ESSAYS ON THE BEHAVIOUR OF FINNISH RETAIL INVESTORS IN THE STOCK MARKET

Mika Pirneskoski[1]

University of Oulu

[1] Corresponding address: Department of Accounting and Finance, P.O.Box, FIN-90014 University of Oulu, Finland. Phone: +358 8 553 25 87. E-mail: mika.pirneskoski@oulu.fi

1 Introduction

The rationality of financial markets, and equally of investors, is one of the most debated issues in the modern financial economics. Since 1960's the supporters of the Efficient Market Hypothesis have provided a vast amount of evidence on market's informational efficiency. The hypothesis states that the prices on traded assets already reflect all known information and instantly change to reflect new information. Thus, constantly outperforming the market by using only market information should be impossible. In less stringent versions of the efficient market hypothesis the prices should reflect all past price information and all publicly known information respectively.

Recent critics of the Efficient Market Hypothesis on the other hand argue that investors, specifically retail investors, are in fact irrational and exhibit several cognitive biases such as overreaction, overconfidence and representative bias. These biases are often attributed to several well-documented psychological factors, e.g. most notably fear and greed, that are present in everyday life. As a result, investors tend to make financially ruinous investment decisions and worsen the performance of their investment portfolios. One typical example is investment in highly priced growth stocks (high P/E ratio), which have historically returned less than value stocks.

However, recent research in the cognitive sciences and financial economics suggests that there is an important link between emotions and rationality in decision-making. Lo and Repin (2002) report that even the most experienced traders exhibit significant emotional response during certain market events. These events include increased price-volatility or intraday breaks in trends. In addition, Steenbarger (2002) presents evidence on the relationship between emotions and trading performance. Furthermore, Lo, Repin and Steenbarger (2005) find a strong link between emotional reactivity and trading performance. They report that the day traders whose emotional response for monetary gains and losses were more intense did significantly worse in the market. This implies a negative correlation between emotional reactivity and trading behaviour. Lo et al. also report that they did not find any specific trader personality types in their study. They suggest that different personality types can act equally well as traders after proper instruction and practice.

The recent evidence suggests that investors should learn to control their emotions in order to be able to exhibit rational market behaviour. Correspondingly, Lo et al. (2005) report that almost any investor, with proper instruction and training, can prosper in the stock market. Thus, experience should be one of the key issues when determining the market performance of different investors and investor groups. Institutional investors have superior market experience in the form of trading and normally also in the form of years in the market. Moreover, they are a more homogeneous group. Therefore our focus will be on retail investors. Retail investors have heterogeneous backgrounds, experience and sometimes also varied motives. Some retail investors invest in the long-run, whereas others want to maximise their short-run performance. Analysis on retail investors should give us more information on the role of experience and learning on the investment decisions and trading performance.

We have developed this thesis in the following manner. The first paper classifies the different types of retail investors in the Finnish stock market statistically. We analyse the typical behaviour of retail investors and form investor groups based on their market behaviour. We find that most of the investors are extremely passive and hold an underdiversified portfolio. As the main contribution of the thesis is to study the role of experience and learning to retail investors' market behaviour we decided to use only the most active retail investor group, i.e. day traders, in the subsequent papers. By employing this method we are able to capture the learning process in more depth and more accurately. Moreover, the first paper describes the whole population of retail investors and gives us a better understanding how they operate as a heterogeneous group.

We decided to employ this particular method for two important reasons. First, the day traders are far more homogeneous as a group than the whole retail investor population. Thus, it is easier to study the effect of experience using a group with approximately same background. Second, by forming different investor groups of the whole population, it is easy to see why the learning processes of retail investors should be studied using the most active investor group. The more passive groups do not trade, thus their learning effect, e.g. from trading experience, would have been marginal.

The data used throughout the study is based on the Finnish Central Securities Depository's (FCSD) share ownership records. The record includes the initial balance of FCSD's share ownership record beginning from January 2005 and all changes in these records until December 31, 2002 for all publicly quoted companies represented in the Book Entry System. The Book Entry System is an electronic share ownership and trading record. All changes in the data are updated daily, thus the data allows us to study the portfolio and its composition of any investor at any time during the time-span.

The Book Entry System is a compulsory registration of stock holdings for Finnish citizens and institutions. The data is not a complete register of stock ownership in Finland, as foreign investors are partially exempt from registration. They can opt for registration in a street name. As a result, the ownership records of foreign investors are combined to a larger pool of nominee registered holdings. Therefore, their shareholdings or trades cannot be separated from each other by scientific investigation.

The main findings of the thesis are summarised as follows. Finnish retail investors are a heterogeneous investor group. However, most of the investors hold a small, underdiversified portfolios, are extremely passive and do not exhibit a certain investment strategy. We confirm the earlier finding that men are more active in the market and the tendency to ride the momentum increases along with an increase in the portfolio value. Furthermore, we find that recent trading volume explains future trading performance. The evidence on recent market performance is two-fold. The performance of the lowest performing groups seems to be persistent, but the investors with highest recent performance seem to suffer in the near future.

Finnish day traders do suffer from disposition effect and choose not to complete their day trades if the market movement is unfavourable or unexpected. Furthermore, market experience and sophistication have a positive effect on the trading performance, whereas trading experience seems to lower the trading performance after controlling for investor level fixed effects.

Finally, we report that previously experienced earnings announcement day trading returns have a statistically and economically significant effect on future trading behaviour. Controlling for previous market and trading experience, we find that positive returns decrease the probability not to participate in earnings announcement day trading in the future. In addition, personal experience has long-term effects on trading behaviour and earnings announcement trading performance is influenced by investor experience.

The remainder of the introductory chapter is organised as follows. Section 2 presents an overview of the previous literature. Section 3 summarises the main findings of the three papers included in this work.

2 Previous literature

Arrow (1964) and Pratt (1964) have shown that an investor with a reasonable wealth has a marginal utility schedule with high elasticity and therefore has higher risk tolerance than her less wealthy counterparts. A range of empirical studies, e.g. Friedman & Savage (1948) suggest that the elasticity of utility is at its highest for rich people, but not for ultra rich. This implies that at first the utility function is concave but then reshapes into a convex function only to return to concave form after a certain level of wealth. Second, there is empirical evidence, e.g. Bodie & Samuelson (1989), to support the idea that young investors with high future income have a high tendency to hold their wealth in rather risky assets as they can recoup their losses through increased work in the future. Third, the last point is the most ambiguous of these three. There is empirical evidence, e.g. Lewellen, Lease & Schlarbaum (1977), to show that elderly investors tend to invest in less volatile safer assets than their younger counterparts. On the other hand, Samuelson (1969) suggests that under isoelastic marginal utilities investors would have the same risk tendency throughout their life, i.e. the age of an investor should not affect one's risk aversion at any part of her life.

Studies on investor objectives and characteristics

The life cycle hypothesis of Modigliani & Brumberg (1954) and Friedman's (1957) permanent income hypothesis state that one's consumption at any life cycle is dependent on expected resources, labour income, as well as inherited wealth, over one's lifetime. This implies to rather stable consumption rate throughout one's life, as households would typically save during their productive years and respectively live on those savings during retirement or periods of unemployment. In these two studies, however, the idea of different investment objectives was not taken into account. This would imply that on the basis of Modigliani's & Brumberg's and Friedman's theories we cannot draw any conclusions about the behaviour of investors of different age groups.

Multiple objectives of investors have been studied by e.g. Solow (1987), Barlow, Brazer & Morgan (1966) and Thaler (1980). These studies show that investor objectives depend not only on current and expected income, but also on retirement plans, willingness to leave bequests, education, and precaution for potential emergencies, to name a few. To support multiple objectives theory Katona (1960) observed that savings objectives are related to consumption needs under varying horizons and uncertainty over investor's life cycle. Furthermore, Potter (1971) provides evidence to support the multiplicity of objectives, but his study involved only identifications of objectives to hold one particular asset type, i.e. the common stocks.

The effect of socio-economic factors on investor objectives have been studied by e.g. Lewellen et al. (1977) and Baker & Haslem (1974). Lewellen et al. suggest that elderly investors were more interested in a stable dividend income rather than substantial capital gains. Furthermore, they noticed that investors with more initial wealth were more likely to be interested in long-term goals. Equivalently Baker & Haslem's study shows how sensitivity to dividend yield, capital appreciation and risk is dependent on socio-economic factors. They noticed that risk sensitivity was mostly influenced by age, sex, marital status, education and current income in the respective order of significance. This has also been verified by recent empirical studies that we shall go through later in the chapter. Baker & Haslam's study also gives further evidence on Lewellen et al's view of elder investors being more interested in a stable dividend yield rather than capital gains.

Gender and marital status sensitivity on investor objectives have been studied in detail by Haynes & Helms (1990, 1992) and Lease, Lewellen & Schlarbaum (1976). Haynes & Helms suggest that the composition of portfolio is indifferent for married couples and single men. They also argue that men and married couples have a higher tendency on allocating their wealth in real estates, common stocks and corporate bonds, whereas single women preferred to hold less risky government bonds. Lease et al. had similar findings in their earlier study as they suggest that especially elderly single women were more conservative and dividend driven, holding more diversified portfolio than any other socio-economic group. Baker & Haslem's (1984) study gives further evidence to support different objectives for males and females indicating women's greater emphasis on dividend yield and price stability.

Studies on investor characteristics, asset holdings and portfolio performance

Probably the most studied investor characteristic's effect on asset holding is the effect of wealth on investor behaviour. Nearly every study examines that particular relationship in addition with other things being analysed. The most common result is a positive correlation between one's wealth and the ownership of risky assets. E.g. Cohen, Lewellen, Lease & Schlaurbaum (1975) suggest that risky asset holdings increase in line with the increase in wealth, whilst other factors, e.g. sex, age and income, were kept constant. More recent study to confirm this relation was carried out by Ramaswami, Srivastava & McInish (1992). They conclude that income and net wealth have a positive effect on holdings of riskier assets.

The relationship between education and portfolio selection has been studied by Lease et al. (1976) and Barlow et al. (1966). Lease et al. report that highly educated investors tend to prefer more diversified portfolios than the less educated ones. This result is further supported by Barlow et al. who show that households headed by professional employees with high education have higher preference for current yield low risk ratio than their less educated counterparts. The information level of different educational groups may explain these results. More educated investors are likely to be more aware of the stock market and the way it operates. Therefore, they know that portfolio risk can be reduced in great amount with good portfolio diversification without lowering the portfolio return. We shall go through the evidence on informational advantage later in this chapter.

Investor performance literature

Most academic literature provides evidence that retail investors rarely beat the market or even the institutional investors. In addition, retail investors' level of sophistication is often questioned. E.g. Black (1986), De Long et al. (1990) and Lee et al (1991) provide evidence that their investments decisions are often driven by liquidity demand and/or psychological reasoning unrelated to the underlying security values. Furthermore, they seem to hurt their portfolio performance by trading too much, holding undiversified portfolios, exhibiting home bias and as presented earlier selling winning stocks too early and holding losing stocks for too long. (E.g. Blume and Friend (1975) and Grinblatt & Keloharju (2001).)

Grinblatt and Keloharju (2000) report that Finnish households act as contrarians, buying losers and selling winners. In addition, they underperform compared to "sophisticated" investors, namely foreign investors, Finnish finance and insurance institutions, during the sample period. Barber and Odean (2002) report that active and wealthy young men, who switched from phone-based to online trading during 1992-1995, increased their trading activity, traded more speculatively and eventually performed below par. What makes it interesting is that prior to the switch they beat the market by 2 percent annually.

However, there is also strong evidence amongst the academic literature that some retail investors actually perform superiorly compared to the market. Barber and Odean (2000) show that the top-performing quartile of the retail investors outperforms the market by 6 percent per annum. In addition, Ivkovich and Weisbrenner (2005) and Ivkovich et al. (2005) note that they generate high returns by exhibiting home-bias and individuals with underdiversified portfolios outperform those with diversified portfolios. Furthermore, Kaniel et al. (2005) document that stocks heavily bought by retail investors earn abnormal positive returns during the following month. Finally, Coval et al. (2005) report that top-performing decile of retail investors buy stocks that earn daily abnormal returns of 1.2 – 1.5 percent during the following week. Correspondingly the bottom-performing decile loses approximately 1.2 percent a day during the same time. Their results are robust to risk adjustments, small stock removal etc. They also present a trading strategy exploiting information in investors' trades that earns 0.5 percent risk-adjusted daily return.

Overconfidence literature

According to academic literature lack of trading plan and over-trading can be caused by behavioural biases. Many traders seem to trade "on the fly" without a proper trading plan, because they think they can outsmart the market and the other traders. They ride the wave and normally land in the sand, because they are overconfident. Overconfidence is a well documented phenomenon in the psychological literature as well as in modern finance.

The overconfidence literature is regarded to be motivated by the differences of opinion literature from the 1980's. Varian (1989) generalises the mean-variance framework with diverse information of Grossman (1976) to allow for different prior probabilities. Each investor has a subjective a priori distribution for the value of a risky asset, the distributions are assumed to be normal, but to have different means. Varian finds that the trading volume is solely caused by the differences of opinion. The equilibrium net trading volume is therefore dependent on the deviation of her opinion about the mean from the average opinion. The larger the deviation from the average, the larger the trading volume will be.

Bar-Tal, Sarid, and Kishon-Rabin (2001) state that the phenomenon of overconfidence is defined as the difference between mean reported confidence in the chosen answer and the percentage of items answered correctly. If this difference is positive, participants are said to exhibit overconfidence; if the difference is negative, this implies under-confidence. In most studies about overconfidence, participants have been asked to predict outcomes of events or to answer multiple choice questions that tested general knowledge. Each item had two possible answers. Participants chose the answer they believed to be more likely and assigned probability of, or confidence in, the correctness of the chosen answer.

Furthermore, Lichtenstein and Fischhoff (1977) have shown that overconfidence is influenced by item difficulty. This is called the "hard/easy"- effect, according to which overconfidence is most pronounced for hard questions, those that are answered correctly by relatively few people. Overconfidence typically diminishes and may even turn to underconfidence for very easy items, questions that almost everyone answers correctly. The overconfidence phenomenon has been replicated many times (Bauman, Deber, & Thompson, 1991; Braun & Yaniv, 1992) and in different cultures (Yates, Lee, & Shinotsuka, 1996). The phenomenon persists even when incentives for appropriate confidence are provided (Fischhoff & Macgregor, 1982). This persistence has led theorists to believe that the phenomenon is a fundamental feature of human psychology.

More evidence on the existence of overconfidence is given by its occurrence throughout different professional fields. E.g. lawyers, managers, investment bankers and engineers have been found to exhibit overconfidence in their decision making-processes and judgements, see e.g. Wagenaar and Keren (1986), Russo and Schoemaker (1992), Stael von Holstein (1972) and Kidd (1970) for further information.

However, Gigerenzer, Hoffrage, and Kleinbolting (1991) suggested that the phenomenon of overconfidence is actually an artefact of the experimental setting, occurring in response to the experimenter's choice of questions, which are usually difficult and misleading. An example of a question used in such experiments of Girerenzer et al. is "Which city is farther north? (a) New York or (b) Rome." Gigerenzer et al. claimed that to answer such questions, participants use diagnostic cues, cues that distinguish between the two response- alternatives, and when asked to indicate their confidence in their answer, they do so for the relationship between that cue and the criterion. Because the questions selected for the experiment are tricky, such a calculation leads to overconfidence. Indeed, they showed that random selection of questions from a knowledge domain familiar to the participants eliminates the overconfidence bias.

Harris and Raviv (1993) assume that investors have homogenous a priori beliefs and receive the same public information. Investors however interpret the information differently and differences of opinion are formed. The heterogeneous interpretation is explained to be caused by the differences in the likelihood function when updating probabilities. Kandel and Person (1995) believe that investors have different a priori beliefs and that their valuation of an asset is the sum of two different terms, the liquidation value of the risky asset and an error term. Different investors have different beliefs about the mean value of the error term, and therefore their valuation of the asset must also be different.

Kreinin (1959) reports that investors with optimistic view of future economy and of their personal financial situation are more likely to hold more volatile common stock portfolios than those with more pessimistic expectations. The recent studies include Odean (1998, 1999) and Barber & Odean (2000, 2001). These studies analyse the level of investors’ self-confidence and its effect on portfolio performance. Psychological evidence, e.g. Lundeberg, Fox and Punćochaŕ (1994), shows that men tend to be more overconfident than women. In addition, people tend to be more overconfident in tasks that are from moderately difficult to extremely difficult and correspondingly underconfident in easy tasks. We are sure that we can conclude that investing is at least moderately difficult, which would suggest that investors are likely to be overconfident about it. Odean’s and Barber & Odean’s results can be concluded in the following manner. Male investors tend to be more overconfident in the stock market than female investors as was suggested by psychological studies. Overconfidence about own investment abilities decrease utility received from trading. And finally, as a result, the most overconfident investors, i.e. those investors who trade the most, have the worst portfolio performance.

Disposition effect literature

Shefrin & Statman (1985) introduced the concept of disposition effect, which can be defined as investors’ tendency to hold on to losses too long and realise gains too soon. However, the roots of this phenomenon lie in the prospect theory introduced by Kahneman and Tversky (1979) and mental accounting framework by Thaler (1980, 1985). The availability of account-level transaction data, e.g. Odean (1998) has made the disposition effect a well-documented behavioural pattern among investors.

The prospect theory can be presented as a two-stage process. In the first stage, a decision maker evaluates e.g. investment opportunities in terms of potential gains and losses relative to a certain reference point. In the latter stage, the decision maker faces an S-shaped value function, which is defined over gains and losses relative to the wealth level rather than to an absolute one. The S-shaped value function is concave in the gains region, inferring risk aversive behaviour, and convex in the loss region, inferring risk-seeking behaviour.

The mental accounting framework provides information on how individual decision makers view uncertain monetary choices. Decision makers can view their choices in a broader or narrower account. E.g. a stock holder may evaluate her gains/losses on the portfolio level, i.e. in a broader frame, or she may evaluate her losses/gains on an individual stock level, i.e. narrower frame. However, it must be noted that any investor holding more than one stock in her portfolio has in fact multiple open mental accounts.

Several experimental, e.g. Weber and Camerer (1998), Thaler, Tversky, Kahnemann and Schwartz (1997), and empirical studies show consistence evidence about the existence of the disposition effect. However, there is also evidence questioning the true nature of it, e.g. Kaustia (2004). After the pioneering evidence by Shefrin and Statman (1985), followed by Odean (1998), the amount of disposition effect literature has increased rapidly. Grinblatt and Keloharju (2001) report disposition effect among both individual and institutional investors. They show that the major determinant of both investor types' selling decision is their reluctance to realise losses.

Although the available experimental evidence shows that greater investor sophistication seems to decrease susceptibility to the disposition effect, professional investors are far from being uninfluenced by it. Locke & Mann (2000) use the futures market data, and report that all traders hold losers longer than they do winners. Furthermore, they find that the least successful traders hold the losers for the longest, and vica versa for the most successful traders. In addition, Shapira & Venezia (2001) and Coval & Shumway (2000) report consistent evidence about the disposition effect in the Israeli market and among the market makers in the Chicago Board of Trade respectively. To summarise, the current evidence shows that the disposition effect is substantial yet subject to variations across investor groups and that the nature of it is not yet thoroughly understood.

Kaustia (2003) and (2009) criticises the use of prospect theory as an explanation for disposition effect. The more recent paper shows that the propensity to sell jumps at zero return, but is then fairly constant in the region of losses and correspondingly constant or even increasing in the region of gains. Furthermore the paper finds no evidence that the phenomenon is caused by after-tax portfolio rebalancing, belief in mean-reversion or target prices.

Studies on investors' learning

Reinforcement is a widely accepted psychological phenomenon first brought to public knowledge by Ivan Pavlov in the 1920's. Dinsmoor (2004) points out that Pavlov's definition of reinforcement was strengthening of already-learned weakening response instead of current definition of selecting and strengthening new behaviour. Later, Skinner (1957) articulated the major theoretical constructs of reinforcement and behaviourism. Skinner's early work was mainly theoretical, which is the primary reason for slow adoption in the academia for his theories during that time. However, e.g. Ferster (1967) and Baer & Wolf (1970) conducted theoretical research in that field.

The first reinforcement learning models in the economic research include e.g. Cross (1973), Arthur (1991) and Roth & Erev (1995). The hybrid model by Camerer & Ho (1999) has implications for our model, as their model allows for the reinforcement of actual as well as forgone payoffs. They suggest that the subjects might actually weigh these two types of payoffs in different manner. In addition, some stock market anomalies have been explained by biased learning, e.g. Barberis & al. (1998) and Gervais & Odean (2001).

Even though there is a vast empirical literature on reinforcement as well as Bayesian learning, the empirical literature on how investors actually learn, or do they learn, is somewhat limited. Feng & Seasholes (2005) have studied the effect of investor sophistication and trading experience on behavioural biases found in the stock market. They discover that neither sophistication nor trading experience alone eliminate disposition effect. However, together sophistication and trading experience seems to eliminate the reluctance to realise losses. Correspondingly, Nicolosi, Peng & Zhu (2009) report that portfolio returns improve with account tenure and trade quality also increases with experience. Thus, according to them investors learn from their own investment history and seem to make adjustments to their future trading based on that information, which leads to higher investment performance.

