	(0.088)	(0.082)	(0.087)	(0.065)	(0.072)	(0.129)	(0.080)	(0.059)	(0.095)
6	0.801	0.774	0.892	0.859	0.854	0.874	0.781	0.780	0.941	0.906	0.563	0.575
	(0.088)	(0.107)	(0.073)	(0.072)	(0.087)	(0.093)	(0.088)	(0.115)	(0.124)	(0.135)	(0.111)	(0.122)
7	0.964	1.010	0.744	0.698	0.850	0.796	0.768	0.730	0.848	0.852	0.660	0.658
	(0.078)	(0.078)	(0.053)	(0.049)	(0.076)	(0.090)	(0.048)	(0.067)	(0.108)	(0.111)	(0.081)	(0.100)
8	0.898	0.810	0.799	0.730	0.812	0.826	0.793	0.788	0.628	0.619	0.936	0.930
	(0.062)	(0.052)	(0.077)	(0.074)	(0.053)	(0.066)	(0.090)	(0.098)	(0.100)	(0.101)	(0.131)	(0.157)
9	1.037	1.034	0.881	0.921	0.924	0.906	0.785	0.744	0.973	1.061	0.862	0.884
	(0.086)	(0.099)	(0.100)	(0.116)	(0.118)	(0.109)	(0.052)	(0.058)	(0.177)	(0.211)	(0.063)	(0.101)
10	1.147	1.139	0.698	0.646	1.053	1.065	0.683	0.679	1.147	1.197	0.579	0.576
	(0.066)	(0.080)	(0.086)	(0.099)	(0.108)	(0.116)	(0.059)	(0.049)	(0.138)	(0.168)	(0.105)	(0.083)

Note. RIT averages for the stocks sorted on the basis of the previous day's returns and that day's abnormal trading volume. The rows represent the measures for the different partitions of stocks where partition 1 includes stocks that had the highest previous day's return or the biggest abnormal trading volume. The measures were calculated using both the value and number of trades. The calculations were done only for the first round of the simulation and included all the sample of Baltic participants. Under the null hypothesis that the behavior of participants is not affected by the attention, RIT should be equal to 1. An RIT larger than 1 would indicate that, on average, there were more trades per stock in a particular partition than there were trades per any stock. The standard errors of the time series, as reported in the parenthesis, were computed using the Newey West adjustment for serial correlation.

Table 12: *Averages of Relative Initiated Trades (RIT) by Presence in News, Split According to Players' Knowledge*

	Knowledge: "None"		**Knowledge: "Basic"**		**Knowledge: "Good"**	
	Number	*Value*	*Number*	*Value*	*Number*	*Value*
Panel A: only news that are specifically about company-related events						
News	1.942	1.802	1.894	1.904	1.865	1.889
	(0.227)	(0.140)	(0.173)	(0.193)	(0.309)	(0.358)
No News	0.937	0.947	0.937	0.934	0.945	0.944
	(0.020)	(0.014)	(0.015)	(0.017)	(0.017)	(0.020)
Panel B: news related to the company, to its subsidiaries or parent company						
News	2.410	2.209	2.421	2.422	2.284	2.286
	(0.303)	(0.210)	(0.240)	(0.259)	(0.432)	(0.480)
No News	0.913	0.926	0.909	0.907	0.925	0.925
	(0.022)	(0.016)	(0.018)	(0.019)	(0.021)	(0.023)
Panel C: all company related news and market overviews						
News	6.471	6.654	7.414	7.684	7.960	8.025
	(0.850)	(0.872)	(1.135)	(1.368)	(1.395)	(1.431)
No News	(0.744	0.740	0.707	0.705	0.696	0.692
	(0.031)	(0.030)	(0.035)	(0.033)	(0.031)	(0.031)
Panel D: taking into account the time of news						
News	1.882	1.744	2.048	2.090	1.869	1.862
	(0.148)	(0.133)	(0.235)	(0.235)	(0.311)	(0.360)
No News	0.940	0.950	0.928	0.924	0.942	0.944
	(0.014)	(0.011)	(0.017)	(0.018)	(0.019)	(0.021)

Note. Compiled by the authors. The table reports the Buy-Sell Imbalance (BSI) and Relative Initiated Trades (RIT) averages for the stocks sorted into two partitions according to their presence in news. The rows represent the measures for the stocks that appeared in the news and those that did not. The results are divided into four panels distinguishing between different levels of news. The measures were calculated using both the value and number of trades. The calculations were done only for the first round of the simulation and included all the sample of Baltic participants. Under the null hypothesis that investors are equally buyers and sellers on the days of high and low attention, BSI should be equal to 0. Positive BSI would indicate that on average on the days of high attention participants purchase more then sell. Under the null hypothesis that the behavior of participants is not affected by the attention, RIT should be equal to 1. An RIT larger than 1 would indicate that, on average, there were more trades per stock in a particular partition than there were trades per any stock. The standard errors of the time series, as reported in the parenthesis, were computed using the Newey West adjustment for serial correlation.

***Table 13**: Averages of Relative Initiated Trades (RIT) Calculated Using Returns and Abnormal Trading Volume as Proxies for Attention and Split According to Players' Occupation, as Specified in the Registration Questionnaire*

	High-school Students				**Graduate and Undergraduate Students**				**Working**			
	Returns		**Volume**		**Returns**		**Volume**		**Returns**		**Volume**	
	Number	Value	Number	Value	Number	Value	Number	Value	Number	Value	Number	Value
1	1.815	1.704	1.721	1.737	1.726	1.841	1.663	1.707	1.402	1.521	1.553	1.662
	(0.155)	(0.131)	(0.163)	(0.207)	(0.216)	(0.220)	(0.131)	(0.131)	(0.090)	(0.108)	(0.084)	(0.122)
2	1.068	1.065	1.324	1.415	1.061	1.003	1.493	1.505	0.975	0.990	1.549	1.589
	(0.076)	(0.103)	(0.117)	(0.160)	(0.065)	(0.087)	(0.127)	(0.127)	(0.073)	(0.086)	(0.124)	(0.131)
3	0.847	0.842	1.340	1.319	0.826	0.758	1.274	1.255	0.821	0.847	1.219	1.289
	(0.075)	(0.065)	(0.090)	(0.095)	(0.063)	(0.078)	(0.073)	(0.076)	(0.031)	(0.036)	(0.104)	(0.080)
4	0.871	0.875	0.966	0.966	0.958	0.979	0.982	1.097	1.143	1.117	1.070	1.048
	(0.100)	(0.103)	(0.103)	(0.104)	(0.109)	(0.118)	(0.084)	(0.101)	(0.187)	(0.178)	(0.094)	(0.083)
5	0.857	0.898	0.729	0.712	0.824	0.825	0.729	0.735	0.924	0.961	0.854	0.826
	(0.107)	(0.090)	(0.104)	(0.100)	(0.094)	(0.108)	(0.061)	(0.072)	(0.073)	(0.085)	(0.061)	(0.062)
6	0.884	0.902	0.782	0.784	0.810	0.849	0.763	0.759	0.848	0.786	0.854	0.813
	(0.093)	(0.128)	(0.070)	(0.100)	(0.091)	(0.098)	(0.100)	(0.139)	(0.117)	(0.116)	(0.099)	(0.106)
7	0.916	0.940	0.652	0.663	0.928	0.897	0.772)	0.727	0.904	0.871	0.840	0.760
	(0.081)	(0.090)	(0.036)	(0.050)	(0.096)	(0.090)	(0.090)	(0.096)	(0.082)	(0.096)	(0.062)	(0.043)
8	0.772	0.732	0.856	0.846	0.811	0.807	0.739	0.660	0.894	0.830	0.820	0.816
	(0.074)	(0.087)	(0.143)	(0.120)	(0.078)	(0.117)	(0.083)	(0.089)	(0.065)	(0.052)	(0.063)	(0.080)
9	0.875	0.893	0.895	0.845	0.942	0.924	0.855	0.831	0.996	0.966	0.742	0.742
	(0.110)	(0.084)	(0.060)	(0.073)	(0.121)	(0.140)	(0.088)	(0.087)	(0.109)	(0.127)	(0.063)	(0.065)
10	1.092	1.141	0.755	0.734	1.106	1.110	0.750	0.746	1.086	1.105	0.538	0.496
	(0.095)	(0.101)	(0.069)	(0.060)	(0.123)	(0.117)	(0.084)	(0.068)	(0.080)	(0.127)	(0.065)	(0.071)

Note. RIT averages for the stocks sorted on the basis of the previous day's returns and that day's abnormal trading volume. The rows represent the measures for the different partitions of stocks where partition 1 includes stocks that had the highest previous day's return or the biggest abnormal trading volume. The calculations were done only for the first round of the simulation and included all the sample of Baltic participants. Under the null hypothesis that the behavior of participants is not affected by the attention, RIT should be equal to 1. An RIT larger than 1 would indicate that, on average, there were more trades per stock in a particular partition than there were trades per any stock. The standard errors of the time series, as reported in the parenthesis, were computed using the Newey West adjustment for serial correlation.