Seru, Shumway & Stoffman (2007) investigate the effect of trading experience on the disposition effect and trading performance. They show that more experienced investors are less likely to suffer from the disposition effect and their trading performance is better. In addition, they show that investors as a group tend to learn partly by attrition, but individual level learning is also important. However, they use completely different type of return measure, namely next year's return, whereas we are interested in the net return associated with individual trades. Furthermore, List (2003) and Dhar & Zhu (2006) show that experience plays a significant role in eliminating judgement errors such as endowment and disposition effect. Linnainmaa (2006) provides somewhat contradicting evidence to the existing literature as he argues that less sophisticated investors learn to exit the stock market better than their more sophisticated counterparts. This might be one possible explanation for the relationship between experience and positive market performance.

Kaustia & Knüpfer (2008) find a strong positive link between actual IPO returns and future IPO subscription activity. This is a strong finding supporting positive reinforcement, as personally experienced good returns are an important factor determining future activity in their study. Furthermore, they state that investors participating in their first IPO and experiencing a positive return are twice as likely to participate in the next offering compared to investors with cold first IPO. This is a long-term phenomenon as there is a 26 percentage unit difference in the subscription activity of the hot and cold IPO groups by the tenth IPO offering. They suggest that this is due to the primary effect long-recognised in marketing literature and analysed by Bereby-Meyer & Roth (2006) in strategic games.

There is a vast experimental literature providing support for reinforcement. Camerer & Ho (1999) argue that their test subjects give actual payoffs twice the weight given to forgone payoffs. Charness & Levin (2005) report that roughly half of the decisions of their subjects violate Bayes' rule and confirm that Bayesian' and reinforcement learning lead to different choices. Finally, Erev & Roth (1998) find that their simple one-parametric reinforcement learning model outperforms equilibrium predictions for all values of the parameter. Psychological and neurological studies also confirm the existence of reinforcement learning, e.g. Huettel & al. (2002) and Knutson & Peterson (2004).

Feng & Seasholes (2005) study the effect of investor sophistication and trading experience on behavioural biases found in the stock market. They discover that neither sophistication nor trading experience alone eliminate disposition effect. However, together sophistication and trading experience seems to eliminate the reluctance to realise losses. Correspondingly, Nicolosi, Peng & Zhu (2009) report that portfolio returns improve with account tenure and trade quality also increases with experience. Thus, according to them investors learn from their own investment history and seem to make adjustments to their future trading based on that information, which leads to higher investment performance. In our setting we assume that experience helps investors to learn from their personal investments history and thus the profitability of earnings announcement day trades increases with account tenure.

3 Overview of the essays

3.1 Empirical classification of private investors in the Finnish stock market: A cluster analysis approach

The first essay studies the behaviour of Finnish retail investors in the Helsinki Stock Exchange. We classify investors with homogenous behavioural patterns into different investor groups in order to gain a better overview of the Finnish retail investor structure using a market-wide data set available from Finnish Central Securities Depository. In addition, we try to establish a linkage between behavioural patterns and demographic characteristics of the investors using existing financial explanations. Our sample includes all the observations of retail investors' holdings, trades and demographic characteristics.

We explain the behaviour of different investor groups in terms of the properties of their investment portfolios. The simplest classification would be to classify the portfolios according to the size of the portfolio, i.e. the market value and the number of stocks held in it. However, such examination would not be very informative, and therefore we base our study on four different features that the investors may exhibit.

First, the market value and the number of stocks held in the portfolio are used to reflect the size of investor's portfolio. Second, the number of purchase transactions measures the activity level of a particular investor. Third, the risk of investors' portfolio is measured with the portfolio's beta coefficient and with the average number of stocks held in the portfolio. Fourth, the strategy an investor follows is characterised with the performance of one's purchase transactions within the past 250 trading days. Positive sign for this variable corresponds to momentum strategy, whereas negative sign implies contrarian strategy to be followed.

The empirical analysis was performed in four different stages using standard cluster analysis. In the first stage we chose the appropriate variables to be clustered. In the second stage we use an approach suggested by Art, Gnanadesikan, and Kettenring (1982) to obtain approximate estimates of the pooled within-cluster covariance matrix when the clusters were assumed to be multivariate normal with equal covariance matrices. This procedure is used to improve the efficiency of the analysis, the optimising procedure seems to perform well with spherical clusters, but poorly with elongated elliptical clusters that were to be clustered in this study. (Everitt, 1980.) The third stage of the empirical analysis includes the most significant part of the empirical investigation in this study. The canonical variables produced by the first procedure are clustered with the optimising clustering procedure based on Späth (1985) in order to produce the final clusters. Finally, we examine the demographic characteristics of clustered observations in the fourth stage. This includes examination of each cluster in terms of investors' wealth, age and sex.

We find that Finnish retail investors exhibit rather homogenous market behaviour. Most of the investors hold a small portfolio, as 75 per cent of the investors in the sample have a portfolio with a market value less than 10 000 euros. In addition, most portfolios are poorly diversified. The number of stocks in a typical Finnish retail investor portfolio varies between one and three.

Classical economic theories suggest that investors should be rather homogenous in the market. Our study proves that suggestion correct for retail investors. However, investors should also act rationally in the market, i.e. hold a well-diversified portfolio. Our study confirms the contrary. The asset allocation of most investors is largely concentrated, which suggests that they are not acting rationally and diversifying asset-specific risk sufficiently. However, there seems to be a relationhip between this type behaviour and portfolio size. This would imply that investors with larger portfolios are better informed and more aware of the market than investors with small portfolios.

The overall activity level of the Finnish retail investors is very low. The typical Finnish investors hardly traded during the sample period. The clustering analysis shows that activity level seems to be negatively correlated with average age of the investor group. In addition, the male investors were found to be more active than the female investors. Furthermore, the results do not support the hypothesis that certain strategies are occupied by certain investor groups. However, the tendency for momentum-behaviour seems to increase as the portfolio size increases.

3.2 Essay 2: Retail traders and daily bets: Sing when you're winning?

The second essay investigates the profitability of retail traders' daily bets in the Finnish stock market. Our analysis aims to answer the following questions: (1) Does the past trading activity affect the profitability of retail investors' future daily bets, (2) does the past performance give indication on the future profitability of retail investors' future bets, (3) how do unexpected market changes affect retail investors' daily bets, and (4) Does experience, e.g. market experience, trading experience and investor sophistication, affect retail investors trading performance? We analyse the performance of Finnish day traders during 1995-2003 in order to find more evidence on these phenomena.

The data set used in our study is based on the Finnish Central Securities Depository's (FCSD) share ownership records. The record includes the initial balance of FCSD's share ownership record and all changes in these records between January 1 1995 and December 31, 2003 for all publicly quoted companies represented in the Book Entry System. Each record includes a data, individual investor identification code, investor type identification code – a domestic household in this case -, stock code, price, volume and various demographic characteristics.

First, we sum the value of buy and sell transactions for all the day traders on each stock for each day trade. The intraday return of the sells is calculated as the volume-weighted average price of the sell transactions divided by the volume-weighted closing price. The same method is used to calculate the intraday return of the buy portfolio. In case of multiple day trades for the same trading day, all the day trades are pooled together in order to form a day trade portfolio using the same analogy as in a single day trade scenario. Then we construct a trading return measure for each day trader by subtracting the return on the buy portfolio from that of the sell portfolio. In order to account for daily variation, we take a five-day moving average for each trading day. Thus, we able to construct a more reliable measure showing the performance of investors' day trades and its persistence

Second, we classify the day traders based on their past day trading activity. In day t , we sum the total value of day trading from the past six months, and form five exclusive day trade categories. Using these day trader categories we analyse the five-day trading performance of each day trader group at day t. Third, we partition the day traders into five different categories based on their past trading performance. We calculate the mean standardised trading returns from the past six months at day t. Using this partition we analyse the average five-day trading return for each category at day t. Updates are made on a daily basis.

Fourth we divide day trades into two different categories; complete day trades and partial day trades. Complete day trade is a round-trip during the same trading day, i.e. buying and selling exactly the same number of shares of one particular stock. Partial trade corresponds to any other sort of day trade. Then we calculate four different day trade performance measures; daily gross profit, daily net profit, daily gross return and daily net return. Finally the day traders are divided into five different investor groups according to their trading activity and investors sophistication.

In the final part we run a regression analysis to determine whether the more experienced retail traders have better day trading performance than their less experienced counterparts. We regress the net daily trading return of each of the retail traders on experience variables, which are market experience, trading experience and investor sophistication.

We find that higher total trading volume during the past six-month period leads to higher weekly trading return. Thus, there is a strong positive relationship between trading volume and trading returns in the future. Second, the day traders with the highest return-risk measure for the past six-month period actually experience a reversal in their trading returns for the subsequent period. However, there seems to be consistency in other return-risk groups suggesting that, at least to some extent, trading returns result from skill rather than pure luck. Third, retail day traders seem to suffer from disposition effect and do not realise their day trading losses fully. This finding holds for different trading activity and investor sophistication groups implying that even the most experienced and sophisticated investors probably do not have a proper day trading plan. Finally, we provide evidence that market experience and market sophistication have a positive effect on day trading performance, whereas trading experience has the opposite effect. This should not be viewed as conclusive evidence on the worthlessness of trading experience, but more as a conclusion that holding market experience and market sophistication constant, excess trading decreases day trader's performance.

3.3 Essay 3: reinforcement learning and event trading; evidence from earnings announcements

In the third paper, we study the effect of previously experienced trading returns from earnings announcement to the future trading behaviour of retail day traders. We investigate if personally experienced negative returns actually decrease the probability of future day trading and the probability to day trade during the next earnings announcement. Furthermore, we analyse the effect of personally experienced negative returns on the time of the next day trade and whether the effect has long-term consequences. Finally, we study the effect of experience on earnings announcement day trading performance.

The analysis is executed in the following manner. First, we calculate the trading performance measures for day trading, the daily net profit. We determine the profit earned by each investor during each earnings announcement day trade, which is simply the difference between sale cash flow and purchase cash flow. However, if the day trade is partial, we take into account only the realised part of the day trade. Second, we take into account the transaction cost associated with the trade. The level of transaction costs for the data period is considerably hard to determine. Thus, we use the price level of 2003 for the whole sample, which might underestimate the level of transaction costs in the beginning of the data period. Furthermore, we do not have the information about the brokerage house used by the trader, thus we assume that each investor is acting rationally and using the cheapest one. Finally we determine the daily net trading return by dividing the net profit by the daily trading volume.

We study the effect of past earnings announcement day trading performance on future trading activity using three types of analyses. In the first part, we divide the sample into two and investigate how trading behaviour in the latter half is affected by trading returns in the first period? In the second part of the analysis, we analyse investors' past performance's, up to that earnings announcement, effect on future trading activity. Finally, we run a regression analysis to determine whether the more experienced day traders have better earnings announcement day trading returns than their less experienced counterparts. We regress each daily earnings announcement trading return of each of the retail traders on experience variables, account tenure, trading experience, and investor sophistication.

Our analysis provides evidence that previously experienced earnings announcement day trading returns have statistically and economically significant effect on future earnings announcement day trading behaviour. Controlling for previous market and trading experience, we find that positive returns decrease the probability not to participate in earnings announcement day trading in the future. Our results also show support for the long-term effects of personal experience. Of the investors who experienced positive initial event day return 58 percent have event traded during the next two years after the first earnings announcement day trade. The figure for investors experiencing a negative first event trade return is 42 percent. The finding is statistically and economically significant. Finally we find a positive relationship between experience and earnings announcement day trading performance.

REFERENCES

Arthur, B. V. (1991). Designing economic agents that act like human agents: A behavioural approach to bounded rationality. American Economic Review 81, 353-359.

Arrow, K.J. (1964). The role of securities in the optimal allocation of risk bearing. Review of Economic Studies 31(2), 91-96.

Baer, D. & Wolf, M. (1970). The entry into natural communities of reinforcement. In R. ulrich, T. Stachnik, & J. Mabry (eds.), Control of human behavior (Vol.2, pp. 319-324). Gleenview, IL: Scott, Foresman.

Baker, H. & Haslem, J. (1974). The impact of investor socio-economic characteristics on risk and return preferences. Journal of Business Research 10(2), 469-476.

Bar-Tal, Y., Sarid, A. & Kishon-Rabin, L. (2001). A test of the overconfidence phenomenon using audio signals. Journal of General Psychology. January ;128(1):76-80.

Barber, B.M. & Odean, T. (2001). Boys will be boys: gender, overconfidence, and common stock investment. The Quarterly Journal of Economics 116(2), 261-292.

Barber, B.M. & Odean, T. (2002). Online investors: Do the slow die first? The Review of Financial Studies 15(2), 455-487.

Barber, B.M., Lee, Y-I., Liu, Y-J. & Odean, T. (2004). Do individual day traders make money? Evidence from Taiwan. Working paper.

Barber, B.M., Lee, Y-I., Liu, Y-J. & Odean, T. (2005).Who loses from trade? Evidence from Taiwan. Working paper.

Barberis, N., Shleifer, A. & Vishny, R. (1998). A model of investor sentiment. Journal of Financial Economics 49, 307-343.

Barlow, R.Brazer, H. & Morgan, J. (1966). Economic □ehaviour of the affluent. The Brooking Institution, Washington, DC.

Bauman, A. O., Deber, R. B., & Thompson, G. G. (1991). Overconfidence among physicians and nurses: The "micro certainty, macro certainty" phenomenon. Social Science and Medicine, 32, 167-174.

Bereby-Meyer, Y. & Roth, A. (2006). The speed of learning in noisy games: Partial reinforcement and the sustainability of cooperation. American Economic Review 96, 1029-1042.

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

Blume, M. & Friend, I. (1975). The asset structure of individual portfolios with some implications for utility functions. Journal of Finance 30, 585-604.

Bodie, Z. & Samuelson, W. F. (1989). Labor supply flexibility and portfolio choice. National Bureau of Economic Research. Working paper series.

Braun, P. A. & Yaniv, I. (1992). A case study of expert judgment: Economists' probabilities vs. base-rate forecasts. Journal of Behavioral Decision Making, 5: 217-231.

Camerer, C. & Ho, T-H. (1999). Experience-weighted attraction learning in normal form games. Econometrica 67, 827-874.

Charness, G. & Levin, D. (2005). When optimal choices feel wrong: A laboratory studt of Bayesin updating, complexity and affect. American Economic Review 95, 1300-1309.
Cohen, R., Lewellen, W., Lease, R. & Schlaurbaum, G. (1975). Individual investor risk aversion and investment portfolio composition. Journal of Finance XXX(3), 605-620.
Coval, J. & Shumway, T. (2001). Do behavioral biases affect prices? Journal of Finance 60, 1-34.
Coval, J., Hirshleifer, D. & Shumway, T. (2005). Can individual investors beat the market? Working paper, Harvard Business School.
Cross, J. (1973). A stochastic learning model of economic behaviour. Quarterly Journal of Economics, 87, 239-266.
De Long, J.B, Shleifer, A., Summers, L. H. & Waldmann, R. J. (1990). Noise trader risk in financial markets. Journal of Political Economy 98, 703-738.
Dhar, R. & Zhu, N. (2006). Up close and personal? An individual level analysis of the disposition effect. Management Science 52, 726-740.
Dinsmoor (2004). The etymology of basic concepts in the experimental analysis of behavior. Journal of the Experimental Analysis of Behavior, 82 (3): 311-316.
Feng, L. & Seasholes, M. (2005). Do investor sophistication and trading experience eliminate behavioural biases in financial markets? Review of Finance 9, 305-351.
Ferster, C. (1967). Arbitrary and Natural Reinforcement 1967, The Psychological Record, 22, 1-16
Fischhoff, B., & Macgregor, D. (1982). Subjective confidence in forecasts. Journal of Forecasting, 1, 155-172.
Friedman, M. (1957). A theory of the consumption function. Princeton University Press. Princeton, CA.
Friedman, M. & Savage, L.J. (1948). The utility analysis of choices involving risk. The Journal of Political Economy 56(4), 279-304.
Gervais, S. & Odean, T. (2001). Learning to be overconfident. Review of Financial Studies 14, 1-27.
Gigerenzer, G., Hoffrage, U., & Kleinbolting, H. (1991). Probabilistic mental models: A Brunswikian theory of confidence. Psychological Bulletin *98*, 506-528.
Grinblatt, M. & Keloharju. M. (2000). The investment behaviour and performance of various investor types: a study of Finland's unique data set. The Journal of Financial Economics 55(1), 43-67.
Grinblatt, M. & Keloharju. M. (2001). How distance, language and culture influence stockholdings and trades. Journal of Finance 56, 1053-1073.
Grossman, S. J. (1976). On the efficiency of competitive stock markets where traders have diverse information. Journal of Finance, 30.
Harris, M. & Raviv, A. (1993). Differences of opinion make a horse race. Review of Financial Studies 6, 473-506.

Haynes, P.J. & Helms, M.M. (1990). The demographics of managing finances. Personal Financial Planning 4(1), 23-27.
Haynes, P.J. & Helms, M.M. (1992). Analysing customer attitudes. Personal Financial Planning 6(1), 23-28.
Huettel, S., Mack, P. & McCarthy, G. (2002). Perceiving patterns in random series: Dynamic processing of sequence in prefrontal cortex. Nature Neuroscience 5, 485-490.
Ivkovich, Z. & Weisbrenner, S. (2005) Local does as local is: Information content of the geography of individual investors' common stock investments. Journal of Finance 60, 267-306.
Ivkovich, Z., Sialm, C. & Weisbrenner, S. (2005). Portfolio concentration and the performance of individual investors. Working paper, University of Illinois.
Kahneman D & Tversky A (1979) Prospect theory: an analysis of decision under risk. Econometrica 47: 263-291.
Kandel, E. & Person, N. D. (1995). Differential interpretation of public signals and trade in speculative markets. Journal of Political Economy 103(4), 831-872.
Kaniel, R., Saar, G. & Titman, S. (2005). Individual investor trading and stock returns. Working paper, NYU.
Katona, G. (1960). The powerful consumer. McGraw-Hill, New York.
Kaustia, M. (2003). "What Causes the Disposition Effect? An Empirical Evaluation", Essay No. 1 in Essays on Investor Behavior and Psychological Reference Prices, Doctoral thesis, Helsinki School of Economics, A-213.
Kaustia, M. (2004.) Market-Wide Impact of the Disposition Effect: Evidence from IPO Trading Volume. Journal of Financial Markets 7(2), 207-235.
Kaustia, M. (2009). Prospect theory and the disposition effect. Journal of Financial and Quantitative Analysis. Forthcoming.
Kaustia, M. & Knüpfer, S. (2008). Do investors overweigh personal experience. Evidence from IPO subscriptions. Journal of Finance 63(6), 2679-2702.
Kidd, J.B. (1970). The utilization of subjective probabilities in production planning. Acta Psychologica XXXIV, 338-347.
Knutson, B. & Peterson, R. (2004). Neurally reconstructing expected utility. Games and Economic behaviour 52, 305-315.
Kreinin, M.E. (1959). Factors associated with stock ownership. Review of Economcics and Statistics 41(1), 76-80.
Lease, R.C., Lewellen, W.G. & Schlarbaum, G.C. (1976). Market segmentation: Evidence on the individual investor. Financial Analyst Journal 32(5), 53-60.
Lee, C. M. C., Shleifer, A. & Thaler, R. H. Investor sentiment and the closed-end mutual funds. Journal of Finance 46, 75-109.
Lewellen, W.G., Lease, R.C. & Schlarbaum, G.C. (1977). Patterns of investment strategy and ehaviour among individual investors. The Journal of Business 50(3), 296-333.

Lichtenstein, S., & Fischhoff, B. Do those who know more also know more about how much they know? The calibration of probability judgements. Organizational Behavior and Human Performance, 3, 552-564.

Linnainmaa, J. (2005). The individual day trader. University of California, Berkeley, working paper.

Linnainmaa, J. (2006). Learning from experience. Working paper, University of Chicago.

List, John A. (2003). Does Market Experience Eliminate Market Anomalies? Quarterly Journal of Economics (2003), 118(1), 41-71.

Lo, A. & Repin, D. (2002). The psychophysiology of real-time financial risk processing. Journal of Cognitive Neuroscience 14(3), 323-339.

Lo, A., Repin, D. & Steenbarger, B. (2005). Fear and greed in financial markets: A clinical study of day traders.

Locke P R & Mann S C (2005) Professional trader discipline and trade disposition. Journal of Financial Economics 76: 401-444.

Lundeberg, M.A., Fox, P.W. & Punćochaŕ, J. (1994). Highly confident but wrong: gender differences and similarities in confidence judgements. Journal of Educational Psychology, LXXXVI(1), 114-121.

Modigliani, F. & Brumberg, R. (1954). Utility analysis and the consumption function: an interpretation of cross-section data. In: Abel, A (ed.). Collected Papers of Franco Modigliani, Vol. 2. MIT Press, Cambridge, MA.