Table 14: *Averages of Relative Initiated Trades (RIT) Calculated According to Presence in News as Proxy for Attention and, Split According to Players' Occupation, as Specified in the Registration Questionnaire*

	High-school Students		**Graduate and Undergraduate Students**		**Working**	
	Number	*Value*	*Number*	*Value*	*Number*	*Value*
Panel A: only news that are specifically about company-related events						
News	2.106	2.002	1.732	1.865	1.998	1.852
	(0.238)	(0.194)	(0.215)	(0.230)	(0.265)	(0.215)
No News	0.932	0.936	0.948	0.941	0.930	0.936
	(0.017)	(0.015)	(0.017)	(0.016)	(0.021)	(0.019)
Panel B: news related to the company, to its subsidiaries or parent company						
News	2.576	2.486	2.226	2.341	2.572	2.350
	(0.296)	(0.284)	(0.260)	(0.301)	(0.331)	(0.262)
No News	0.906	0.911	0.923	0.917	0.902	0.910
	(0.020)	(0.018)	(0.017)	(0.017)	(0.022)	(0.020)
Panel C: all company related news and market overviews						
News	7.245	7.192	7.319	7.817	7.122	7.211
	(0.944)	(1.017)	(1.165)	(1.373)	(1.081)	(1.123)
No News	0.707	0.716	0.718	0.705	0.722	0.717
	(0.035)	(0.034)	(0.032)	(0.026)	(0.038)	(0.039)
Panel D: taking into account the time of news						
News	2.120	2.086	1.780	1.923	2.058	1.934
	(0.261)	(0.218)	(0.174)	(0.201)	(0.279)	(0.242)
No News	0.931	0.931	0.945	0.939	0.926	0.932
	(0.015)	(0.014)	(0.013)	(0.013)	(0.021)	(0.018)

Note. Compiled by the authors. The table reports the Buy-Sell Imbalance (BSI) and Relative Initiated Trades (RIT) averages for the stocks sorted into two partitions according to their presence in news. The rows represent the measures for the stocks that appeared in the news and those that did not. The results are divided into four panels distinguishing between different levels of news. The measures were calculated using both the value and number of trades. The calculations were done only for the first round of the simulation and included all the sample of Baltic participants. Under the null hypothesis that investors are equally buyers and sellers on the days of high and low attention, BSI should be equal to 0. Positive BSI would indicate that on average on the days of high attention participants purchase more then sell. Under the null hypothesis that the behavior of participants is not affected by the attention, RIT should be equal to 1. An RIT larger than 1 would indicate that, on average, there were more trades per stock in a particular partition than there were trades per any stock. The standard errors of the time series, as reported in the parenthesis, were computed using the Newey West adjustment for serial correlation.

***Table 15**: Averages of Relative Initiated Trades (RIT) Calculated Using Returns and Abnormal Trading Volume as Proxies for Attention and Split According to Players' Possession of a Real Investment Portfolio, as Specified in the Registration Questionnaire*