Nicolosi, G., Peng, L. & Zhu, N. (2009). Do Individual Investors Learn from Their Trade Experience? Journal of Financial Markets (forthcoming).

Odean, T. (1998). Are investors reluctant to realize their losses? Journal of Finance 53, 1775-1798.

Odean, T. (1999). Do investors trade too much? American Economic Revies 89, 1279-1298.

Potter, R.E. (1971). An empirical study of motivations of common stock investors. Southern Journal of Business 6(1) 41-48.

Pratt, J.W. (1964). Risk aversion in the small and in the large. Economica 32(1), 122-136.

Ramaswami, S.N., Srivastava. R.K. & McInish, T.H. (1992). An exploratory study of portfolio objectives and asset holdings. The Journal of Economic Behavior and Organisation 19(2), 285-306.

Roth, A. & Erev, I. (1995). Learning in extensive-form games: Experimental data and simple dynamic models in the intermediate term. Games and Economic Behaviour 8, 164-212

Russo, J. E. & Schoemaker, P. J. H. (1992). Managing overconfidence. Sloan Management Review, XXXIII, 7-17.

Samuelson, P.E. (1969). Lifetime portfolio selection by dynamic stochastic programming. Review of Economics and Statistics 51(3) 239-246.

Seru, A., Shumway, T. & Stoffmann, N. (2009) Learning by Trading. Available at SSRN: http://ssrn.com/abstract=891694.

Shapira Z. & Venezia I. (2001) Patterns of behavior of professionally managed and independent investors. Journal of Banking and Finance 25: 1573-1587.

Shefrin H. & Statman M. (1985) The disposition to sell winners too early and ride losers too long. Journal of Finance 40: 777-791.

Skinner, B. (1974). About Behaviorism. Knopf, New York.

Solow, R.M. (1987). Comments on how much (or little) life cycle is there in micro data? The cases of the United States and Japan. In: Rudiger, D., Fisher, S. & Bossons, J. (eds.). Macroeconomics and Finance, 224-228. MIT Press, Cambridge, MA.

Stael von Holstein, C-A. S. (1972). Probabilistic forecasting: an experiment relatedo the stock market. Organizational Behaviour and Human Performance, VIII, 139-158.

Steenbarger, B. (2002). The psychology of trading: Tools and techniques for minding the markets. New York, Wiley.

Thaler, R. (1980). Toward a positive theory of consumer choice. Journal of Economic Behavior and Choice 1(1), 39-60.

Thaler, R. H., Tversky, A., Kahneman, D. & Schwartz, A. (1997). The effect of myopia and loss aversion on risk taking: An experimental test. Quarterly Journal of Economics 112: 647-661.

Varian, H. (1989). “Differences of opinion in financial markets” in Financial risk: Theory, evidence and implications. Ed. Courtenay Stone. Boston, Kluwer Academic.

Wagenaar, W. & Keren, G. B. (1986). Does the expert know? The reliability of Predictions and Confidence Ratings of Experts. Intelligent Decision Support in Process Environments. Hollnagel, Mancini & Woods (eds.). Springer: Berlin.

Weber M & Camerer C (1998) The disposition effect in securities trading: An experimental analysis. Journal of Economic Behavior and Organization 33: 167-184.

Yates, J. F., Lee, J-W., & Shinotsuka, H. (1996). Beliefs about overconfidence, including its cross-national variation. Organisational Behaviour and Human Decision Processes, 65, 138-147.

Original Essays

Empirical classification of private investors in the Finnish stock market: A cluster analysis approach

Mika Pirneskoski*
University of Oulu

Abstract

We examine the behaviour of Finnish private investors in the Helsinki Stock Exchange. Our aim is to classify investors with homogenous behavioural patterns into clusters in order to gain a better overview of the Finnish private investor structure using a unique data set available from Finnish Central Securities Depository. In addition, we try to establish a linkage between behavioural patterns and demographic characteristics of the investors using existing financial explanations. We find that the Finnish private investors form a homogeneous investor mass, but seem not to exhibit rational market behaviour. Moreover, most investors are very passive and hold small and poorly diversified portfolios.

JEL classification: G11

Keywords: Classification of private investors, cluster analysis, investor behaviour, demographic characteristics, investment strategy

1. INTRODUCTION

Simple economic theory suggests that any individual participating in a stock market would hold a well-diversified portfolio. Furthermore, traditional academic literature also sees individual investors as rational market participants, who share homogenous beliefs. Investors are understood to construct their investment portfolios according to their own preferences as a mixture of efficient and diversified market portfolio and risk-free asset. However, it appears that many, if not most, investors neither behave in a consistent manner suggested by the theory nor do they share homogenous beliefs. Even among the relatively informed and wealthy investors, it appears that the proportion of wealth held in different financial assets varies significantly and their portfolios are rather poorly diversified.

In addition, current literature highlights the differences between the investment behaviour of individual investors. One distinction across different investors can be found in trading activity. Some investors are found to occupy a passive buy-and-hold strategy, whereas other investors are found to trade very actively, even on intraday basis. Recent academic evidence suggests that investor are worse off with excess trading, e.g. Barben & Odean (2002), but the research area needs additional evidence in order to be able to draw robust conclusions on the matter.

Other investment strategies investors are found to occupy are so called growth- and value- strategies. In growth- strategy investors invest on growth firms, who typically operate on emerging business areas and the growth expectations are very high. Typically growth firms have high market-to-book ratios compared to the average market market-to-book ratios and are typically associated with higher risk than the other stocks. Correspondingly, value firms operate in traditional industries and have traditionally operated for many decades and possibly have lower-than-average market-to-book ratio. However, rather stable return of the value firms makes them a suitable investment object for certain investors. In addition, it has been suggested that value firms may actually provide a higher-than-average return in the long run.

The investor characteristics listed above are perhaps the most common and the most researched. However, there are various other features worth mentioning. For example, some investors construct their portfolios with high systematic risk, whereas other investors seek for a more defensive position. In addition, some investors typically invest on IPO- firms, whereas some investors require a history of stock returns for several decades, however these two topics are not examined in our study. For some of the investment strategies and investor characteristics can be explained rationally, but some phenomena remain rationally unexplainable.

The linkage between these phenomenon and investors characteristics remains largely unsolved in the current finance literature. Therefore, we try to link the different behavioural assumptions with the rational expectations approach, and thereby gain a better understanding of the behaviour of private investors in the stock market. However, first we construct a framework that tries to explain the reasons behind differences in stock market behaviour of different investors. Second, we try to link the behavioural characteristics of the investors with their demographic qualities in order to explain the potential differences in behaviour patterns.

The study is carried out in the Finnish stock market for two important reasons. First, the data set available from the Finnish Central Securities Depository is unique in nature as it reports all the asset holdings and market transactions of the Helsinki Stock Exchange from the past five years. The current data is very comprehensive and extremely large, yet the Helsinki Stock Exchange is relatively small world-wide. Therefore, it would be computationally almost impossible to obtain such data from a larger stock exchange. Second, the asset holdings of Finnish people have been traditionally on a relatively low-level compared e.g. to that of the American people. However, the Finns have started to allocate more of their wealth on stock holdings during the past ten to fifteen years. Therefore, it is very interesting to examine the behaviour of Finnish investors and to study whether the investing behaviour of different Finns is either homogeneous or heterogeneous in nature.

The aim of the paper is to classify investors with homogenous behavioural patterns into clusters in order to gain a better overview of Finnish private investor structure. In addition, we try to explain the behavioural patterns of the private investors with existing financial models. Furthermore we explore the demographic characteristics of the investors, in order to find whether they give plausible explanations for the behavioural patterns or not.

The paper is organised as follows. Section 2 presents an overview of the previous literature and describes the hypotheses to be tested. Section 3 describes the data used in the study and empirical design of the statistical analysis. Section 4 presents the empirical results acquired with cluster analysis. Finally, section 5 offers concluding discussion regarding investor classification.

2 PREVIOUS LITERATURE AND THE HYPOTHESES

The previous literature on investor behaviour is vast and rather ambiguous and no similar study to ours has yet been performed, at least to the best of our knowledge. In addition, most of the studies examining the effect of socio-economic factors on investor behaviour were carried using a research design, in which the empirical data was gathered using questionnaires. Whereas we use a register of shareholdings for Finnish stocks in order to derive the investor characteristics from existing data by using statistical analysis.

Hypothesis 1: Investor's ability to bare risk increases in line with the increase in investor's wealth.

Hypothesis 2: Retail invertors' portfolio's diversification increases along with the increase in investor's wealth.

Hypothesis 3: Young male investors are more willing to invest in riskier assets than female and elderly investors are.

Hypothesis 4: Certain investor characteristics, such as age, sex and/or wealth, affect the activity level of different retail investor groups.

Investor's ability to take more risk in her investment decisions can be seen as a decrease in investor's degree of risk aversion. Wealthier retail investors are able to take more risk and expect a higher return for their investment. They also can have longer investment periods as liquidity needs do not constrain their investment goals. Moreover, wealthier investors are said to be more sophisticated investors and thus are able to recognise the need for portfolio diversification.

One typical explanation for different investment behaviour is risk aversion. Different investors have different risk attitudes and therefore may be looking for totally different investment opportunities. A finance theory might suggest that a portfolio should be avoided by some investor as too risky, but is on the other hand perfectly suitable for another investor's investment purposes. What are the factors that give basis to these statements? There are many.

First, the latter investor may be wealthier than the first one and is therefore further away from the threat of falling below the level of decent subsistence. Thus, she can bear more risk in order to acquire better return for her investment. Second, the latter investor may command a high salary at present and can look forward to a substantial salary also in the future. Thus, with such high present value of wealth, it is only reasonable for her to invest more into common stocks with high volatility than the first investor should. Correspondingly, the first investor may be living on her pension and previous savings, therefore it would be more prudent for her to invest in safer assets. Third, the latter investor may be in her prime and therefore has many investment periods ahead. Thus, she is likely to invest in the long run. In the long run a well-diversified common stock portfolio, at least historically, has produced substantially better return than a bond portfolio has. The first investor on the other hand may operate in a shorter run and cannot rely on portfolio producing a good return in the long run. Therefore, it is more sensible for her to invest in assets that have lower volatility and therefore less insecure return.

So, what conclusion can we draw from these arguments? First, e.g. Arrow (1964) and Pratt (1964) have shown that an investor with a reasonable wealth has a marginal utility schedule with high elasticity and therefore has higher risk tolerance than her less wealthy counterparts. A range of empirical studies, e.g. Friedman & Savage (1948) suggest that the elasticity of utility is at its highest for rich people, but not for ultra rich. This implies that at first the utility function is concave but then reshapes into a convex function only to return to concave form after a certain level of wealth. Second, there is empirical evidence, e.g. Bodie & Samuelson (1989), to support the idea that young investors with high future income have a high tendency to hold their wealth in rather risky assets as they can recoup their losses through increased work in the future. Third, the last point is the most ambiguous of these three. There is empirical evidence, e.g. Lewellen, Lease & Schlarbaum (1977), to show that elderly investors tend to invest in less volatile safer assets than their younger counterparts. On the other hand, Samuelson (1969) suggests that under isoelastic marginal utilities investors would have the same risk tendency throughout their life, i.e. the age of an investor should not affect one's risk aversion at any part of her life.

The life cycle hypothesis of Modigliani & Brumberg (1954) and Friedman's (1957) permanent income hypothesis state that one's consumption at any life cycle is dependent on expected resources, labour income, as well as inherited wealth, over one's lifetime. This implies to rather stable consumption rate throughout one's life, as households would typically save during their productive years and respectively live on those savings during retirement or periods of unemployment. In these two studies, however, the idea of different investment objectives was not taken into account. This would imply that on the basis of Modigliani's & Brumberg's and Friedman's theories we cannot draw any conclusions about the behaviour of investors of different age groups.

Multiple objectives of investors have been studied by e.g. Solow (1987), Barlow, Brazer & Morgan (1966) and Thaler (1980). These studies show that investor objectives depend not only on current and expected income, but also on retirement plans, willingness to leave bequests, education, and precaution for potential emergencies, to name a few. To support multiple objectives theory Katona (1960) observed that savings objectives are related to consumption needs under varying horizons and uncertainty over investor's life cycle. Furthermore, Potter (1971) provides evidence to support the multiplicity of objectives, but his study involved only identifications of objectives to hold one particular asset type, i.e. the common stocks. These studies are potentially beneficial for our study, as the multiple objectives named in the studies mentioned affect investor's risk aversion. Therefore, we can conclude that investors, who are e.g. close to retirement age, are more likely to exhibit more risk-averse investment behaviour than their younger counterparts.

The effect of socio-economic factors on investor objectives have been studied by e.g. Lewellen et al. (1977) and Baker & Haslem (1974). Lewellen et al. suggest that elderly investors were more interested in a stable dividend income rather than substantial capital gains. Furthermore, they noticed that investors with more initial wealth were more likely to be interested in long-term goals. Equivalently Baker & Haslem's study shows how sensitivity to dividend yield, capital appreciation and risk is dependent on socio-economic factors. They noticed that risk sensitivity was mostly influenced by age, sex, marital status, education and current income in the respective order of significance. In practice these results suggest that elder, highly educated, married women are more likely to invest in less risky assets than young bachelors. This is very sensible, should we analyse the human nature. During the early years of employment the size of one's household is typically smaller and one only has to take into an account her own needs. As the size of the household increases as one gets married and has children, the objectives are likely to change. Then investors must also consider children's education, especially in the United States, potential investments in real assets such as house etc. Haslam's study also gives further evidence on Lewellen et al's view of elder investors being more interested in a stable dividend yield rather than capital gains.

Gender and marital status sensitivity on investor objectives have been studied in detail by Haynes & Helms (1990, 1992) and Lease, Lewellen & Schlarbaum (1976). Haynes & Helms suggest that the composition of portfolio is indifferent for married couples and single men. They also argue that men and married couples have a higher tendency on allocating their wealth in real estates, common stocks and corporate bonds, whereas single women preferred to hold less risky government bonds. Lease et al. had similar findings in their earlier study as they suggest that especially elderly single women were more conservative and dividend driven, holding more diversified portfolio than any other socio-economic group. Baker & Haslem's study gives further evidence to support different objectives for males and females indicating women's greater emphasis on dividend yield and price stability.

Probably the most studied investor characteristic's effect on asset holding is the effect of wealth on investor behaviour. Nearly every study examines that particular relationship in addition with other things being analysed. The most common result is a positive correlation between one's wealth and the ownership of risky assets. E.g. Cohen, Lewellen, Lease & Schlaurbaum (1975) suggest that risky asset holdings increase in line with the increase in wealth, whilst other factors, e.g. sex, age and income, were kept constant. More recent study to confirm this relation was carried out by Ramaswami, Srivastava & McInish (1992). They conclude that income and net wealth have a positive effect on holdings of riskier assets.

Education's effect on portfolio selection has been studied by Lease et al. (1976) and Barlow et al. (1966). Lease et al. report that highly educated investors tend to prefer more diversified portfolios than the less educated ones. This result is further supported by Barlow et al. who show that households headed by professional employees with high education have higher preference for current yield low risk ratio than their less educated counterparts. The information level of different educational groups may explain these results. More educated investors are likely to be more aware of the stock market and the way it operates. Therefore, they know that portfolio risk can be reduced in great amount with good portfolio diversification without lowering the portfolio return.

Grinblatt & Keloharju (2000) suggest that the foreign investors operating in the Finnish stock market are more likely to employ a momentum strategy and yield higher returns than the domestic investors are. On the other hand, domestic investors tend to employ contrarian strategy and yield lower return than their foreign counterparts. Grinblatt & Keloharju have the same initial data set in their study as we use in ours. These results do not straightway suggest that momentum strategy leads to higher portfolio return than contrarian strategy, but their study gives us a potential research question to study. Can there really be found a correlation between investment strategy, in terms of momentum and contrarian strategies, and portfolio return?

The effect of socio-psychological factors on investor characteristics and portfolio performance has been a rather popular research topic in finance during the past few years. However, there are also older studies to examine this relationship. E.g. Kreinin (1959) reports that investors with optimistic view of future economy and of their personal financial situation are more likely to hold more volatile common stock portfolios than those with more pessimistic expectations. The recent studies include Odean (1998, 1999) and Barber & Odean (2000, 2001). These studies include examinations on investor's level of self-confidence and its effect on portfolio performance. Psychological evidence, e.g. Lundeberg, Fox and Punćochaŕ (1994), shows that men tend to be more overconfident than women. In addition, people tend to be more overconfident in tasks that are from moderately difficult to extremely difficult and correspondingly underconfident in easy tasks. We are sure that we can conclude that investing is at least moderately difficult, which would suggest that investors are likely to be overconfident about it. Odean's and Barber & Odean's results can be concluded in the following manner. Male investors tend to be more overconfident in the stock market than female investors as was suggested by psychological studies. Overconfidence about own investment abilities decrease utility received from trading. And finally, as a result, the most overconfident investors, i.e. those investors who trade the most, have the worst portfolio performance.

3 RESEARCH DESIGN AND DESCRIPTION OF THE DATA

We attempt to explain the behaviour of different investor groups in terms of the properties of their investment portfolios. The simplest classification would be to classify the portfolios according to the size of the portfolio, i.e. the market value and the number of stocks held in it. When we refer to portfolio size in this study, we typically refer to market value of the portfolio and the number of stocks held in it, if not otherwise stated. However, examination that includes only portfolio size would not be very informative, and therefore we base our study on four different features that the investors may exhibit.

First, the market value and the number of stocks held in the portfolio are used to reflect the size of investor's portfolio. Second, the number of purchase transactions should correlate with the activity level of a particular investor. The proxy for activity level could have also been chosen to be the number of sale transactions, as their correlation is relatively high. However, we feel that the activeness of an investor may be better captured with the purchase transactions, as the Finnish small investors have only activated during the past couple of years leading to a drastic increase in the market value of investor portfolios. Third, the risk of portfolio is measured with the beta coefficient, and also with the number of stocks held in the portfolio. Higher beta coefficient implies higher risk, as the volatility of the portfolio is higher, whereas larger number of stocks has the opposite effect on the risk level of one's portfolio. Fourth, the strategy an investor may occupy is characterised with the performance of one's purchase transactions within the past 250 trading days. Positive sign for this variable implies that the investor occupies momentum strategy, whereas negative sign implies contrarian strategy to be exhibited. However, it must be noted that most of the small investors do not consciously occupy either of the strategies.

Cluster analysis encompasses a number of different classification algorithms, which can be classified into two broad families: hierarchical and non-hierarchical clustering. This study could have been performed using either clustering procedure. The latter alternative suits our objectives better as the former, first, as it is better suited for clustering large samples, which consist of more than 10 000 objects. Second, in non-hierarchical clustering procedure the number of clusters can be determined in advance, and therefore the number of clusters remains relatively small. Hierarchical method may have produced more than 100 clusters, which would not have been appropriate for our purpose.

The empirical research in this study was performed in four different stages. In the first stage we chose the appropriate variables to be clustered in order to acquire the most appropriate information the data contains. We chose to perform only one clustering set up to explain the behaviour of market participants. Alternative solution would have been to divide the examination of different features into different clustering algorithms, but we feel that some information may have been lost had that alternative been executed. Furthermore, the analysis of the results is easier as one must not compare the different clustering results to one another, because no two clustering problems are similar in nature.

In the second stage includes we use an approach suggested by Art, Gnanadesikan, and Kettenring (1982) to obtain approximate estimates of the pooled within-cluster covariance matrix when the clusters were assumed to be multivariate normal with equal covariance matrices. This procedure is widely used before using the optimising clustering procedure, i.e. non-hierarchical clustering, as the optimising procedure seems to perform well with spherical clusters, but poorly with elongated elliptical clusters that were to be clustered in this study. (Everitt, 1980.) In practice, the procedure produces canonical variables from the initial variables that can be easily and correctly clustered with the optimising procedure in the third stage. The canonical variables are linear transformations of the initial variables.

The third stage of the empirical analysis includes the most significant part of the empirical investigation in this study. The canonical variables produced by the first procedure are clustered with the optimising clustering procedure based on Späth (1985) in order to produce the final clusters. The output of the optimising clustering procedure is actually clustering result for the canonical variables. As we are not interested in the properties or the values of the canonical variables within each cluster, the resulting clusters were analysed using the initial data set in order to get the correct values and the properties for each cluster.

After the original clustering procedure we examine the demographic characteristics of clustered observations in the fourth stage. This includes examination of each cluster in terms of investors' wealth, age and sex. By these means we try to establish a connection between the particular demographic characteristics and investment behaviour of Finnish small investors. This step should provide very good empirical evidence on the initial hypotheses stated earlier.

The data set used in our study is based on the Finnish Central Securities Depository's (FCSD) share ownership records. The record includes the initial balance of FCSD's share ownership record and all changes in these records until December 31, 2000 for all publicly quoted companies represented in the Book Entry System. The Book Entry System is an electronic share ownership and trading record. All changes in the data are updated daily, thus the data allows us to study the portfolio and its composition of any investor at any time during the time-span. Our data records only the ownership of individual investors and excludes institutional ownership completely as we are mainly interested in classifying individual investor groups.

The Book Entry System is a compulsory registration of stock holdings for Finnish citizens and institutions. The data is not a complete register of stock ownership in Finland, as foreign investors are partially exempt from registration. They can opt for registration in a street name. As a result, the ownership records of foreign investors are combined to a larger pool of nominee registered holdings. Therefore, their shareholdings or trades cannot be separated from each other by scientific investigation.

The data excludes also indirect stockholdings. This means that the holdings of investment companies owned by one person are considered to be institutional ownership rather than individual. For the same reason the indirect ownership through mutual funds is not included in the data.

Our data set has 526 399 observations. The number of observations was higher in the initial data set, but we decided to drop the outliers in order to produce better clustering results. This is a common procedure when clustering techniques are applied to larger data set, as they are very sensitive to outliers and extreme values. We included approximately 99 per cent of the observations for each variable in the final data set. In the end the number of observations in the data was approximately five per cent smaller than at the beginning.

Each observation had initially 22 attributes assigned to them, however some of the attributes were not used. Table 1 lists the identification variable and the other important variables existing in the data. There are also some other variables that remain unlisted in table 1, as they were not used at any part of the clustering procedure.

Table 1. Variables used in the study

Variables	Content of the variable
ID	Investor identification number
GENDER	Gender of the investor (1 = male, 2 = female)
AGE	Age of the investor
RP	Return of the portfolio per annum
STDRP	Volatility of the portfolio
BETA	Beta coefficient of the portfolio
VALUE	The average value of the portfolio
STOCK	The average number of stock in the portfolio
BDAYS	Number of days of buy- transaction occurrence
BOBS	Number of buy- transactions
B01	One-month return of the purchased stocks
B12	Twelve-month return of the purchased stocks

Gender and Age are used as socioeconomic variables in the study. Gender-variable states the gender of the investor, and gets value of 1 in the case of a male investor and value of 2 in the case of a female investor. Male investors are normally found to occupy more active and risky behaviour in the market. Age-variables correspondingly shows the age of an investor. Elder investors are assumed to take a more cautious approach towards the market, and their portfolios are assumed to be less risky than their younger counterparts.

The value-weighted annual return of the portfolio shows the annual overall performance of the investor's portfolio. This variable can be used to analyse the dispersion of the performance of Finnish small investors. It is very interesting to discover, first, how disperse the returns of different investors are, and second, what are the median and mean returns for Finnish investors during the investigation period.

The annual standard deviation and beta- coefficient of the portfolio can be used to estimate the risk level of an investor portfolio. High standard deviation and large beta- coefficient of one's portfolio would imply that the investor is a "risk-loving" investor, i.e. she would exhibit a rather low degree of risk aversion. Correspondingly lower standard deviation and smaller beta- coefficient would suggest more risk-averse nature of an investor.

Market value of the portfolio can be used to approximate the wealth of an investor as well as the intensity of one's investing behaviour. The latter approximation is based on the assumption that an investor with a large investment portfolio is likely to monitor the market situation more carefully than an investor with a relatively small portfolio does. We can further assume that the investors holding a larger portfolio may be more educated about the functionality of stock markets in general.

The number of stocks held in the portfolio shows the degree of diversification of one's investment portfolio. We assume that a rational investor would hold a well-diversified portfolio. However, we found that most of the Finnish small investors do not exhibit rational market behaviour, instead they normally hold a one-stock portfolio.

The number of buy-transactions and -occurrence can be used in order to study the activity of an investor in the Finnish stock market. A large number of either transactions indicates active market behaviour and vice versa. The correlation between the sale and buy transactions is rather high, see table 5. Thus, it would have been plausible to use either of the variables to measure the activity level of an investor. However, we decided to choose the number of purchase transactions as a proxy for market activity, as the number of Finnish households operating in the Helsinki Exchange has increased significantly during the investigation period. There it is natural to assume that more investors have purchased stocks than sold them during that period.

Mean return of buy-transactions during the past month and 250 trading days indicates the investment strategy an investor occupies. Positive sign in the mean return of buy-transactions would suggest that the investor occupies a momentum strategy, in which she invests in past winners. Correspondingly negative sign in the mean return of the transactions implies a contrarian-strategy to have been used by the investor.

4 EMPIRICAL RESULTS

Table 2 reports the basic statistics for the most used variables in the data. The table shows that mean portfolio return is 24 per cent per annum. This suggests that the portfolio return for the investigation period has been significantly higher than the historical stock market return. However, the standard deviation of the portfolios is also rather high, i.e. 20 per cent per annum. This indicates that different investors experience rather different returns in the Finnish stock market.

Table 2. Basic statistics for the variables used in the study.

Variable	Mean	Std Dev	Min	Max
RP	0.24	0.20	-2.00	2.85
STDRP	0.31	0.12	0.07	2.98
STOCK	2.82	3.26	1.00	152.66
VALUE	24.73	641.60	0.18	347 261
BETA	0.94	0.48	- 2.08	2.16
BOBS	3.85	28.71	0.00	6.621
SOBS	2.91	28.99	0.00	7.596
B01	0.11	0.22	0.00	1
B12	0.09	0.19	0.00	1

The values for VALUE, BOBS, and SOBS are in 1000. The number of observations is 526 399.

The market value of the portfolios varies very significantly across the data. The mean market value for all portfolios is 24 793 euros, whereas the standard deviation is 641 610 euros. This result shows that there is a large variety of different types of investors in the market, which can also be seen from the minimum and maximum values for the portfolio value.

The average value of the beta-coefficient for all portfolios is rather close to unity, i.e. 0.94, as would be expected. In addition, the standard deviation is also relatively low. This result indicates that the average portfolio in the Finnish stock market has rather similar risk loading compared to the HEX25 portfolio index.

According to the data, it seems that most of the Finnish investors are very passive. The average number of buy-transactions is 3.85, whereas the number of sale-transactions is even lower, i.e. 2.91. However, divergence in the market is very large as suggested by the large standard deviation in the both values. The maximum values are 6 621 and 7598 for buy- and sale-transactions respectively. From that finding, we can safely assume that there are intra-day traders among the Finnish small investors.

The variables used to study the behaviour of Finnish small investor, i.e. the one-month return and twelve-month return of the purchased stocks, indicate that the Finnish investors would occupy a momentum-strategy in the market as opposed to the findings of Grinblatt and Keloharju (2002). However, the standard deviations for both variables are rather high. Thus, the results are insufficient to confirm any such behaviour. In addition, it can be safely assumed that a standard small investor does not consciously occupy momentum-strategy in her trading behaviour.

Table 3 reports the correlation matrix for the variables used in our study. It shows that the only strong correlation is between variables SOBS, number of sale-transactions, and BOBS, number or purchase-transactions. In addition, the correlation between one-month return-, B01, and twelve-month return of the purchased stocks is relatively high. These correlations are rather clear, as it is sensible that if an investor is an active market participant the number of sale and purchase transactions have a strong correlation. The correlations for other variables are relatively weak, and some variables do not correlate with each other at all. The most interesting non-correlation is between market value and return of the portfolio. One could easily assume that an investor with a large portfolio would spend more time following the market and have better knowledge of the market as a whole, and therefore would command better return. However, there seems to be no such linkage according to our data.

Table 3. Correlation matrix.

	RP	STDRP	STOCK	VALUE	BETA	BOBS	SOBS	B01	B12
RP	1	0.03	-0.11	-0.01	-0.22	0.01	0.01	-0.08	-0.09
STDRP		1	-0.31	-0.01	0.35	-0.03	-0.01	-0.06	-0.14
STOCK			1	0.08	-0.03	0.27	0.18	0.37	0.42
VALUE				1	0.00	0.05	0.04	0.03	0.03
BETA					1	0.01	0.01	0.07	0.02
BOBS						1	0.96	0.19	0.18
SOBS							1	0.13	0.12
BO1								1	0.72
B12									1

The deviations of the portfolios of the Finnish small investors are relatively high, as can be seen in the table 4. The over-all volatility of their portfolios was 20 per cent per annum, whereas the return was 24 per cent. The median of the portfolio return is slightly lower 21 per cent per annum. Surprising result is that the portfolio return per annum decreases as the number of stocks held in the portfolio increases. It would be sensible to assume that the portfolio return might increase in line with portfolio diversification. This result, on the other hand, is influenced by good performance by Nokia, by far the most popular stock in the Finnish market.

The median value of the portfolio volatility decreases as the portfolio diversification increases. However, the theory does not give any suggestions about the magnitude of the decrease. Here the mean volatility of portfolios consisting of four or more stocks was approximately one third lower than that of one-stock portfolios. That can be considered as a rather significant decrease in volatility.

Table 4. The distribution of the most important variables in the data

	STOCK	Min	25%	50%	75%	Max
			Panel A			
RP	1	-0.64	0.17	0.38	0.38	2.53
	2	-0.81	0.09	0.21	0.33	2.50
	3	-1.14	0.08	0.20	0.31	2.38
	>3	-1.77	0.09	0.18	0.28	2.51
	ALL	-1.77	0.11	0.23	0.38	2.53
			Panel B			
STDRP	1	0.11	0.31	0.31	0.38	2.98
	2	0.10	0.23	0.29	0.36	2.85
	3	0.10	0.21	0.27	0.34	2.50
	>3	0.07	0.09	0.18	0.28	2.51
	ALL	0.07	0.24	0.31	0.35	2.98
			Panel C			
VALUE	1	0.18	226.86	782.45	2 166.78	44 926 700
	2	0.23	942.93	2 316.50	5 731.89	85 578 700
	3	3.16	1661.47	3 941.37	9 330.71	43 088 900
	>3	12.75	6098.57	15 773.50	42 186.00	347 262 000
	ALL	0.18	666.72	2483.04	9544.58	347 262 000
			Panel D			
BETA	1	-1.89	0.87	1.04	1.04	1.90
	2	-1.82	0.41	0.89	1.19	1.89
	3	-1.49	0.47	0.85	1.21	1.89
	>3	-1.69	0.62	0.95	1.26	2.00
	ALL	-1.89	0.60	1.04	1.17	2.00

The beta-coefficients of the portfolios behave in rather strange manner. The median and mean beta-coefficients of one-stock and more-than-three-stock portfolios are rather close to unity, whereas those of the two- and three-stock portfolios are around 0.85. This would imply investors holding a two- or three-stock portfolio invest in less riskier stocks, in average, than other investor types. One must still notice that the standard deviations within each group are relatively large. However, an over-all median portfolio has a beta-coefficient of 1.04.

Table 5 reports the clustering results for all households in our data set. We can see from table 5 that the observations are quite poorly distributed among the five clusters. Over 75 percent of the observations are placed into the cluster one. Note that we have numbered the clusters according to their number of members, so that the largest cluster is cluster one and the smallest is cluster five. There is a plausible explanation for the poor distribution of the variables. As we could see from the table 4, majority of Finnish small investors hold only one stock in their portfolio and are very passive. We can see that those investors form cluster one, as the number of stocks and number of trades is lower than in any other cluster, as can be seen from the table 6. Moreover, the market value of the portfolios in cluster one remains very small. However, the intra-cluster deviations are rather high, except for the number of buy-transactions, within the cluster one. One should also note that we have excluded all the passive investors, who have not traded during the investigation period from the cluster analysis.

Table 5. Properties of the clustering results for all households

Cluster	Frequency	Within cluster mean distance	Std. Dev. of distance	Nearest cluster	Distance btw. cluster centroids
1	200 672	2.09	1.34	2	2.82
2	48 296	3.71	2.54	1	2.82
3	12 405	7.38	4.29	1	17.46
4	2416	14.73	8.84	4	40.31
5	544	30.02	17.71	5	88.21

The clustering result for all private investors shows how concentrated and homogenous the Finnish stock market is. More than 95 percent of the private investors are assigned to two inter-jointed clusters with very short cluster centroid distance. In addition, the other three clusters are very well separated from the two largest clusters.

Clusters 1 and 2 are relatively similar to one another as can be seen from the tables 5 and 6. The largest difference between the clusters is the magnitude of the beta coefficient and the twelve-month return of the buy-transactions. It would seem that the investors in cluster 2 invest in less riskier stocks than the investors in cluster 1, and have slightly larger and more diversified portfolios. Other attributes of the investors are relatively similar.

Table 6. The clustering results for all households and the values for age, gender, and market value- variables in each cluster.

		Cluster				
Variable	Statistic	1	2	3	4	5
STOCK	Mean	3.78	6.06	10.14	11.96	12.23
	Std.dev	(2.31)	(4.98)	(7.02)	(8.42)	(9.83)
STDRP	Mean	0.27	0.30	0.26	0.27	0.29
	Std.dev	(0.08)	(0.15)	(0.11)	(0.14)	(0.16)
BOBS	Mean	2.55	2.57	44.88	134.03	328.13
	Std.dev	(5.13)	(3.37)	(16.91)	(36.23)	(75.70)
B12	Mean	0.09	0.36	0.36	0.35	0.32
	Std.dev	(0.15)	(0.31)	(0.14)	(0.12)	(0.11)
BETA	Mean	0.97	0.75	1.00	0.99	0.99
	Std.dev	(0.47)	(0.50)	(0.38)	(0.39)	(0.38)
AGE	Mean	51.50	50.90	49.70	50.96	50.99
	Std.dev	(18.46)	(18.18)	(13.14)	(12.08)	(11.84)
GENDER	Mean	1.38	1.34	1.15	1.11	1.08
	Std.dev	(0.48)	(0.47)	(0.36)	(0.32)	(0.27)
VALUE	Mean	24.59	786.37	1487.31	3645.84	3296.03
	Std.dev	(3687.32)	(18075.29)	(9839.72)	(19101.83)	(9923.04)

VALUE is reported in 1000. VALUE-variable was not part of the cluster analysis, and as the diversion in portfolio size is really large, the standard deviations in VALUE are extremely large.

The three smaller clusters, i.e. clusters 3, 4 and 5 are very different from the first two clusters. The largest difference is in the trading activity. Whereas, the clusters 1 and 2 consisted mainly of passive investors, investors in clusters 3, 4 and 5 are very active. Their portfolios are also larger, in monetary terms, and better diversified. From socioeconomic and demographic point of view, these investors are also more likely to be men as the gender-variable is relatively close to one. The surprising result is that the standard deviation of the annual return does not decrease in line with the increase in the degree of diversification. This could be caused by the attribute that the wealthier investors are less risk-averse, and therefore have riskier portfolios. However, this view is not supported by the beta-coefficient of the different clusters, as they are relatively similar.

Clusters four and five include the largest small investors, who have larger, in monetary terms, and more- diversified investment portfolios. The difference between these clusters lies in the activity level of the respective clusters. Investors in cluster 4 are very active, but the investors extremely active on average. We can see that the number of investors in clusters 4 and 5 is relatively small indicating that only a small fraction of Finnish small investors are very active in the market.

The age- variables shows no clear indication that elder investors hold a larger and a more-diversified stock portfolio as suggested by the economic theory. This can be seen from Table 6, as the average age in each cluster is relatively similar. In addition, the standard deviation increases from cluster 1 to cluster 5, implying that there is likely to be more young investors in the larger clusters. However, effect of age on activity should be examined fixing behaviour-affecting variables such as investor wealth.

The gender-variable shows that stock market is dominated by male investors, as the gender variable gets a value of one for male investors and a value of two for female investors. This can probably explained by the cultural aspect that men usually manage the financial matters within a typical Finnish family. However, we can see that the proportion of male investors increases as the portfolio size and activity increases. This may also imply that male investors are more eager to day-trade than the women are and have larger proportion of their wealth invested in the stock market. This is supported by previous literature that states that young female investors are more likely to invest in government bonds and other low risk investment opportunities rather than directly in the stock market. Correspondingly, previous literature also states that male investors are eager to invest directly in the stock market.

The clustering result for all households is relatively good, expect for the distribution of the observations. Clusters 1 and 2 are very tight clusters and are well- isolated from the other clusters. This can be explained by the similarity of the portfolios of the investors in the two clusters. They have small, poorly diversified portfolios and do not trade actively. On average, the other three clusters are rather well isolated from one another.

As the clustering results were dominated by the passive investors holding only one stock in their portfolio, we decided to deepen our analysis for those investors in the further analysis. Thus, we would be able to analyse the characteristics of the investors, who are the most abundant in the market in more detail. As a result, investors from clusters 2, 3, 4 and 5 are excluded in the remaining analysis.

Table 7. Properties of the results of the second-step clustering.

Cluster	Frequency	Within cluster mean distance	Std. Dev. of distance	Nearest cluster	Distance btw. cluster centroids
1a	150 496	1.93	1.07	2	9.66
1b	19 390	5.07	2.31	2	11.37
1c	14 582	5.25	2.20	4	9.66
1d	9 830	5.95	2.34	2	10.22
1e	6 374	6.48	2.54	1	13.11

The clustering result is very concentrated also in the second-step clustering process. However, all clusters are of considerable size, and they are well separated from each other.

Table 7 reports the clustering results for the households of the initial cluster 1. Most of the investors are still assigned to the largest cluster. However, all the clusters are well separated from each other, which can be seen by comparing the within cluster mean distance and distance between cluster centroids. Therefore, it is easier to draw more robust conclusions from this analysis. In addition, each cluster now has a considerable amount of investors assigned to them.

Table 8 reports the clustering results for the cluster 1 of the initial analysis. We can see that again cluster 1a, we number the clusters of the second stage by numbers 1a-1e, consists of passive investors holding a relatively poorly diversified portfolio. By comparing cluster 1 and cluster 1a of, we find that the two clusters are very similar. The largest difference is in the number of buy-transactions, which is rather plausible as the active investors of the cluster 1 are assigned to other cluster. One could argue that the cluster 1a represents the typical Finnish small investor. A representative of this average investor would be a 50-year-old investor holding a rather small, poorly diversified, and static portfolio. In addition, these investors seem to be a bit more risk averse than the other investors in the market, which can be seen from the beta-coefficient of the cluster one. The volatility of their portfolio seems to be at the same level as that of the other investors, as they do not benefit from the virtues of diversification.

Table 8. The clustering results for the initial cluster 1 and the values for age, gender ,and market value- variables in each cluster.

		Cluster				
Variable	Statistic	1a	1b	1c	1d	1e
STOCK	Mean	3.27	3.89	5.28	6.52	7.92
	Std.dev	(1.65)	(1.73)	(2.65)	(3.47)	(4.40)
STDRP	Mean	0.27	0.26	0.27	0.27	0.27
	Std.dev	(0.07)	(0.08)	(0.08)	(0.08)	(0.09)
BOBS	Mean	0.27	4.17	8.56	13.66	20.58
	Std.dev	(0.80)	(3.00)	(3.14)	(3.79)	(3.24)
B12	Mean	0.01	0.34	0.28	0.28	0.30
	Std.dev	(0.03)	(0.14)	(0.15)	(0.16)	(0.14)
BETA	Mean	0.93	1.07	1.10	1.07	1.07
	Std.dev	(0.48)	(0.43)	(0.40)	(0.39)	(0.37)
AGE	Mean	52.65	48.84	47.48	47.47	47.93
	Std.dev	(19.04)	(17.84)	(15.77)	(14.50)	(13.48)
GENDER	Mean	1.42	1.33	1.24	1.19	1.17
	Std.dev	(0.49)	(0.47)	(0.43)	(0.39)	(0.38)
VALUE	Mean	21.45	20.10	30.09	45.30	67.91
	Std.dev	(4093.71)	(5296.7)	(849.39)	(2019.45)	(4834.30)

VALUE is reported in 1000. VALUE-variable was not part of the cluster analysis, and as the diversion in portfolio size is really large, the standard deviations in VALUE are enormous.

By looking at the other clusters, we can find similar results to the initial clustering analysis. The activity seems to increase again as the portfolio size increases. Table 8 shows that the average age of the investors also decreases as the activity increases as predicted by the economic theories. In addition, the active investors are also more likely to be men, which is also supported by the previous studies and economic theories.

The results we obtained were rather robust. The most common features of the investors in both clustering phases remained largely unchanged, when the number of clusters was from three to ten. In addition, the demographic features of the clusters were also largely unchanged, when we used different behavioural variables in the clustering procedures.

5 CONCLUSIONS

The aim of our study was to study the linkage between different behavioural assumptions with the rational expectations approach and to link the behavioural characteristics of the investors with the demographic characteristics of the Finnish small investors. The study was carried out in Helsinki Stock Exchange due to the uniqueness of the data set available.

First, we introduced the concept of risk aversion in order to explain the potentially different behaviour of investors. Second, we studied the characteristics affecting risk aversion of individual investors. By combining these two aspects we were able to construct a framework in which to analyse the behaviour of Finnish small investors.

We discovered that Finnish small investors are rather exhibit rather homogenous market behaviour. Majority of the investors hold a small portfolio, as 75 per cent of the investors hold a portfolio whose market value is less than 10 000 euros, and usually exhibit only little diversification. The number of stocks in a typical Finnish small investor portfolio varies from one to three. The economic theories suggest that the investors should be rather homogenous in the market. Our study proves that suggestion correct. However, the theories also suggest that investors should act rationally in the market, i.e. hold a well-diversified portfolio. Our study confirms the contrary. The asset allocation of most investors is to such extent concentrated that it cannot or at least should not be called rational. However, the rationality of investors' behaviour seemed to increase as a function of portfolio size. This would imply that wealthier investors are probably better informed and more aware of the market as a whole than their less wealthy counterparts.