	Invest significant amount				**Invest: insignificant amount**				**Invest: in the future**				**Invest: no**			
	Returns		**Volumes**		**Returns**		**Volumes**		**Returns**		**Volumes**		**Returns**		**Volumes**	
	Number	*Value*	*Number*	*Value*	*Number*	*Value*	*Number*	*Value*	*Number*	*Value*	*Number*	*Value*	*Number*	*Value*	*Number*	*Value*
1	1.747	1.912	1.650	1.723	1.591	1.856	1.662	1.873	1.661	1.527	1.720	1.699	1.690	1.527	1.653	1.699
	(0.195)	(0.222)	(0.127)	(0.192)	(0.100)	(0.135)	(0.108)	(0.134)	(0.173)	(0.176)	(0.134)	(0.167)	(0.133)	(0.176)	(0.142)	(0.168)
2	0.842	0.764	1.506	1.504	1.128	1.195	1.548	1.523	1.008	1.002	1.549	1.513	1.034	1.002	1.309	1.397
	(0.150)	(0.154)	(0.104)	(0.152)	(0.112)	(0.119)	(0.143)	(0.175)	(0.035)	(0.046)	(0.133)	(0.155)	(0.069)	(0.046)	(0.089)	(0.121)
3	0.814	0.809	1.260	1.320	0.754	0.771	1.141	1.181	0.929	0.958	1.266	1.246	0.835	0.958	1.313	1.347
	(0.049)	(0.068)	(0.116)	(0.153)	(0.059)	(0.092)	(0.079)	(0.084)	(0.043)	(0.073)	(0.065)	(0.072)	(0.045)	(0.073)	(0.094)	(0.090)
4	1.010	0.857	1.157	1.082	0.976	0.974	1.007	1.076	1.072	1.044	1.029	1.061	0.946	1.044	0.979	1.055
	(0.089)	(0.076)	(0.138)	(0.171)	(0.183)	(0.173)	(0.077)	(0.081)	(0.190)	(0.187)	(0.102)	(0.107)	(0.100)	(0.187)	(0.090)	(0.099)
5	0.914	0.953	0.785	0.832	0.838	0.851	0.916	0.770	0.903	0.909	0.777	0.853	0.851	0.909	0.776	0.732
	(0.090)	(0.098)	(0.098)	(0.098)	(0.088)	(0.093)	(0.067)	(0.061)	(0.123)	(0.123)	(0.106)	(0.114)	(0.090)	(0.123)	(0.075)	(0.076)
6	0.920	0.696	0.799	0.764	0.839	0.768	0.688	0.598	0.812	0.855	0.749	0.755	0.825	0.855	0.817	0.800
	(0.092)	(0.109)	(0.149)	(0.159)	(0.150)	(0.148)	(0.082)	(0.090)	(0.089)	(0.088)	(0.119)	(0.132)	(0.093)	(0.088)	(0.053)	(0.078)
7	0.757	0.754	0.760	0.675	0.849	0.828	0.844	0.756	0.967	1.043	0.717	0.738	0.912	1.043	0.759	0.715
	(0.087)	(0.102)	(0.133)	(0.117)	(0.095)	(0.107)	(0.063)	(0.070)	(0.113)	(0.139)	(0.079)	(0.066)	(0.102)	(0.139)	(0.056)	(0.053)
8	0.973	0.990	0.940	0.950	0.827	0.771	0.953	0.914	0.772	0.765	0.776	0.724	0.850	0.765	0.740	0.676
	(0.075)	(0.115)	(0.151)	(0.124)	(0.109)	(0.046)	(0.123)	(0.158)	(0.057)	(0.079)	(0.080)	(0.076)	(0.054)	(0.079)	(0.075)	(0.080)
9	0.853	0.983	0.756	0.795	1.070	0.957	0.778	0.813	0.786	0.787	0.789	0.847	0.993	0.787	0.881	0.826
	(0.103)	(0.146)	(0.095)	(0.133)	(0.123)	(0.108)	(0.085)	(0.090)	(0.106)	(0.098)	(0.082)	(0.094)	(0.110)	(0.098)	(0.060)	(0.065)
10	1.158	1.260	0.434	0.404	1.116	1.028	0.504	0.535	1.088	1.110	0.657	0.598	1.065	1.110	0.791	0.773
	(0.127)	(0.151)	(0.102)	(0.102)	(0.104)	(0.107)	(0.071)	(0.060)	(0.100)	(0.104)	(0.098)	(0.106)	(0.103)	(0.104)	(0.070)	(0.063)

Note. Compiled by the authors. RIT averages for the stocks sorted on the basis of the previous day's returns and that day's abnormal trading volume. The rows represent the measures for the different partitions of stocks where partition 1 includes stocks that had the highest previous day's return or the biggest abnormal trading volume. The measures were calculated using both the value and number of trades. The calculations were done only for the first round of the simulation and included all the sample of Baltic participants. Under the null hypothesis that the behavior of participants is not affected by the attention, RIT should be equal to 1. An RIT larger than 1 would indicate that, on average, there were more trades per stock in a particular partition than there were trades per any stock. The standard errors of the time series, as reported in the parenthesis, were computed using the Newey West adjustment for serial correlation.