The activity level of the Finnish small investors is very low. The typical Finnish investors hardly traded during the investigation period. The second-step clustering analysis shows that activity level seemed to increase as the average age of the investor group decreased. In addition, the male investors were found to be more active than the female investors.

The results obtained in the study do not give strong support to suggest any certain strategies to be occupied by certain investor groups. However, in the second-step clustering analysis we found that the tendency for momentum-behaviour increases as the portfolio size increases. However, more analysis must be done in order to be able to draw robust conclusions about that.

There are many questions still to be answered in the future studies. By keeping other variables fixed, how does the age of an investor really affect investment behaviour. In addition, how different is the female stock market behaviour from that of the male investors.

REFERENCES

Arrow, K.J. (1964). The role of securities in the optimal allocation of risk bearing. Review of Economic Studies 31(2), 91-96.

Art, D., Gnanadesikan, R., and Kettenring, R. (1982). Data-based metrics for cluster analysis. Utilitas Mathematica 21A. 75-99.

Baker, H. & Haslem, J. (1974). The impact of investor socio-economic characteristics on risk and return preferences. Journal of Business Research 10(2), 469-476.

Barber, B.M. & Odean, T. (2000). Trading is hazardous to your wealth: the common stock investment performance of individual investors. Journal of Finance LV(2), 773-806.

Barber, B.M. & Odean, T. (2001). Boys will be boys: gender, overconfidence, and common stock investment. The Quarterly Journal of Economics 116(2), 261-292.

Barlow, R.Brazer, H. & Morgan, J. (1966). Economic □ehaviour of the affluent. The Brooking Institution, Washington, DC.

Bensmail, H and DeGennaro, R (2004). Analysing imputed financial data: A new approach to cluster analysis. Working paper 2004-20. Federal Reserve Bank of Atlanta.

Cinca, S., Molinero, M., and Larraz, G. (2001). Country and size effects in financial rations: A European perspective. Discussion Papers in Accounting and Finance. University of Southampton.

Cohen, R., Lewellen, W., Lease, R. & Schlaurbaum, G. (1975). Individual investor risk aversion and investment portfolio composition. Journal of Finance XXX(3), 605-620.

Dahstedt, R., Salmi, T., Luoma, M. & Laakkonen. A., (1994). On the usefulness os standard industrial classifications in comparative financial statement analysis. European Journal of Operational Research 79(2), 230-238.

Friedman, M. (1957). A theory of the consumption function. Princeton University Press. Princeton, CA.

Gerrans, P. (2004). Australian managed fund ratings and individual investors. Australian Journal of Management 29(1), 87-108.

Grinblatt, M. & Keloharju. M. (2000). The investment □ehaviour and performance of various investor types: a study of Finland's unique data set. The Journal of Financial Economics 55(1), 43-67.

Haynes, P.J. & Helms, M.M. (1990). The demographics of managing finances. Personal Financial Planning 4(1), 23-27.

Haynes, P.J. & Helms, M.M. (1992). Analysing customer attitudes. Personal Financial Planning 6(1), 23-28.

Katona, G. (1960). The powerful consumer. McGraw-Hill, New York.

Kreinin, M.E. (1959). Factors associated with stock ownership. Review of Economcics and Statistics 41(1), 76-80.

Lease, R.C., Lewellen, W.G. & Schlarbaum, G.C. (1976). Market segmentation: Evidence on the individual investor. Financial Analyst Journal 32(5), 53-60.

Lewellen, W.G., Lease, R.C. & Schlarbaum, G.C. (1977). Patterns of investment strategy and □ehaviour among individual investors. The Journal of Business 50(3), 296-333.

Lundeberg, M.A., Fox, P.W. & Punćochaŕ, J. (1994). Highly confident but wrong: gender differences and similarities in confidence judgements. Journal of Educational Psychology, LXXXVI(1), 114-121

Modigliani, F. & Brumberg, R. (1954). Utility analysis and the consumption function: an interpretation of cross-section data. In: Abel, A (ed.). Collected Papers of Franco Modigliani, Vol. 2. MIT Press, Cambridge, MA.

Odean, T. (1998). Volume, volatility, price and profit when all traders are above average. Journal of Finance, LIII(5), 1887-1934.

Odean, T. (1999). Do investors trade too much? American Economic Review, LXXXIX(4), 1279-1298.

Potter, R.E. (1971). An empirical study of motivations of common stock investors. Southern Journal of Business 6(1) 41-48.

Pratt, J.W. (1964). Risk aversion in the small and in the large. Economica 32(1), 122-136.

Ramaswami, S.N., Srivastava. R.K. & McInish, T.H. (1992). An exploratory study of portfolio objectives and asset holdings. The Journal of Economic Behavior and Organisation 19(2), 285-306.

Samuelson, P.E. (1969). Lifetime portfolio selection by dynamic stochastic programming. Review of Economics and Statistics 51(3) 239-246.

Shaffer, S. (1991). Aggregate deposit insurance funding and taxpayer bailouts. Journal of Banking and Finance 15(4-5), 1019-1037.

Späth, H. (1985). Clustering Dissection and Analysis. Theory, FORTRAN Programs, Examples. Ellis Horwood Limited. Chichester, UK.

Thaler, R. (1980). Toward a positive theory of consumer choice. Journal of Economic Behavior and Choice 1(1), 39-60.

Tobin, J. (1958). Life cycle saving and balanced growth. In: Fellner, (ed.). Ten economic essays in the tradition of Irving Fisher. Wiley, New York.

von Altrock, C. (1995). Fuzzy logic and neuro fuzzy applications explained. Inform Software Corporation. Prentice Hall, Germany.

RETAIL TRADERS AND DAILY BETS; SING WHEN YOU’RE WINNING?

Abstract

Individual investor engages in day trading, if she buys and sells the same stock on the same trading day. Day trading has become increasingly popular during the past decade. However, academic literature suggests that individual investors actually hurt their portfolio performance by excess trading. Moreover, it would also seem that investors’ behaviour is not as homogeneous as previously assumed. Therefore, we analyse the performance of Finnish day traders during 1995-2003 in order to find more evidence on these phenomena. First, we divide the intra-day traders into five different categories based on their past levels of trading activity and trading performance, and analyse whether heavy traders and/or traders with a good track record perform better than an occasional day trader? Second, we analyse the realised and unrealised gross/net profits/returns for completed day trades, i.e. the position is closed during that trading day, and for partially executed day trades according to investors' level of day trading activity and number of day-traded stocks. Finally, we study the effect of market experience, trading experience and market sophistication on overall trading performance.

1 INTRODUCTION

"In this business if you're good, you're right six times out of ten. You're never going to be right nine times out of ten." – Peter Lynch

The year 2008 has brought the world's biggest rogue trading scandal to date, as Jérôme Kerviel's, a Société Générale's trader, actions cost the bank approximately 4.9 billion euros. Kerviel took bets worth over 50 billion euros on the future direction of European shares, his position exceeding the value of the company by 15 billion euros. (http://news.bbc.co.uk) Kerviel's example may be a good warning sign for several retail traders who engage in active day trading. Even the professional traders cannot succesfully outguess the market, let alone the mostly unsophisticated retail investors who, to make the situation even worse, face significantly higher transaction costs. Their daily bets may severely hurt the performance of their portfolios even in the long-run, if these daily bets are not completely closed in case of unfavourable price movement.

Day trading has become increasingly popular among the retail investors over the past decade. According to U.S. Senate Permanent Subcommittee on Investigations "a growing number of people are giving up their existing careers or withdrawing their savings to become full-time professional day-traders." In addition, Google returns more than 4 970 000 hits for "day trading". However, academia seems to be somewhat lagging in this progression. This is not probably due to lack of interest, but more to a lack of proper data. Fortunately, there are several recent papers covering this phenomenon, e.g. Barber, Lee, Liu & Odean (2004) and Linnainmaa (2003) and (2005).

It is a documented fact that retail investors are becoming more involved in daily trading. Market movements are mostly unpredictable, yet retail traders are willing to bet on the future direction of share prices. What drives this sort of behaviour? We can safely assume that it is not rationality. So, is it greed, overconfidence or blatant ignorance of the nature of day trading? Day trading, to a large extent, is a zero-sum game, in which David rarely beats Goliath. However, this fact is often ignored by the average retail investor, who thinks she can outguess the rest of the market about the future direction of a share price.

Academic literature does not provide answers for this irrational market behaviour exhibited by some retail investors. Therefore, we start approaching the question in a more pragmatic manner. New York Times' day trading portal (http://daytrading.about.com) lists reasons why an average day trader is not successful in the long-run: (1) Lack of trading plan, (2) failure to control emotions, (3) failure to accept and limit losses, (4) lack of commitment, and (5) over-trading. What could an academic infer from this? An average day-trader seems to suffer, at least, from overconfidence (1) & (5) as well as of disposition effect (2) & (3). The discussion regarding the related literature is in Section 2.

If the probability of an upward movement and a downward movement of a share price are approximately equally likely, retail traders' bet would, on average, bring a negative profit, because of transaction costs. However, on a basis of probability calculations, there must be some retail investors who make mostly profitable bets (e.g. the probability of six successful daily bets is approximately 1/64). Is it luck that drives the success of certain day traders, or do e.g. experience and private information affect profitability of their bets? The existing academic literature is somewhat limited, yet increasing quite fast, and some of the earliest studies were conducted using small sample of accounts from one brokerage firm. Thus, drawing conclusive inferences from these studies, e.g. NASAA (North American Securities Administrators Association) sponsored study published in 2000, which concluded that day traders lose money, is rather difficult.

Thus, we are studying the profitability of retail traders' daily bets in the Finnish market, in order to answer the following questions. (1) Does the past trading activity affect the profitability of retail investors' future daily bets, (2) does the past performance give indication on the future profitability of retail investors' future bets, (3) how do unexpected market changes affect retail investors' daily bets, and (4) Does experience, e.g. market experience, trading experience and investor sophistication, affect retail investors trading performance?

Our findings are as follows. First, the higher the total trading volume during the past six-month period is the higher the day trader's weekly trading returns are. We find a strong negative trend in the weekly trading returns as the volume of trading decreases. This may be caused e.g. by the learning effect or the market sophistication of wealthier investors. Second, the day traders having the highest return-risk measure for the past six months actually experience a reversal in their trading returns for the subsequent period. This may be a consequence of excess trading caused by overconfidence resulting from very high past trading returns. Moreover, there seems to be consistency in other return-risk groups suggesting that, at least to some extent, trading returns result from skill rather than pure luck. Third, retail day traders seem to suffer from disposition effect and do not realise their day trading losses fully. This finding holds for different trading activity levels and number of day-traded stocks implying that even the most experienced and sophisticated investors probably do not have a proper day trading plan. Finally, we document that market experience and market sophistication have a positive effect on trading returns, whereas trading experience has the opposite effect. This should not be viewed as conclusive evidence on the worthlessness of trading experience, but more as a conclusion that holding market experience and market sophistication constant, excess trading decreases day trader's performance.

The remainder of the paper is organised as follows. Section 2 overviews the literature regarding potential pitfalls of a typical day trader and develops the four hypotheses tested in our paper. Section 3 describes the data and methodology used in the study. The empirical results are presented in Section 4 and Section 5 concludes the paper.

2 Hypotheses development and related literature

Hypothesis 1 & 2: Past trading performance and activity do affect the profitability of retail investors' daily bets.

Retail investors learn "their trade" by being active in the stock market. Thus experienced investors, with a solid past performance, fare better in the market than their less experienced counterparts. Most of the previous studies use trading volume as a measure of activity, e.g. Barber & al. (2004), but we examine whether the actual number of day trades have the same kind of effect on retail traders' performance. Our hypothesis is that it is not actually the volume but the experience that an investor gains from separate trades that drives the potential learning of the investors.

The previous literature is somewhat ambiguous. Some of the studies show that some individual investors are able to earn abnormal returns, e.g. Barber & al. (2004), whereas majority of the literature confirms that most individual investors hurt their performance by (excess) trading. Barber and Odean (2000) show that the top-performing quartile of the retail investors outperforms the market by 6 percent per annum. In addition, Ivkovich and Weisbrenner (2005) and Ivkovich et al. (2005) note that they generate high returns by exhibiting home-bias and individuals with underdiversified portfolios outperform those with diversified portfolios. Furthermore, Kaniel et al. (2005) document that stocks heavily bought by retail investors earn abnormal positive returns during the following month. Finally, Coval et al. (2005) report that top-performing decile of retail investors buy stocks that earn daily abnormal returns of 1.2 – 1.5 percent during the following week. Correspondingly the bottom-performing decile loses approximately 1.2 percent a day during the same time. Their results are robust to risk adjustments, small stock removal etc. They also present a trading strategy exploiting information in investors' trades that earns 0.5 percent risk-adjusted daily return.

Moreover, Harris & Schultz (1998) analyse the performance of Small Order Execution System (SEOS of Nasdaq) bandits. They use the trading records from two brokers, covering 20 000 trades over a three week period, who try to profit from the fragmented order flow. These traders were found to earn a small daily profit, although the lose money almost as frequently as they make money. Garvey & Murphy (2001) use a sample of 15 professional day traders and 96 000 trades over a three month period in 2000. These traders used firms' capital and paid no commission in return for a shared profit. Garvey & Murphy report that these 15 traders were able to earn a small daily profit by placing limit orders inside the current best quotes offered by the dealers in the market. Jordan & Diltz (2002) study the professional U.S day traders and show that most of them are losing money; roughly 20 percent of the traders are even marginally profitable after adjusting for transaction costs. In addition, the day trading profits were found to be related to ups and downs of NASDAQ. Seasholes & Wu (2004) use the Chinese data from the Shanghai Stock Exchange with ten very active day traders. They were found to make money by buying stock hitting their upper price limits and selling them the next day. Barber, Lee, Liu & Odean (2004) analyse the performance of Taiwanese day traders during 1995-1999. Eight out of ten of them were found to lose money. However, the most active traders and traders with a strong past performance earned a small daily profit.

Individual investors' level of sophistication is often questioned. E.g. Black (1986), De Long et al. (1990) and Lee et a.l (1991) provide evidence that individual investors' investments decisions are often driven by liquidity demand and/or psychological reasoning unrelated to the underlying security values. Furthermore, individual hurt their portfolio performance by trading too much, holding undiversified portfolios, exhibiting home bias and as presented earlier selling winning stocks too early and holding losing stocks for too long. (E.g. Blume and Friend (1975), Odean (1998, 1999), Grinblatt & Keloharju (2001).) Barber et al. (2005) suggest that trading -, market-timing losses and commissions reduce the return of individual investors 3.6 percent annually. Thus, they rarely beat the market or the institutional investors. In addition, Hirshleifer et al. (2001) and Cohen et al. (2002) suggest that individual investors fail to react correctly to cash flow news and earnings announcement, thus trading unprofitably compared to other investor groups.

Linnainmaa (2003) and (2005) uses the same data set from the Finnish Central Securities Depository as we do. Linnainmaa reports that the performance of the day traders is inferior to that of the control sample. Furthermore, he shows that there is a negative relation between day trading profits and portfolio's long-term performance. Day traders were also found to migrate towards holding uncomfortable portfolios because of behavioural biases.

As discussed above, the evidence on the effect of previous trading performance and activity is broad and ambiguous. We use the same data set as Linnainmaa and the same method as Barber & al. (2004) in order to study the phenomenon in the Finnish stock market among private day traders. However, the foremost task is to show that the individual Finnish day traders are not homogenous and thus enable further research in this paper. Hypotheses 1 & 2, though so numbered, are not the most important ones in this paper.

Hypothesis 3: Individual day traders suffer from disposition effect and do not complete their bets if the market movement is unexpected (to them).

Shefrin & Statman (1985) introduced the concept of disposition effect, which can be defined as investors' tendency to ride losses too long and realise gains too soon. However, the roots of this phenomenon lie in the prospect theory introduced by

Kahneman and Tversky (1979) and mental accounting framework by Thaler (1980, 1985). The disposition effect is well documented in the academic literature, see e.g. Thaler, Tversky, Kahnemann and Schwartz (1997) and Weber and Camerer (1998), therefore it can be safely assumed that individual retail traders' trading behaviour is not unaffected by the phenomenon. Thus, retail traders would complete mostly such day trades that are profitable to them, and only partially, or not at all, complete day trades, where market movement is unexpected. Linnainmaa (2003) reports that the day trading profits and returns for complete day trades are significantly higher than those of partial day trades. We expand the method used by Linnainmaa by linking the hypothesis 1 to the hypothesis 3. Thus, we study whether day traders with different background (namely trading activity and number of day-traded stocks) react differently to unexpected market movements and are some day traders more prone to hold losing stocks than others.

The evidence on the execution of complete and partial day trades is rather limited. Linnainmaa (2005) gives a detailed description of it, but the trades are classified on the basis of how the trade is executed, e.g. whether the trader first buys it and then sells or vica versa. We concentrate on evaluating how the past trading activity affects the execution of complete and partial daily bets. There might be differences between individual day traders on how they are able to interpret the arriving market information, i.e. the learning effect. Thus, more experienced day traders might be better off in their bets than their less experienced counterparts.

Kaustia (2003) shows that even the active day traders are prone to disposition effect in the Finnish stock market. The returns from complete day trades are superior to the trades where investor bought the stock during the same day, but chose not to complete the day trade. Furthermore, recent paper by Kaustia (2009) finds evidence that the prospect theory does not explain the investors' tendency to suffer from disposition effect.

Hypothesis 4: Investor experience improves trading performance of retail investors.

Feng & Seasholes (2005) have studied the effect of investor sophistication and trading experience on behavioural biases found in the stock market. They discover that neither sophistication nor trading experience alone eliminate disposition effect. However, together sophistication and trading experience seems to eliminate the reluctance to realise losses. We study the effect of experience and investor sophistication on daily trading performance. The assumption is that the more experienced and sophisticated retail traders make better bets about the future direction of the stock market. Thus, their trading performance should be better than that of the less experienced and sophisticated investors.

Correspondingly, Nicolosi, Peng & Zhu (2009) report that portfolio returns improve with account tenure and trade quality also increases with experience. Thus, according to them investors learn from their own investment history and seem to make adjustments to their future trading based on that information, which leads to higher investment performance. In our setting we assume that experience helps investors to learn from their personal investments history and thus the profitability of daily bets increases with account tenure.

Seru, Shumway & Stoffman (2007) investigate the effect of trading experience on the disposition effect and trading performance. They show that more experienced investors are less likely to suffer from the disposition effect and their trading performance is better. In addition, they show that investors as a group tend to learn partly by attrition, but individual level learning is also important. However, they use completely different type of return measure, namely next year's return, whereas we are interested in the net return associated with individual trades. Furthermore, they do not use as precise trade partition as we do.

Furthermore, List (2003) and Dhar & Zhu (2006) show that experience plays a significant role in eliminating judgement errors such as endowment and disposition effect. Thus, we assume that trading experience helps retail traders to learn about their private signal precision. This would in turn decrease the probability of excess trading, which is known to hurt portfolio performance, e.g. Barber & Odean (2000).

3.1 Helsinki Stock Exchange

Helsinki Stock Exchange (HEX) is part of the Nordic Exchange, including also Copenhagen, Stockholm, Riga, Tallinn and Vilnius Stock Exchanges. Trading on HEX is divided into sessions. Each trading day starts with a pre-trading session, during which manual trades, so called after market II -trades in this phase, and pre-opening trades can be recorded. Each trading starts with an opening call at 9.45 AM, and it is part of the continuous trading session, which ends at 6.30 PM. Trading takes place in a fully automated limit order book, the automated trading and information system (HETI). During the brief termination phase, 6.30 PM – 6.40 PM, after the closing call order management and manual trade registration is prevented. During post-trading session, 6.40 PM – 7.00 PM, manual trades, so called after market I -trades in this phase, can be concluded. In addition, order management is possible allowing good-till-date order (GTD) cancellation as well as those order changes for GTD orders that have no effect on order priority. (www.hex.fi)

The HEX trading system shows the five best price levels of the book to the market participants. Financial institutions receive market-by-order book that shows each order and submitter of the order separately, whereas the public can view the book in market-by- price form, in which only the total number of shares outstanding for each price level is reported. There are no market makers or specialists in the HEX, as the market is completely order-driven and investors trade by submitting limit orders. For immediate execution, an investor must place the order at the best price level on the opposite side of the book; these orders are called market orders. Time and price priority between separate limit orders is enforced, i.e. all the older orders outstanding must be executed before a new order may be. The minimum tick size in HEX is 0.01 euros.

The level of transaction costs for the data period is considerably hard to determine. Transaction costs declined rather sharply in the turn of the century as new brokerage houses, e.g. EQ Bank (formerly EQ Online) and E-trade, entered the market and forced the traditional players to decrease their prices as well. Thus, we will use the price level of 2003 for the whole data period, which might underestimate the level of transaction costs in the beginning of the data period. Furthermore, we do not have the information about the brokerage house used by the trader, thus we assume that she is acting rationally and using the cheapest one[2]. This assumption is rather valid as EQ Bank had a market share of 50 percent in 2004. (Talouselämä 2004.)

We use an example to illustrate the difference in transaction costs between different brokerages. If a retail investors completes five trades with a combined worth of 12 500 euros per year and holds five stock in her portfolio the difference between the cheapest and the most expensive brokerage is 110,50 euros, the cheapest costs only 66,50 euros a year, whereas the most expensive 177 euros a year. The difference in the prices is nearly one percent of the total amount traded. All the estimates given in this paper are the most optimistic ones, the retail traders might have actually used a lot more expensive brokerage and their return/profit may actually be significantly less.

[2] E-Trade is actually the cheapest brokerage house, but its market share is very small and it entered the market at the end of the data period. Thus, we are using the cheapest of the large brokerage houses in our estimation.

3.2 Data

We have acquired the complete trading history of all individual day traders in the Helsinki Stock Exchange from January 1, 1995 through December 31, 2002. Each record includes a data, individual investor identification code, investor type identification code – a domestic household in this case -, stock code, price, volume and various demographic characteristics.

The data set used in our study is based on the Finnish Central Securities Depository's (FCSD) share ownership records. The record includes the initial balance of FCSD's share ownership record and all changes in these records until December 31, 2003 for all publicly quoted companies represented in the Book Entry System. The Book Entry System is an electronic share ownership and trading record. All changes in the data are updated daily, thus the data allows us to study the portfolio and its composition of any investor at any time during the time-span. Our data records only the ownership of individual investors and excludes institutional ownership completely as we are primarily interested in analysing individual day traders.

The Book Entry System is a compulsory registration of stock holdings for Finnish citizens and institutions. The data is not a complete register of stock ownership in Finland, as foreign investors are partially exempt from registration. They can opt for registration in a street name. As a result, the ownership records of foreign investors are combined to a larger pool of nominee registered holdings. Therefore, their shareholdings or trades cannot be separated from each other by scientific investigation.

The data excludes also indirect stockholdings. This means that the holdings of investment companies owned by one person are considered to be institutional ownership rather than individual. For the same reason the indirect ownership through mutual funds is not included in the data.

3.3 Methodology

We define a daily bet (day trade) as the purchase and sale (in any order) of the same stock during the same trading day by an investor. A day trader is defined as an individual investor who makes at least one daily bet during the sample period. The term day trader normally refers, especially in the U.S., to a professional investor whose primary goal is to earn a living with the day trading profits, see SEC report (2000) for more information. However, we are interested in analysing the behaviour and daily performance of any retail trader who behaves like a professional day trader. Although the execution of a single day trade constitutes for being classified as a day trader, those occasional traders are primarily trading in small amounts and are pooled in to the same subgroup. Therefore they can be used as a benchmark for the proper day traders in order to study e.g. the learning curve of individual traders.

First, we sum the value of buy and sell transactions for all the day traders on each stock for each trading day, during which at least a single day trade has taken place. The intraday return of the sells is calculated as the volume-weighted average price of the sell transactions divided by the volume-weighted closing price. The same analogy is used to calculate the intraday return of buys. If a trader executes more than one day trade on a given trading day, all the day trades are pooled together in order to form a day trade portfolio using the same analogy as in a single day trade scenario. Furthermore, on each day, we construct a trading return measure for each day trader by subtracting the return on the buy portfolio from that of the sell portfolio. In order to account for daily variation, we take a five-day moving average for each trading day. Thus, we able to construct a more reliable measure, that shows the performance of investors' day trades and its persistence, see equation (1),

$$TR_t^p = R_t^s - R_t^b , \qquad (1)$$

where R_t^s is the return of the sell portfolio during the past five trading days, and correspondingly R_t^b is the same return for the buy portfolio. The returns for each portfolio is calculated as

$$R_t^{s/b} = \frac{\sum_{i=1}^{n} x_{it} R_{it}}{\sum_{i=1}^{n} x_{it}}, \qquad (2)$$

where R_{it} is the intra-day return of the stock i on day t, n is the number different a stocks sold/purchased during that particular day, and x_{it} is the compound of the intra-day returns for each stock i from the time of sell/purchase through to $t-1$ multiplied by the initial price of the stock. For more information see Barber et al. (2005), they use the same methodology for constructing returns for sell and buy portfolios in their paper.

Second, we classify the day traders based on their past day trading activity. In day t , we sum the total value of day trading (DT) from the past six months, and form five exclusive day trade categories. The partitions are the following:

400 000 € $<$ DT
200 000 € $<$ DT $\leq$ 400 000 €
50 000 € $<$ DT $\leq$ 200 000 €
10 000 € $<$ DT $\leq$ 50 000 €
DT $\leq$ 10 000 €

Using these day trader categories we analyse the five-day trading performance of each day trader group at day t.

Third, we partition the day traders into five different categories based on their past trading performance. We calculate the mean standardised trading returns from the past six months at day t. The categories are the following:

0.02 < TR / σ(TR)

$$
\begin{aligned}
0.00 < TR / \sigma(TR) &\leq 0.02 \\
-0.02 < TR / \sigma(TR) &\leq 0.00 \\
-0.04 < TR / \sigma(TR) &\leq -0.02 \\
TR / \sigma(TR) &\leq -0.04
\end{aligned}
$$

Using this partition we analyse the average five-day trading return for each category at day t. Updates are made on a daily basis.

In the second part, first we divide day trades into two different categories; complete day trades and partial day trades. Complete day trade is a round-trip during the same trading day, i.e. buying and selling exactly the same number of shares of one particular stock. Partial trade corresponds to any other sort of day trade, e.g. a day trader might buy 3000 shares, but she sells only 2000 of them during the same trading days. Then we calculate four different performance measures for day trading; daily gross profit, daily net profit, daily gross return and daily net return in the following manner,

$$
\begin{aligned}
\Pi_{i,t} = {} & P_{s,i,t}V_{s,i,t} - P_{b,i,t}V_{b,i,t} \\
& + \max(V_{b,i,t} - V_{s,i,t}, 0)(P_{c,t} - P_{b,i,t}) \\
& + \max(V_{s,i,t} - V_{b,i,t}, 0)(P_{s,i,t} - P_{c,t})
\end{aligned} \tag{3}
$$

$$
\hat{\Pi}_{i,t} = \Pi_{i,t} - 8.25€ - 0.002(P_{s,i,t}V_{s,i,t} + P_{b,i,t}V_{b,i,t}) \tag{4}
$$

$$
r_t = \frac{\sum_i \Pi_{i,t}}{\sum_i (P_{s,i,t}V_{s,i,t} + P_{b,i,t}V_{b,i,t})} \tag{5}
$$

$$\hat{r}_i = \frac{\sum_i \hat{\Pi}_{i,t}}{\sum_i (P_{s,i,t}V_{s,i,t} + P_{b,i,t}V_{b,i,t})}. \tag{6}$$

$P_{s,i,t}, P_{b,i,t}$ and $P_{c,t}$ are sale, purchase and same-day closing prices, respectively, for each individual stock, investor and day. $V_{b,i,t}$ and $V_{s,i,t}$ are the number of shares bought and sold during that particular trading day by one particular investor. The adjustments for net profit and return account for a fixed fee of 8.25 euros and a proportional fee of 0.2 percent of the total value of the trade.

Then the day traders are divided into five different investor groups according to their number of day trades (TA = trading activity) and number of day trades stocks (NSS = number of speculative stocks) in their portfolio using the following criteria;

$TA \leq 40$	$NSS \leq 4$
$40 < TA \leq 120$	$4 < NSS \leq 12$
$120 < TA \leq 280$	$12 < NSS \leq 24$
$280 < TA \leq 360$	$24 < NSS \leq 36$
$360 < TA$	$36 < NSS$

Finally, we run a regression analysis to determine whether the more experienced retail traders have better daily trading returns than their less experienced counterparts. We regress each daily net trading return of each of the retail traders on experience variables, the number of years traded (EXP), i.e. account tenure, total number of yearly trades (TA), trading activity, and number of speculative stocks per year (NSS), trade diversification/market sophistication. We are hoping to establish that investor performance increases with experience, but excess trading on the other hand decreases that effect. Specifically, we estimate the regression

$$r_{i,t} = \alpha_i + \beta_i EXPVAR_{i,t} + \beta_2 EXPVAR_{i,t}^2 + \delta X_{i,t} + \chi_t + \varepsilon_{i,t} \,. \quad (7)$$

EXPVAR-variable is the experience variable used, i.e. the number of years traded, the total number of trades per year or the number of speculative stocks per year. The squared *EXPVAR*-variable is used in the second part of the analysis, i.e. robustness check. Finally, χ is the yearly dummy-variable. The regression equation used in each regression is more closely specified in the specific table providing the regression estimates.

4 EMPIRICAL RESULTS

Table 1 reports the descriptive statistics of the data. Our sample contains 1 195 282 retail investors, of whom 24 113 are classified as day traders. Day trader is defined as a trader who executes at least one day trade during the sample period. Eventhough the day traders account only for about 2 per cent of the trading population, their share of the total value of retail investors' trading is 34 per cent. Thus, they form a significant part of the retail investors' trading volume. This can be seen from the average total volume of trading, which almost 1 100 000 Euros for day traders compared to non-day traders 64 000 Euros. However, most retail investors' trading volume during the sample period is less than 20 000 Euros.

A more comprehensive descriptive statistics for day traders and non-day traders are reported in Table 2. Day traders hold more diversified portfolios, trade more, are slightly younger and are more likely to be men than the non-day trading retail investors. The day traders' trading activity is roughly 13 times larger than that of the non-day traders, namely 58.45 trades compared to 4.46 trades, during the sample period. In addition, the size of their trades is significantly larger. Whilst the mean buy and sell for non- day traders are roughly 4200 and 5300 euros, the corresponding figures for day traders are larger than 9000 euros. Furthermore, the fraction of female traders is significantly lower amongst the day traders. Correspondingly the average portfolio of a day trader is composed of 14 stocks, whereas non-day traders hold less than three stocks in their portfolio on average.

Table 1. Basic statistics of the data.

Mean daily value of all trade and day trade				
Investor type	n	Total value of trade	Mean value of trade	% of trade
All individuals	1 195 282	7.61E+10	63 646.42	1
Day traders	24 113	2.58E+10	1 071 735.72	0.34
Total value of trade	n	Total value of trade	Mean value of trade	% of trade
> 500k €	19 893	4.91E+10	2 470 222.37	0.65
101k - 500k €	64 979	1.37E+10	210 512.93	0.18
20k - 100k €	195 621	8.61E+09	43 992.21	0.11
< 20k €	914 789	4.65E+09	5 083.76	0.06

Mean value of trade corresponds to the total amount of buys and sells during the sample period for an average day trader. Correspondingly the total value of trade takes into account all day traders' buys and sells for a certain investor group.

Table 3 reports the five-day moving average and one-day average returns partitioned by the amount of day trade during the past six months. It can be clearly seen that the larger the amount of day trade, the better the average is. For the largest day traders, DT > 400 000€, the average 5-day trading return is 5.8 (1.2 percent a day) percent before transaction costs. However, this is caused by very good returns by the top decile, whose daily returns are over 10 percent (not reported in the table, available upon request). The second largest day trade group, 200 000 € < DT ≤ 400 000 €, performs also rather well earning a weekly profit of 3.4 percent. The third day trade group, 50 000 € < DT ≤ 200 000 €, earns roughly 0.3 percent a week before transaction costs, whereas fourth, 10 000 € < DT ≤ 50 000 €, and fifth group, DT ≤ 10 000 €, earns negative 5-day returns. Altogether the average weekly performance of all day traders is -1.0 percent.

Table 2. Overview of day traders and non-traders market behaviour.

Overview of day traders					
Value of trade	n	# of stocks	# of trades	Total of buys	Total of sells
All	24 113	13.93	58.45	540 626.06	531 109.66
> 500k €	7 629	19.61	112.02	1 524 579.45	1 507 210.65
101k - 500k €	9 552	13.73	45.05	128 837.11	120 660.01
20k - 100k €	5 530	8.74	20.45	29 970.05	26 795.03
< 20k €	1 402	4.80	8.15	6 214.78	5 289.71
Value of trade	Mean of buys	Mean of sells	% of trade	Birth	% of women
All	9 249.15	9 086.34	0.34	1 955	0.16
> 500k €	13 610.34	13 455.29	0.30	1 952	0.12
101k - 500k €	2 859.75	2 678.24	0.03	1 955	0.16
20k - 100k €	1 465.38	1 310.14	0.00	1 958	0.18
< 20k €	762.17	648.72	0.00	1 960	0.20
Overview of non-day traders					
Value of trade	Mean of buys	Mean of sells	% of trade	Birth	% of women
All	1 171 169	2.53	4.46	19 071.96	23 819.08
> 500k €	12 264	10.91	48.20	943 115.63	1 177 775.34
101k - 500k €	55 427	7.73	19.35	90 080.48	113 714.11
20k - 100k €	190 091	4.45	7.99	19 647.01	23 973.62
< 20k €	913 387	1.71	2.23	2 236.19	2 837.71
Value of trade	Mean of buys	Mean of sells	% of trade	Birth	% of women
All	4 276.76	5 341.27	0.66	1 953	0.34
> 500k €	19 566.84	24 435.33	0.34	1 951	0.19
101k - 500k €	4 655.10	5 876.42	0.15	1 950	0.22
20k - 100k €	2 458.67	3 000.11	0.11	1 951	0.26
< 20k €	1 001.19	1 270.51	0.06	1 954	0.36

Number of stocks is the number of stocks held in one's portfolio during the sample period. The stocks are not necessarily held at the same time. Numbers of trades corresponds to the number of buy and sell transactions. Total of buys /sells is the cumulative value of one's trading transactions, whereas mean of buys/sells tells the mean value of these transactions. Percentage of trade is investor groups' share of the total trading value of all individual investors. Birth reports the average birth year of an investor and percentage of women tells the portion of female investor in particular investor group

We can see from table 3 that more than every second day trader is earning negative day trade returns even before transaction costs. The rather large, positive means for day trade groups 1 and 2 are earned by the top decile of the both respective groups. In other groups, the returns are more equally distributed and in fact, the median returns in the two most active groups are the worst.

Table 3. 1 and 5-day moving average day trader performance on day trading volume.

DT	N	Median	5-day mean	1-day mean
All	78323	-0.002	-0.010	-0.002
			(-51.11)	(-10.22)
1	6642	-0.005	0.058	0.012
			(14.12)	(3.86)
2	5004	-0.003	0.034	0.007
			(5.82)	(2.11)
3	16729	-0.002	0.003	0.001
			(2.06)	(1.68)
4	24307	-0.002	-0.010	-0.002
			(-14.30)	(-3.63)
5	25641	-0.001	-0.008	-0.002
			(-11.41)	(-3,12)

We classify the day traders based on their past day trading activity. In day t, we sum the total value of day trading (DT) from the past six months, and form five exclusive day trade categories. The partitions are the following: (1) 400 000 € < DT, (2) 200 000 € < DT ≤ 400 000 €, (3) 50 000 € < DT ≤ 200 000 €, (4) 10 000 € < DT ≤ 50 000 €, and (5) DT ≤ 10 000 €. The values in parentheses are Student's t-values.

Table 4 reports the five-day and one-day moving average day returns partitioned by the past six months' standardised return. Although, the number of participants in the first group is rather small, namely 274, it is rather surprising to see that very good past performance seems to reverse and their 5-day return is -2.0 percent (-0.4 percent a day). This could be explained by increased overconfidence and trading after good trading performance, i.e. day traders start trading more and more aggressively, thus worsening their trading performance significantly. For the moderately performing day traders, group 2, the weekly performance continues to be positive, namely 3.8 percent. This is once again mostly earned by the top decile. For the groups 3, 4 and 5 the weekly returns remain negative are -0.7, -0.06, and -0.10 percent respectively. Medians are negative in each group implying that every other day trader is earning negative returns even before transaction costs.

Table 4. 1 and 5-day moving average day trader performance on past trading performance.

TR/TR(σ)	N	Median	5-day mean	1-day mean
All	78323	-0.002	-0.010	-0.002
			(-50.11)	(-8.96)
1	274	-0.003	-0.020	-0.004
			(-2.04)	(-1.65)
2	15703	-0.002	0.038	0.009
			(15.99)	(4.82)
3	60994	-0.002	-0.007	-0.001
			(-11.79)	(-3.24)
4	1135	-0.002	-0.006	-0.001
			(-2.51)	(-1.98)
5	217	-0.003	-0.010	-0.002
			(-4.46)	(-2,21)

We partition the day traders into five different categories based on their past trading performance. Then we calculate the mean standardised trading returns from the past six months at day t. The categories are the following: (1) $0.02 < TR / \sigma(TR)$, (2) $0.00 < TR / \sigma(TR) \leq 0.02$, (3) $-0.02 < TR / \sigma(TR) \leq 0.00$, (4) $-0.04 < TR / \sigma(TR) \leq -0.02$, and (5) $TR / \sigma(TR) \leq -0.04$. The values in parentheses are Student's t-values.

.

Gross/net profits/returns are reported in Table 5. The returns are partitioned by the trading activity of each day trader. The table shows no significant difference in daily gross or net returns for different activity groups for complete day trades. The daily net returns vary from 0.3 percent for the least active group to 0.1 percent for the most active groups; correspondingly the gross returns vary between 0.4 and 0.6 per cent. However, the net profit decreases as the trading activity increases, implying that the more experience day traders might not be able to use their trading experience properly. Furthermore, the results are affected by the measure, trading activity, which does not account for the magnitude of the trades.

Table 5. **Day trader performance for complete -, partial day trades and unrealised returns on partial day trades based on past trading activity.**

		Day trader performance			
TA	N	Gross profit €	Net profit €	Gross return	Net return
		Complete day trades			
1	102074	149.73	-14.45	0.004	0.001
		(29.47)	(-2.86)	(93.17)	(32.40)
2	38105	171.01	44.92	0.004	0.001
		(21.13)	(5.69)	(49.56)	(17.46)
3	23525	126.19	12.46	0.005	0.002
		(3.14)	(0.30)	(41.73)	(17.04)
4	35654	166.47	70.82	0.005	0.002
		(13.80)	(5.89)	(50.91)	(18.95)
5	35434	164.55	94.56	0.007	0.003
		(18.69)	(11.03)	(47.15)	(19.27)
		Partial day trades			
TA	N	Gross profit €	Net profit €	Gross return	Net return
1	49473	-647.49	-877.47	-0.020	-0.023
		(-1.95)	(-2.64)	(-13.10)	(-14.76)
2	16204	686.03	522.78	-0.010	-0.013
		(1.30)	(0.99)	(-3.72)	(-4.68)
3	9382	-407.05	-552.97	-0.014	-0.017
		(-0.49)	(-0.66)	(-3.94)	(-4.71)
4	12859	520.66	400.44	-0.008	-0.011
		(1.08)	(0.83)	(-2.57)	(-3.51)
5	14441	-611.46	-690.70	-0.017	-0.021
		(-1.99)	(-2.24)	(-5.48)	(-6.86)
		Unrealised returns for partial day trades			
TA	N	Gross profit €	Net profit €	Gross return	Net return
1	49473	39.43	-231.00	0.003	-0.000
		(1.19)	(-6.96)	(41.65)	(-2.54)
2	16204	-46.10	-249.40	0.002	-0.001
		(-1.52)	(-7.96)	(14.05)	(-7.35)
3	9382	-7.47	-182.80	0.003	-0.001
		(-0.14)	(-3.30)	(11.40)	(-4.04)
4	12859	57.20	-96.46	0.003	-0.001
		(1.19)	(-1.99)	(14.33)	(-3.24)
5	14441	-49.11	-145.06	0.003	-0.003
		(-1.63)	(-4.67)	(11.39)	(-10.54)

Gross profit is the monetary profit, in euros, of one's day trading before commissions. Net profit takes commissions into account. Gross and net returns are constructed similarly. Values in parentheses are Student's t-values. The categories are the following; (1) TA ≤ 40, (2) 40 < TA ≤ 120, (3) 120 < TA ≤ 280, (4) 280 < TA ≤ 360 and (5) TA > 360.

Daily returns for partial day trades tell a completely different story. All the gross and net returns for partial day trades are negative, as well as all the statistically significant gross and net profits. The gross and net returns are at their lowest for the most active investor group suggesting that as one trades excessively, some of the trades must be, at least partially, executed at a significant discount. Net returns vary from -1.1 percent for the group four to -2.3 percent for the most active day traders. The daily net profits show how harmful the partial day trades are for investors' wealth. The most active group loses almost 900 euros daily, because of their failed partial day trades. Even the least active group loses over 600 euros a day.

We suggest that partial day trades are actually bets, in which the market movement is in the wrong direction for the day trader. Therefore, they do not realise the loss completely, but they tend to leave a portion of the day trade position in their portfolio. This behaviour is consistent with the disposition effect widely reported in the literature.

The unrealised profits/returns for partial day trades show how the remaining part of the day trade position faired. Table 5 shows that the net profits and returns are negative for each investor group. This indicates that investors tend to hold some of the day traded stocks, when the price of the stock falls. The net profits are the worst for the two most active investor groups whose portfolio's value drops by roughly 250 euros from the time of purchase. The best off is the group 4 who lose "only" 96 euros a day.