***Table 16**: Averages of Relative Initiated Trades (RIT) Calculated According to Presence in News as Proxy for Attention and Split According to Players' Possession of a Real Investment Portfolio, as Specified in the Registration Questionnaire*

	Invest: significant amount		**Invest: insignificant amount**		**Invest: in the future**		**Invest: no**	
	Number	*Value*	*Number*	*Value*	*Number*	*Value*	*Number*	*Value*
Panel A: only news that are specifically about company-related events								
News	2.001	1.956	2.050	2.260	1.784	1.644	1.942	1.823
	(0.198)	(0.218)	(0.235)	(0.253)	(0.214)	(0.140)	(0.224)	(0.172)
No News	0.929	0.930	0.927	0.912	0.945	0.953	0.941	0.946
	(0.022)	(0.020)	(0.021)	(0.024)	(0.016)	(0.011)	(0.014)	(0.012)
Panel B: news related to the company, to its subsidiaries or parent company								
News	2.482	2.448	2.541	2.635	2.205	2.043	2.494	2.380
	(0.235)	(0.237)	(0.284)	(0.315)	(0.267)	(0.209)	(0.350)	(0.288)
No News	0.902	0.905	0.902	0.892	0.922	0.932	0.913	0.918
	(0.024)	(0.020)	(0.021)	(0.025)	(0.019)	(0.014)	(0.018)	(0.015)
Panel C: all company related news and market overviews								
News	8.924	9.678	7.812	8.307	6.699	6.674	7.101	7.062
	(2.022)	(2.403)	(1.125)	(1.133)	(0.889)	(1.039)	(1.111)	(1.148)
No News	0.670	0.653	0.686	0.654	0.738	0.749	0.726	0.733
	(0.034)	(0.033)	(0.043)	(0.042)	(0.030)	(0.026)	(0.029)	(0.026)
Panel D: taking into account the time of news								
News	1.953	1.894	2.385	2.531	1.841	1.688	1.988	1.911
	(0.214)	(0.253)	(0.268)	(0.304)	(0.276)	(0.205)	(0.220)	(0.213)
No News	0.934	0.931	0.905	0.894	0.940	0.949	0.938	0.943
	(0.020)	(0.021)	(0.021)	(0.024)	(0.019)	(0.014)	(0.011)	(0.010)

Note. Compiled by the authors. The table reports the Buy-Sell Imbalance (BSI) and Relative Initiated Trades (RIT) averages for the stocks sorted into two partitions according to their presence in news. The results are divided into four panels distinguishing between different levels of news. The measures were calculated using both the value and number of trades. The calculations were done only for the first round of the simulation and included all the sample of Baltic participants. Under the null hypothesis that investors are equally buyers and sellers on the days of high and low attention, BSI should be equal to 0. Positive BSI would indicate that on average on the days of high attention participants purchase more then sell. Under the null hypothesis that the behavior of participants is not affected by the attention, RIT should be equal to 1. An RIT larger than 1 would indicate that, on average, there were more trades per stock in a particular partition than there were trades per any stock. The standard errors of the time series, as reported in the parenthesis, were computed using the Newey West adjustment for serial correlation.

***Table 17**: Averages of Relative Initiated Trades (RIT) Calculated Using Returns and Abnormal Trading Volume as Proxies for Attention and Split According to Players' Gender, as Specified in the Registration Questionnaire*