Next we partitioned daily gross/net profits and returns with respect to number of day trades stocks in the portfolio. The results are shown in Table 6. The table shows no significant difference in daily gross or net returns for different groups for complete day trades. The daily net returns vary from 0.2 percent for the groups 1-4 to 0.1 percent for the group that has the smallest number of day-traded stocks in their portfolio; correspondingly the gross returns vary between 0.4 and 0.5 per cent. In addition, all the statistically significant gross and net returns are positive and vary between 136.57 euros and 172.26 euros for gross profits and between 22.90 euros and 49.64 euros for net profits. However, there isn't any statistical difference between the groups (not reported in the table, available upon request.)

Daily profits/returns for partial day trades give us completely different evidence. All the statistically significant profits and returns for partial day trades are negative. The returns are at their lowest for the investor group that has the highest number of day traded stocks suggesting that as one diversifies day trading, the trader might lose some of the information advantage she possesses compared to an average investor. The daily net returns vary from -3.0 percent for the group five to -1.3 percent for the group having the least number of day trades stocks.

Table 6. Day trader performance for complete -, partial day trades and unrealised returns on partial day trades based on number of speculative stocks.

Day trader performance					
Complete day trades					
NSS	N	Gross profit €	Net profit €	Gross return	Net return
1	67529	165.80	49.64	0.005	0.001
		(25.25)	(7.78)	(58.36)	(16.74)
2	46898	136.57	-13.52	0.005	0.002
		(6.52)	(-0.62)	(56.41)	(22.09)
3	33195	164.05	35.83	0.004	0.002
		(12.00)	(2.63)	(45.91)	(15.72)
4	22575	172.26	45.12	0.004	0.002
		(17.77)	(4.88)	(39.98)	(15.51)
5	64595	148.58	22.90	0.005	0.002
		(27.02)	(4.35)	(83.30)	(38.67)
Partial day trades					
1	28411	299.22	148.64	-0.010	-0.013
		(0.86)	(0.43)	(-4.69)	(-6.30)
2	18881	384.23	175.30	-0.008	-0.010
		(0.58)	(0.27)	(-2.96)	(-4.06)
3	13716	-915.42	-1118.85	-0.015	-0.018
		(-1.94)	(-2.37)	(-5.12)	(-6.04)
4	9987	-574.60	-725.86	-0.020	-0.023
		(-1.41)	(-1.77)	(-5.60)	(-6.36)
5	31364	-775.80	-950.66	-0.027	-0.030
		(-1.97)	(-2.42)	(-13.13)	(-14.47)

Unrealised returns for partial day trades					
1	28411	295.26	144.29	-0.010	-0.013
		(0.85)	(0.41)	(-4.68)	(-6.23)
2	18881	387.34	177.96	-0.008	-0.010
		(0.59)	(0.27)	(-3.01)	(-4.09)
3	13716	-887.96	-1089.53	-0.016	-0.019
		(-1.91)	(-2.34)	(-5.34)	(-6.26)
4	9987	-565.48	-716.79	-0.019	-0.022
		(-1.38)	(-1.75)	(-5.26)	(-6.02)
5	31364	-791.34	-970.53	-0.027	-0.030
		(-1.99)	(-2.44)	(-13.23)	(-14.56)

Gross profit is the monetary profit, in euros, of one's day trading before commissions. Net profit takes commissions into account. Gross and net returns are constructed similarly. Values in parentheses are Student's t-values. The categories are the following; (1) NSS ≤ 4, (2) 4 < NSS ≤ 12, (3) 12 < NSS ≤ 24, (4) 24 < NSS ≤ 36 and (5) NSS > 36.

The daily net profits and returns confirm the evidence how harmful the partial day trades are for investors' portfolio performance and wealth. The investors in groups 3 and 5 lose approximately 1000 euros daily, because of their failed partial day trades. For partial day trades, there is also statistically significant difference between the groups 1/2 and 4/5 supporting the evidence that day trade diversification is not profitable for investors. We once again suggest that partial day trades are actually bets about the future market movement. If the market movement is in the "wrong" direction, the trader does not complete the day trade and leave a portion of the day trade position in their portfolio. As mentioned earlier, this behaviour seems to be consistent with the disposition effect widely reported in the literature.

The unrealised daily profits/returns for partial day trades show how the remaining part of the day trade faired. One can see from the Table 6 that the gross and net returns are negative for each investor group. Correspondingly all the statistically significant gross and net profits are also negative. The values are of the same magnitude as the realised part of the partial day trades indicating that there is no positive market movement during the remaining trading day.

Finally we run a two-part regression analysis for which the results are shown in Tables 7 and 8. First, we regressed the daily returns for all day trades, complete day trades, partial day trades and unrealised partial trades on experience, amount of trading per year and number of day traded stocks. Secondly, we let the experience factor to be non-linear as normally suggested by the literature.

Table 7. Trading returns and learning.

	All trades		Complete trades		Partial trades		Remaining position	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Intercept	0.039	0.033	0.099	0.096	-0.034	-0.051	-0.274	-0.278
	(0.42)	(0.34)	(4.00)	(3.85)	(-0.14)	(-0.21)	(-4.56)	(-4.52)
EXP	0.011	0.036	0.023	0.044	-0.041	0.025	0.0718	0.0878
	(0.27)	(0.65)	(2.95)	(3.67)	(-0.38)	(0.21)	(3.69)	(2.49)
EXPsq		-0.006		-0.005		-0.015		-0.004
		(-1.45)		(-2.25)		(-3.91)		(-0.66)
DT	-0,0005	-0,0005	-0.0007	-0.007	0.0004	0.0003	-0.0005	-0.0005
	(-3.54)	(3.49)	(-4.79)	(-4.86)	(0.97)	(0.88)	(-2.42)	(-2.47)
NSS	0.00062	0.0061	0.0005	0.0005	0.088	0.0003	0.008	0.008
	(3.37)	(3.38)	(2.67)	(2.62)	(0.57)	(0.53)	(2.65)	(2.62)
N	336266	336266	336266	336266	336266	336266	336266	336266
Yr fixed	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ind fixed	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

This table reports the estimates of regression of the form

$$\textit{Trading return}_{i,t} = \alpha_i + \beta_1 \textit{ Experience}_{i,t} + \beta_2 \textit{ Experience\^{}2}_{i,t} + \gamma_t + \varepsilon_{i,t},$$

where Experience is measured by market experience (EXP), trading experience (DTY) or market experience in different stocks (NSS). Market experience is also allowed to take non-linear form. The dependent variable $r_{all,t}$ in this estimation is the trading return of an individual day trader *i* at time *t*. We also include year dummies as well as individual intercepts in each of the regressions. The figures below the regression estimates are the t-statistics associated with the specific estimate. The table includes all the day trade observations during the sample period.

The results are very consistent. When analysing the results for the daily returns of all day trades, we can see that the number of yearly trades decreases retail investors' performance as expected. However, the descriptive statistics suggested that number of day-traded stocks should also decrease trading performance, but this seems not to be the case after controlling for experience, number of yearly trades, year effects and individual effects. Actually diversifying one's day trading actually seems to be worthwhile.

The results for complete day trades are quite similar to those of all trades. However, there is one vital difference. Experience improves retail investor's trading performance as expected. We argue that the more experienced trades are more likely to guess (know) the market movement of a particular stock correctly, and thus they execute more complete day trades. Number of yearly day trades worsens investors' performance and diversifying day trading improves it. Thus the results are consistent with the evidence for all trades.

For partial day trades only the intercept term is statistically significant. Unlike for complete day trades, for which the value is positive, the intercept is negative indicating that on average partial day trades are unprofitable for retail investors. This would seem to support our hypothesis that day trades are actually bets about the movement of the market/a particular stock, and if the movement is unfavourable then the day trade is not completely executed. The other terms are not statistically significant, so it would seem that all types of retail investors suffer from this phenomenon.

The results for the unrealised return of the day trading position are quite similar to those of complete day trades with one significant difference. The intercept term is negative for the unrealised position. This indicates that it would be more sensible to complete the day trade and not to leave a portion of the day-traded stock in the portfolio, at least on a very short term. However, it would seem that experience and day trade diversification actually decreases the loss from unrealised position, whereas number of yearly trades actually increases it.

Table 8 shows the robustness checks for the regression analysis. We regress each of the explanatory variables individually on daily returns of all trades, complete day trades, partial day trades and unrealised day trade position and let the variable be non-linear. For all trades, only number of yearly trades is statistically significant and negative as expected when using all variables and their squares and experience and number of yearly trades and their squares. However, in individual regression number of yearly trades and its square are not statistically significant.

For complete day trades, which are the “purest” day trades, the results are quite similar to those reported in Table 8. Experience and day trade diversification have a positive effect on daily returns, whereas number of yearly day trades decreases one’s performance. The squares of each variable are very interesting. The value for the square of experience is negative, which is the natural assumption for all the squares. The effect increases at a decreasing speed as experience grows. The same applies for number of yearly trades, but with opposite sign. The effect is negative, but it seems to dampen as the number of yearly trades increases. However, for day trade diversification the both the signs are positive implying that the effect is actually increasing with increasing rate. However, we should note that when using the two variables in other regression the results are not consistent. All the intercept terms are once again positive and statistically significant giving further evidence on our hypothesis that day trades are actually bets about the market movement. Once the bet is successful, the day trade is completed.

Table 8. Trading returns and learning.

	Panel A						
	Dependent variable $r_{all,t}$						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Intercept	0.039	0.091	0.071	0.044	0.043	0.078	0.045
	(0.40)	(5.86)	(2.56)	(0.45)	(0.40)	(2.79)	(0.43)
EXP	0.040			0.045	0.036		0.041
	(0.70)			(0.81)	(0.68)		(0.76)
EXPsq	-0.006			-0.006	-0.006		-0.007
	(-1.43)			(-1.57)	(-1.48)		(-1.65)
DT		-0.0003		-0.0004		-0.002	-0.001
		(-0.95)		(-2,78)		(-6.01)	(-6.44)
DTsq/1000		0.0003		0.0004		0.00005	0.006
		(3.96)		(4.18)		(3.76)	(4.24)
NSS			0.0007		-0.0005	0.0006	0.0005
			(0.09)		(-0.10)	(0.87)	(1.08)
NSSsq/1000			0.060		0.073	0.052	0.067
			(0.49)		(3.86)	(0.44)	(3.77)
N	336266	336266	336266	336266	336266	336266	336266

Yr fixed	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ind fixed	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Panel B							
Dependent variable $r_{comp,t}$							
Intercept	0.10	0.17	0.16	0.11	0.10	0.16	0.10
	(4.03)	(9.84)	(8.44)	(4.21)	(3.94)	(8.59)	(3.96)
EXP	0.0404			0.049	0.043		0.046
	(3.73)			(4.12)	(3.60)		(3.79)
EXPsq	-0.005			-0.005	-0.005		-0.005
	(-2.19)			(-2.33)	(-2.18)		(-2.32)
DT		-0.0003		-0.0008		-0.007	-0.001
		(-2.59)		(-4.69)		(-3.57)	(-7.48)
DTsq/1000		0.0002		0.0006		0.00004	0.008
		(4.15)		(4.08)		(3.87)	(3.96)
NSS			0.0019		0.0003	0.0004	0.0006
			(0.71)		(0.01)	(1.54)	(2.18)
NSSsq/1000			-0.007		0.012	-0.006	0.017
			(-4.24)		(3.82)	(-4.95)	(3.65)
N	234160	234160	234160	234160	234160	234160	234160
Yr fixed	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ind fixed	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Panel C							
Dependent variable $r_{part,t}$							
Intercept	-0.047	-0.12	-0.10	-0.051	-0.040	-0.11	-0.041
	(-0.19)	(-4.29)	(-1.42)	(-0.20)	(-0.14)	(-1.50)	(-0.15)
EXP	0.040			0.026	0.030		0.027
	(0.34)			(0.22)	(0.28)		(0.25)
EXPsq	-0.002			-0.015	-0.015		-0.015
	(-4.13)			(-3.95)	(-4.53)		(-4.29)
DT		0.0005		0.0006		0.005	0.005
		(0.74)		(2.77)		(2.02)	(1.22)
DTsq/1000		-0.0001		-0.0002		-0.0002	-0.0002
		(-3.94))		(-4.14)		(-4.23)	(-4.85)
NSS			-0.002		-0.0001	-0.005	-0.006
			(-0.08)		(0.01)	(0.21)	(-0.18)
NSSsq/1000			0.0001		0.0001	0.0001	0.0001
			(0.40)		(0.47)	(0.41)	(0.47)
N	234160	234160	234160	234160	234160	234160	234160
Yr fixed	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ind fixed	Yes	Yes	Yes	Yes	Yes	Yes	Yes

The regressions for partial day trades are not statistically significant for most parts. This may suggest that the experience, trading experience and trade sophistication do not affect the performance of day trading in aborted day trades. The intercept term is negative implying that when the market movements are unanticipated the day trade is not completed. Investors are unwilling to realise the loss completely. This is consistent with the disposition effect literature which states that even professional investors are prone to the effect.

The evidence with unrealised returns for partial day trades is consistent with our earlier results. The intercept terms are negative and in all but one case statistically significant. Correspondingly market experience seems to be positively related to the unrealised return. Comparing this result to the results obtained for partial day trades, it would seem that more experienced trades are better equipped to make the decision when not closing the day trade position completely is sensible. This might be the case e.g. in times of high volatility. Furthermore, the more a retail investors day trades yearly, the worse the performance is for the unrealised portion of one's day trade position.

5 CONCLUSIONS

Day trading has become increasingly popular during the past decade. More and more people are leaving their daily jobs to become professional day traders, especially in the U.S. However, the evidence on the performance of the day traders is limited and divergent, even though most of the studies confirm that average day trader is losing money.

We have listed reasons why an average day trader won't last a long in the game: (1) Lack of trading plan, (2) failure to control emotions, (3) failure to accept and limit losses, (4) lack of commitment, and (5) over-trading. What could an academic infer from this? An average day-trader seems to suffer, at least, from overconfidence (1) & (5) as well as of disposition effect (2) & (3).

We have shown that the performance of a day trader is highly dependent on the day trading volume. The higher the trading volume, the better she does, on average, but even for the most trading day trader group the median performance before transaction costs is negative. This evidence has been also confirmed by other studies, e.g. Barber & Odean (2004).

When day traders are partitioned according to their standardised day trading profits, we find that for the best performers the trend seems to reverse. This might by explained by increased overconfidence, and thus by more risk-taking behaviour. The moderately performing group earns daily profit before transaction costs, whereas negative earners' performance does not improve at any point. This would suggest that the profit-making day traders do not make their profits by chance.

Trading activity also affects the performance of day traders. The effect is most clearly seen for the partial day trades. Our analysis would also suggest that investors are less likely to complete their day trades, if the underlying stock's price falls during the trading day. Therefore the returns on partial day trades are significantly worse than the returns on complete day trades. The phenomenon remains regardless of the use trading activity or the number of day traded stocks. However, when controlling for other variables such as past market experience and market sophistication, the results are exactly the opposite. The more active traders experience better trading returns that their non-active counterparts, but in their peer group they have inferior performance. This is consistent with the excess trading hypothesis verified in earlier studies.

REFERENCES:

Bar-Tal, Y., Sarid, A. & Kishon-Rabin, L. (2001). A test of the overconfidence phenomenon using audio signals. Journal of General Psychology. January ;128(1):76-80.

Barber, B.M. & Odean, T. (2001). Boys will be boys: gender, overconfidence, and common stock investment. The Quarterly Journal of Economics 116(2), 261-292.

Barber, B.M. & Odean, T. (2002). Online investors: Do the slow die first? The Review of Financial Studies 15(2), 455-487.

Barber, B.M., Lee, Y-I., Liu, Y-J. & Odean, T. (2004). Do individual day traders make money? Evidence from Taiwan. Working paper.

Barber, B.M., Lee, Y-I., Liu, Y-J. & Odean, T. (2005).Who loses from trade? Evidence from Taiwan. Working paper.

Bauman, A. O., Deber, R. B., & Thompson, G. G. (1991). Overconfidence among physicians and nurses: The "micro certainty, macro certainty" phenomenon. Social Science and Medicine, 32, 167-174.

BBC News. http://news.bbc.co.uk/1/hi/business/7211796.stm. March 10, 2008.

Benos, A. (1998). Aggressiveness and survival of overconfident traders. Journal of Financial Markets, 1, 353-383.

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

Fischhoff, B., & Macgregor, D. (1982). Subjective confidence in forecasts. Journal of Forecasting, 1, 155-172.

Garvey, R. & Murphy, A. (2001). How profitable day traders trade: an examination of trading profits. University College Dublin, working paper.

Gigerenzer, G., Hoffrage, U., & Kleinbolting, H. (1991). Probabilistic mental models: A Brunswikian theory of confidence. Psychological Bulletin 98, 506-528.

Grinblatt, M. & Keloharju. M. (2000). The investment behaviour and performance of various investor types: a study of Finland’s unique data set. The Journal of Financial Economics 55(1), 43-67.

Grinblatt, M. & Keloharju. M. (2001). How distance, language and culture influence stockholdings and trades. Journal of Finance 56, 1053-1073.

Grossman, S. J. (1976). On the efficiency of competitive stock markets where traders have diverse information. Journal of Finance, 30.

Grossman, S. J. & Stieglitz, J. E. (1980). On the impossibility of informationally efficient markets. American Economic Review 70, 393-408.

Harris, J.H. & Schultz, P.H. (1998). The trading profits of SOES bandits. Journal of Financial Economics 50, 39-62.

Harris, M. & Raviv, A. (1993). Differences of opinion make a horse race. Review of Financial Studies 6, 473-506.

Blume, M. & Friend, I. (1975). The asset structure of individual portfolios with some implications for utility functions. Journal of Finance 30, 585-604.

Braun, P. A. & Yaniv, I. (1992). A case study of expert judgment: Economists' probabilities vs. base-rate forecasts. Journal of Behavioral Decision Making, 5: 217-231.

Caballe, Jordi & Sakovics, Jozsef, (2003). Speculating against an overconfident market. Journal of Financial Markets, vol. 6(2), pages 199-225.

Coval, J. & Shumway, T. (2001). Do behavioral biases affect prices? Journal of Finance 60, 1-34.

Coval, J., Hirshleifer, D. & Shumway, T. (2005). Can individual investors beat the market? Working paper, Harvard Business School.

Day Trading – Resources, articles and subject links. http://daytrading.about.com. March 10 2008.

De Long, J.B, Shleifer, A., Summers, L. H. & Waldmann, R. J. (1990). Noise trader risk in financial markets. Journal of Political Economy 98, 703-738.

Fama, E. F. (1970). Efficient capital markets: A review of theory and empirical work. Journal of Finance 25, 383-417.

Fama, E. F. (1991). Efficient capital markets II. Journal of Finance 46, 1575-1618.

Hirshleifer, D., Myers, J., Myers, L. & Teoh, S. H. (2002). Do individual investors drive post-earnings announcement drift? Working paper, Ohio State University.

Ivkovich, Z. & Weisbrenner, S. (2005) Local does as local is: Information content of the geography of individual investors' common stock investments. Journal of Finance 60, 267-306.

Ivkovich, Z., Sialm, C. & Weisbrenner, S. (2005). Portfolio concentration and the performance of individual investors. Working paper, University of Illinois.

Jordan, D.J. & Diltz, J.D. (2002). The profitability of day traders. Financial Analysts Journal 59, 85-94.

Kahneman D & Tversky A (1979) Prospect theory: an analysis of decision under risk. Econometrica 47: 263-291.

Kandel, E. & Person, N. D. (1995). Differential interpretation of public signals and trade in speculative markets. Journal of Political Economy 103(4), 831-872.

Kaniel, R., Saar, G. & Titman, S. (2005). Individual investor trading and stock returns. Working paper, NYU.

Kaustia, Markku, 2003, "What Causes the Disposition Effect? An Empirical Evaluation", Essay No. 1 in Essays on Investor Behavior and Psychological Reference Prices, Doctoral thesis, Helsinki School of Economics, A-213.

Kaustia, M. 2004. Market-Wide Impact of the Disposition Effect: Evidence from IPO Trading Volume. Journal of Financial Markets 7(2), 207-235.

Kaustia, M. (2009). Prospect theory and the disposition effect. Journal of Financial and Quantitative Analysis. Forthcoming.

Kidd, J.B. (1970). The utilization of subjective probabilities in production planning. Acta Psychologica XXXIV, 338-347.