	Males				**Females**			
	Returns		**Volumes**		**Returns**		**Volumes**	
	Number	*Value*	*Number*	*Value*	*Number*	*Value*	*Number*	*Value*
1	1.671	1.724	1.683	1.722	1.572	1.394	1.500	1.542
	(0.107)	(0.125)	(0.130)	(0.130)	(0.134)	(0.130)	(0.129)	(0.222)
2	1.018	1.009	1.425	1.479	1.143	1.128	1.526	1.558
	(0.056)	(0.070)	(0.090)	(0.130)	(0.095)	(0.099)	(0.130)	(0.179)
3	0.823	0.792	1.259	1.256	0.834	0.952	1.299	1.418
	(0.030)	(0.039)	(0.069)	(0.074)	(0.086)	(0.152)	(0.077)	(0.119)
4	0.960	0.967	1.003	1.017	1.073	1.102	1.033	1.068
	(0.117)	(0.111)	(0.086)	(0.076)	(0.152)	(0.168)	(0.125)	(0.105)
5	0.871	0.875	0.804	0.781	0.906	0.982	0.847	0.840
	(0.079)	(0.075)	(0.062)	(0.061)	(0.112)	(0.113)	(0.070)	(0.089)
6	0.863	0.847	0.790	0.774	0.742	0.800	0.839	0.861
	(0.088)	(0.097)	(0.091)	(0.108)	(0.117)	(0.143)	(0.075)	(0.114)
7	0.897	0.898	0.747	0.728	0.916	0.856	0.762	0.667
	(0.070)	(0.076)	(0.042)	(0.052)	(0.073)	(0.076)	(0.070)	(0.067)
8	0.834	0.818	0.850	0.810	0.812	0.785	0.650	0.669
	(0.047)	(0.044)	(0.097)	(0.093)	(0.074)	(0.093)	(0.064)	(0.069)
9	0.937	0.934	0.818	0.816	1.040	1.090	0.801	0.752
	(0.092)	(0.101)	(0.068)	(0.067)	(0.114)	(0.140)	(0.083)	(0.116)
10	1.118	1.130	0.651	0.647	0.964	0.914	0.762	0.655
	(0.079)	(0.091)	(0.071)	(0.062)	(0.127)	(0.146)	(0.060)	(0.072)

Note. Compiled by the authors. RIT averages for the stocks sorted on the basis of the previous day's returns and that day's abnormal trading volume. The rows represent the measures for the different partitions of stocks where partition 1 includes stocks that had the highest previous day's return or the biggest abnormal trading volume. The measures were calculated using both the value and number of trades. The calculations were done only for the first round of the simulation and included all the sample of Baltic participants. Under the null hypothesis that the behavior of participants is not affected by the attention, RIT should be equal to 1. An RIT larger than 1 would indicate that, on average, there were more trades per stock in a particular partition than there were trades per any stock. The standard errors of the time series, as reported in the parenthesis, were computed using the Newey West adjustment for serial correlation.

***Table 18**: Averages of Relative Initiated Trades (RIT) Calculated According to Presence in News as Proxy for Attention and Split According to Players' Gender, as Specified in the*

	Males		Females	
	Number	*Value*	*Number*	*Value*
Panel A: only news that are specifically about company-related events				
News	1.900	1.879	1.976	1.831
	(0.192)	(0.169)	(0.242)	(0.278)
No News	0.938	0.939	0.935	0.939
	(0.016)	(0.015)	(0.019)	(0.021)
Panel B: all company related news				
News	2.401	2.373	2.388	2.152
	(0.270)	(0.257)	(0.318)	(0.291)
No News	0.912	0.914	0.913	0.923
	(0.019)	(0.017)	(0.022)	(0.021)
Panel C: all comapany related news and market overviews				
News	7.230	7.517	6.543	6.227
	(1.000)	(1.157)	(1.052)	(1.003)
No News	0.712	0.706	0.750	0.769
	(0.035)	(0.031)	(0.029)	(0.029)
Panel D: taking into account the time of news				
News	1.969	1.948	2.018	1.913
	(0.178)	(0.171)	(0.269)	(0.331)
No News	0.934	0.935	0.929	0.935
	(0.014)	(0.013)	(0.019)	(0.022)

Registration Questionnaire

Note. Compiled by the authors. The table reports the Buy-Sell Imbalance (BSI) and Relative Initiated Trades (RIT) averages for the stocks sorted into two partitions according to their presence in news. The rows represent the measures for the stocks that appeared in the news and those that did not. The results are divided into four panels distinguishing between different levels of news. The measures were calculated using both the value and number of trades. The calculations were done only for the first round of the simulation and included all the sample of Baltic participants. Under the null hypothesis that investors are equally buyers and sellers on the days of high and low attention, BSI should be equal to 0. Positive BSI would indicate that on average on the days of high attention participants purchase more then sell. Under the null hypothesis that the behavior of participants is not affected by the attention, RIT should be equal to 1. An RIT larger than 1 would indicate that, on average, there were more trades per stock in a particular partition than there were trades per any stock. The standard errors of the time series, as reported in the parenthesis, were computed using the Newey West adjustment for serial correlation.