Lee, C. M. C., Shleifer, A. & Thaler, R. H. Investor sentiment and the closed-end mutual funds. Journal of Finance 46, 75-109.
Lichtenstein, S., & Fischhoff, B. Do those who know more also know more about how much they know? The calibration of probability judgements. Organizational Behavior and Human Performance, 3, 552-564.
Linnaimaa, J. (2003). Who makes the limit order book? Implications for contrarian strategies, attention-grabbing hypothesis, and the disposition effect. University of California, Los Angeles, working paper.
Linnainmaa, J. (2005). The individual day trader. University of California, Berkeley, working paper.
Locke P R & Mann S C (2005) Professional trader discipline and trade disposition. Journal of Financial Economics 76: 401-444.
Lundeberg, M.A., Fox, P.W. & Punćochaŕ, J. (1994). Highly confident but wrong: gender differences and similarities in confidence judgements. Journal of Educational Psychology, LXXXVI(1), 114-121.
Morris, S. (1995). The common prior assumption in economic theory. Economics & Philosophy, 11, 227-253.
Odean, T. (1998). Are investors reluctant to realize their losses? Journal of Finance 53, 1775-1798.
Odean, T. (1999). Do investors trade too much? American Economic Revies 89, 1279-1298.
Russo, J. E. & Schoemaker, P. J. H. (1992). Managing overconfidence. Sloan Management Review, XXXIII, 7-17.
Seasholes, M. & Wu, G. (2004). Profiting from predictability: smart trades, daily price limits, and investor attention. University of California, Berkeley, working paper.
Seru, A., Shumway, T. & Stoffmann, N. (2009) Learning by Trading. Available at SSRN: http://ssrn.com/abstract=891694.
Shapira Z. & Venezia I. (2001) Patterns of behavior of professionally managed and independent investors. Journal of Banking and Finance 25: 1573-1587.
Shefrin H. & Statman M. (1985) The disposition to sell winners too early and ride losers too long. Journal of Finance 40: 777-791.
Shiller, R.J. (1999). Measuring Bubble Expectations and Investor Confidence, Cowles Foundation Discussion Papers 1212, Cowles Foundation, Yale University.
Stael von Holstein, C-A. S. (1972). Probabilistic forecasting: an experiment relatedo the stock market. Organizational Behaviour and Human Performance, VIII, 139-158.
Talouselämä (2004). Kilpailuta välittäjäsi. 8.11.2004.
Thaler, R. (1980) Toward a positive theory of consumer choice. Journal of Economic Behavior and Organization 1: 39-60.
Thaler, R. (1985) Mental accounting and consumer choice. Marketing Science 4, 199-214.

Thaler, R. H., Tversky, A., Kahneman, D. & Schwartz, A. (1997). The effect of myopia and loss aversion on risk taking: An experimental test. Quarterly Journal of Economics 112: 647-661.

Wagenaar, W. & Keren, G. B. (1986). Does the expert know? The reliability of Predictions and Confidence Ratings of Experts. Intelligent Decision Support in Process Environments. Hollnagel, Mancini & Woods (eds.). Springer: Berlin.

Weber M & Camerer C (1998) The disposition effect in securities trading: An experimental analysis. Journal of Economic Behavior and Organization 33: 167-184.

Yates, J. F., Lee, J-W., & Shinotsuka, H. (1996). Beliefs about overconfidence, including its cross-national variation. Organisational Behaviour and Human Decision Processes, 65, 138-147.

REINFORCEMENT LEARNING AND EVENT TRADING; EVIDENCE FROM EARNINGS ANNOUNCEMENTS

Abstract

Recent evidence, by Kaustia & Knüpfer (2008), shows that retail investors overweigh personal experience in IPO subscriptions. Thus, we study the effect of previously experienced trading returns from earnings announcement to the future trading behaviour of retail day traders. Experimentation has traditionally been considered useless in the stock markets. Thus, it should not matter whether the investor actually invests in a stock and earns a return or merely observes the return afterwards. However, we find that positive experienced returns increase investors' probability to engage in event trading also in the future and the negative experienced returns decrease this probability. This finding is consistent with reinforcement, in which personally experienced outcomes have more weight compared to rational learning models.

1 Introduction

Reinforcement takes place when a certain event following a response causes an increased future probability of that particular response. In the stock market reinforcement implies that personally experienced positive (negative) stock return increases (decreases) the probability of trading that stock also in the future. However, traditionally stocks are not considered to possess qualities of experience goods, such as cheese, wine or movies, implying that investors' decision to trade a stock should be the same regardless of actually having invested in that stock or merely having observed the performance of it.

In traditional Bayesian learning a subject collects evidence that is either consistent or inconsistent with a certain hypothesis. As the subject's experience increases, her degree of belief in the hypothesis should change correspondingly. In the stock market this would imply that the past payoffs of a certain stock are equally important should they be experienced by the subject or not. Correspondingly, reinforcement learning theory predicts that the personally experienced past returns have actually a greater effect on future market behaviour than just observing the information without actually experiencing it. In its purest form, reinforcement theory predicts that only actual and directly experienced outcomes will affect the future behaviour of a subject.

The effect of personal experience on future stock market behaviour gives information about the actual learning process of investors, as it is the key difference between the rational learning models and reinforcement learning. Traditional financial theory assumes that all investors are rational, possess the same information set and observe and absorb new information immediately. Thus, personal experience should not affect the future behaviour of an investor. However, recent evidence by Kaustia & Knüpfer (2008) shows that positive past IPO returns experienced by an investor affects greatly the future subscription activity of that individual.

Reinforcement is a widely accepted psychological phenomenon first brought to public knowledge by Ivan Pavlov in the 1920's. Dinsmoor (2004) points out that Pavlov's definition of reinforcement was strengthening of already-learned weakening response instead of current definition of selecting and strengthening new behaviour. Later, Skinner (1957) articulated the major theoretical constructs of reinforcement and behaviourism. Skinner's early work was mainly theoretical, which is the primary reason for slow adoption in the academia for his theories during that time. However, e.g. Ferster (1967), Baer & Wolf (1970) conducted theoretical research in that field.

The first reinforcement learning models in the economic research include e.g. Cross (1973), Arthur (1991) and Roth & Erev (1995). The hybrid model by Camerer & Ho (1999) has implications for our model, as their model allows for the reinforcement of actual as well as forgone payoffs. They suggest that the subjects might actually weigh these two types of payoffs in different manner. In addition, some stock market anomalies have been explained by biased learning, e.g. Barberis & al. (1998) and Gervais & Odean (2001).

Even though there is a vast empirical literature on reinforcement as well as Bayesian learning, the empirical literature on how investors actually learn, or do they learn, is somewhat limited. Feng & Seasholes (2005) have studied the effect of investor sophistication and trading experience on behavioural biases found in the stock market. They discover that neither sophistication nor trading experience alone eliminate disposition effect. However, together sophistication and trading experience seems to eliminate the reluctance to realise losses. Correspondingly, Nicolosi, Peng & Zhu (2009) report that portfolio returns improve with account tenure and trade quality also increases with experience. Thus, according to them investors learn from their own investment history and seem to make adjustments to their future trading based on that information, which leads to higher investment performance.

Seru, Shumway & Stoffman (2007) investigate the effect of trading experience on the disposition effect and trading performance. They show that more experienced investors are less likely to suffer from the disposition effect and their trading performance is better. Furthermore, List (2003) and Dhar & Zhu (2006) show that experience plays a significant role in eliminating judgement errors such as endowment and disposition effect. Linnainmaa (2006) provides somewhat contradicting evidence to the existing literature as he argues that less sophisticated investors learn to exit the stock market better than their more sophisticated counterparts. This might be one possible explanation for the relationship between experience and positive market performance.

In this paper, we examine empirically what effect previously experienced trading returns have on future market behaviour? Our setting has two major benefits: First, the number of events is limited compared to larger markets and event trading is very concentrated on few largest stocks. Second, we have the allocations of all the retail investors from 1995-2002. The Finnish stock market experienced a huge growth during that time and day trading became more popular also among the retail traders. This allows us to study the effects of first experience in event trading on future market behaviour.

Our main contribution is an empirical test for negative reinforcement. However, some behaviourists argue that punishment is not a form of reinforcement and is only a short-term phenomenon, but we provide evidence in opposition of that view. Most of the previous reinforcement studies are experimental, Kaustia & Knupfer (2008) being the first real empirical study on these issues in the financial markets.

We find that previously experienced event trading returns have statistically and economically significant effect on future event trading behaviour. Controlling for previous market and trading experience, we find that positive returns decrease the probability not to event trade in the future. Thus, this can be seen as punishment-avoiding behaviour. Investors who have experienced negative returns tend to avoid making the same "mistakes" in the future.

Our results also show support for the long-term effects of personal experience. We identify the first ever event trade of investors and study the effect of positive/negative return on future event trades. Of the investors who experienced positive initial event day return 58 percent have event traded during the next years after the first event. The figure for investors experiencing a negative first event trade return is 42 percent. The finding is statistically and economically significant.

The remainder of the paper is as follows; Section two discusses the previous literature and builds the hypotheses to be tested. Section 3 discusses the data and methodology, while in Section 4 we present the empirical results. Finally, Section 5 concludes the paper.

2 Hypotheses development and previous literature

Hypothesis 1: Negative experienced trading return has a negative effect on the future day trading activity of an investor.

Hypothesis 2: Negative experienced trading return decreases the probability of an investor to day trade during the next earnings announcement?

We start our analysis by examining how punishment, in operant conditioning definition, i.e. negative day trading return affects investor's future behaviour. Our hypothesis is that punishment in the form of bad performance creates a negative reinforcement, i.e. it leads to a situation where punishment-avoiding behaviour is reinforced. This implies that the investor experiencing poor performance will decrease her trading it the future compared to investors who experience positive returns.

To the best of our knowledge negative reinforcement has not been studied in the field of finance, but Kaustia & Knüpfer (2008) find a strong positive link between actual IPO returns and future IPO subscription activity. This is a strong finding supporting positive reinforcement, as personally experienced good returns are an important factor determining future activity in their study. Furthermore, they state that investors participating in their first IPO and experiencing a positive return are twice as likely to participate in the next offering compared to investors with cold first IPO.

There is a vast experimental literature providing support for reinforcement. Camerer & Ho (1999) argue that their test subjects give actual payoffs twice the weight given to forgone payoffs. Charness & Levin (2005) report that roughly half of the decisions of their subjects violate Bayes' rule and confirm that Bayesian' and reinforcement learning lead to different choices. Finally, Erev & Roth (1998) find that their simple one-parametric reinforcement learning model outperforms equilibrium predictions for all values of the parameter. Psychological and neurological studies also confirm the existence of reinforcement learning, e.g. Huettel & al. (2002) and Knutson & Peterson (2004). See Kaustia & Knüpfer (2008) for a more thorough discussion of these papers.

Hypothesis 3: Negative experienced trading return increases the time to next day trade on earnings announcement day.

Hypothesis 4: Negative experienced day trading return decreases the probability to participate in earnings announcement day trade in the long-term.

Some behaviourists argue that punishment, i.e. negative actual returns, does not incur reinforcement. It is argued that punishment decreases the likelihood of reinforced action only temporarily. Punishment is seen as a primary process which is completely distinct from reinforcement. We argue that personally experienced negative returns increase the time to next earnings announcement day trade as well as decrease the probability to participate in earnings announcement day trade in the long-term. Investors learn to exhibit punishment-avoiding behaviour and decrease their trading activity in order to do so.

Kausia & Knüpfer (2008) report that investors participating in a hot IPO are twice as likely to subscribe to the subsequent offering compared to investors participating in a cold IPO given that the IPO is their first. This is a long-term phenomenon as there is a 26 percentage unit difference in the subscription activity of the hot and cold IPO groups by the tenth IPO offering. They suggest that this due to the primary effect long-recognised in marketing literature and analysed by Bereby-Meyer & Roth (2006) in strategic games.

Hypothesis 5: Experience increases the profitability of earnings announcement day trades.

We study the effect of experience and investor sophistication on earnings announcement trading performance. The assumption is that the more experienced and sophisticated retail traders learn to interpret the market signals and know when to participate in earnings announcement day trade. In addition, they learn to avoid the disposition effect better and complete their day trades even when they earn negative profit. Thus, their overall trading performance should be better than that of the less experienced and sophisticated investors.

Feng & Seasholes (2005) study the effect of investor sophistication and trading experience on behavioural biases found in the stock market. They discover that neither sophistication nor trading experience alone eliminate disposition effect. However, together sophistication and trading experience seems to eliminate the reluctance to realise losses. Correspondingly, Nicolosi, Peng & Zhu (2009) report that portfolio returns improve with account tenure and trade quality also increases with experience. Thus, according to them investors learn from their own investment history and seem to make adjustments to their future trading based on that information, which leads to higher investment performance. In our setting we assume that experience helps investors to learn from their personal investments history and thus the profitability of earnings announcement day trades increases with account tenure.

Seru, Shumway & Stoffman (2007) investigate the effect of trading experience on the disposition effect and trading performance. They show that more experienced investors are less likely to suffer from the disposition effect and their trading performance is better. In addition, they show that investors as a group tend to learn partly by attrition, but individual level learning is also important. However, they use completely different type of return measure, namely next year's return, whereas we are interested in the net return associated with individual trades. Furthermore, they do not use as precise trade partition as we do. Furthermore, List (2003) and Dhar & Zhu (2006) show that experience plays a significant role in eliminating judgement errors such as endowment and disposition effect. Thus, we assume that trading experience helps retail traders to learn about their private signal precision. This would in turn decrease the probability of excess trading, which is known to hurt portfolio performance, e.g. Barber & Odean (2000).

3 Data and Methodology

We have acquired the complete trading history of all individual day traders in the Helsinki Stock Exchange from January 1, 1995 through December 31, 2002. Each record includes a data on, individual investor identification code, investor type identification code – a domestic household in this case -, stock code, purchase/sell price/volume and various demographic characteristics, such as sex, age and domicile. We match the earnings announcement data with the trading data to have a perfect record of earnings announcement day trades during the sample period.

The data set used in our study is based on the Finnish Central Securities Depository's (FCSD) share ownership records. The record includes the initial balance of FCSD's share ownership record and all changes in these records until December 31, 2002 for all publicly quoted companies represented in the Book Entry System. The Book Entry System is an electronic share ownership and trading record. All changes in the data are updated daily, thus the data allows us to study the portfolio and its composition of any investor at any time during the time-span. Our data records only the ownership of individual investors and excludes institutional ownership completely as we are primarily interested in analysing retail day traders.

The Book Entry System is a compulsory registration of stock holdings for Finnish citizens and institutions. The data is not a complete register of stock ownership in Finland, as foreign investors are partially exempt from registration. They can opt for registration with a street name. As a result, the ownership records of foreign investors are combined to a larger pool of nominee registered holdings. Therefore, their shareholdings or trades cannot be separated from each other by any method. However, the number of foreign retail investors' direct stock holdings is rather small compared to the overall number of investors in the market.

The data excludes also indirect stockholdings. This means that the holdings of investment companies owned by one person are considered to be institutional ownership rather than individual. For the same reason the indirect ownership through mutual funds is not included in the data.

We calculate the trading performance measures for day trading, the daily net profit in the following manner. First, we determine the profit earned by each investor during each earnings announcement day trade, which is just the difference between sale cash flow and purchase cash flow. However, if the day trade is partial, i.e. the position is not completely closed, we take into account only the realised part of the day trade.

$$\begin{aligned}\Pi_{i,t} = {} & P_{s,i,t}V_{s,i,t} - P_{b,i,t}V_{b,i,t} \\ & + \max(V_{b,i,t} - V_{s,i,t}, 0)(P_{c,t} - P_{b,i,t}) \\ & + \max(V_{s,i,t} - V_{b,i,t}, 0)(P_{s,i,t} - P_{c,t})\end{aligned} \tag{1}$$

Second, we take into account the transaction cost associated with the trade. The level of transaction costs for the data period is considerably hard to determine. Transaction costs declined rather sharply in the turn of the century as new brokerage houses, e.g. EQ Bank (formerly EQ Online) and E-trade, entered the market and forced the traditional players to decrease their prices as well. Thus, we will use the price level of 2003 for the whole data period, which might underestimate the level of transaction costs in the beginning of the data period. Furthermore, we do not have the information about the brokerage house used by the trader, thus we assume that she is acting rationally and using the cheapest one3. This assumption is rather valid as EQ Bank had a market share of 50 percent in 2004. (Talouselämä 2004.)

$$\hat{\Pi}_{i,t} = \Pi_{i,t} - 8.25€ - 0.002(P_{s,i,t}V_{s,i,t} + P_{b,i,t}V_{b,i,t}) \qquad (2)$$

Finally we determine the daily net trading return by dividing the net profit by the daily trading volume. This method is analogous to one used by Linnainmaa (2005).

$$\hat{r}_i = \frac{\sum_i \hat{\Pi}_{i,t}}{\sum_i (P_{s,i,t}V_{s,i,t} + P_{b,i,t}V_{b,i,t})}. \qquad (3)$$

$P_{s,i,t}, P_{b,i,t}$ and $P_{c,t}$ are sale, purchase and same-day closing prices, respectively, for each individual stock, investor and day. $V_{b,i,t}$ and $V_{s,i,t}$ are the number of shares bought and sold during that particular trading day by one particular investor. The adjustments for net profit and return account for a fixed fee of 8.25 euros and a proportional fee of 0.2 percent of the total value of the trade

We study the effect of past day trading performance around earnings announcements on future trading activity using three types of analyses. In the first part, we divide the sample into two and investigate how trading behaviour in the latter half is affected by trading returns in the first period? This setting will

---

[3] E-Trade is actually the cheapest brokerage house, but its market share is very small and it entered the market at the end of the data period. Thus, we are using the cheapest of the large brokerage houses in our estimation.

help us answer the first hypothesis, whether negative reinforcement affects retail investors' market behaviour.

We divide our sample into two sub-samples in order to determine equal number of day trader/earnings announcement pairs. The first half of the sample includes 2060 events and the latter 1165. However, most of the events do not have single day trade observation as the day trading is heavily concentrated on the two largest trading stocks Nokia and TeliaSonera. The majority of day traders have only a few day trades during the sample period, so we exclude investors participating only in one earnings announcement day trade from our sample, because the variance of the variable measuring personal experience would decrease significantly if all the observations would be included in the sample. Furthermore, most of the traders with only one earnings announcement day trade enter the market at the end of our sample period, thus we overcome a controlling problem with this procedure.

We run a logit regression to explain the actions in the latter half in order to control for the investor characteristics and yearly differences. The dependent variable gets a value of 1 if the investor does not day trade on an earnings announcement day in the second half of the sample. Correspondingly, if the investor makes one or more event day trades during the second half, the dependent variable gets a value of 0. The independent variable is the value-weighted cumulative return from the earnings announcement day trades from the first half. Experience from earlier earnings announcement trades is also an important measure, as the activity levels of investors seem to be highly persistent. To control for this experience we include a variable measuring first-half earnings announcement day trades into the equation. Other control variables include market experience, trading experience and total value of day trade during the first half. Market experience measures the amount of time from the first stock market transaction and trading experience tells us the number of day trades during the sample period. Finally we include a time-dummy to take into account the differences in the sentiment/market performance during the first half.

In the second part of the analysis, we analyse investors' past performance's, up to that earnings announcement, effect on future trading activity. There is a lot of variation in the cumulative trading returns as the IT bubble was at its largest around the millennium and it had a huge impact on investors' market behaviour. Correspondingly, there is vast evidence on investor overreaction starting from De Bondt & Thaler (1985), so investors might actually overreact on company information during bullish market cycle and correspondingly underreact to company information during bearish market cycle. This procedure helps us overcome the market cycle problems.

Our logit regression model analyses an investor's decision not to day trade during the next earnings announcement conditional on having day traded that stock during the past earnings announcement. The dependent variable gets a value of 1 if the investor decides not to day trade that stock during the next earnings announcement and correspondingly gets a value of 0 if the investors decides to trade. We limit our sample to investors that have at least two day trades on a particular stock during earnings announcement. To control for the investor experience, we include control variables for total number of earnings announcement day trades, market experience, trading experience, market sophistication and past trading volume.

The logit regression above ignores all information besides decision whether to day trade during the next earnings announcement or not. To overcome this problem we model the time to next earnings announcement day trade as a duration model in the third part of the analysis. The explanatory variables are the same as in the previous logit model.

Some behaviourists argue that punishment is not a form of negative reinforcement, but rather a primary process. Thus, it decreases the probability of reinforced response only temporarily. To test for this, we run a following experiment. We use the same sample as in the previous logit regression and duration model, from which we distinguish a positive or a negative first earnings announcement day trade. Then we track the future earnings announcement day trade activity of these investors.

This type of setting enables us to identify the effect of actual experienced first earnings announcement day trade return on the future trading behaviour. Thus, the investors have the same type of market history, i.e. no earnings announcement day trade experience. Furthermore, we study the effect over eight quarters, i.e. two years, in order to examine whether negative reinforcement is a temporary or a long-term effect.

Finally, we run a regression analysis to determine whether the more experienced day traders have better daily trading returns than their less experienced counterparts. We regress each daily earnings announcement trading return of each of the retail traders on experience variables, the number of years traded (EXP), i.e. account tenure, total number of yearly trades (TA), trading activity, and number of speculative stocks per year (NSS), trade diversification/market sophistication. Specifically, we estimate the regression

$$r_{i,t} = \alpha_i + \beta_i EXPVAR_{i,t} + \beta_2 EXPVAR_{i,t}^2 + \delta X_{i,t} + \chi_t + \varepsilon_{i,t}\,.$$

EXPVAR-variable is the experience variable used, i.e. the number of years traded, the total number of trades per year or the number of speculative stocks per year. The squared EXPVAR-variable is used in the second part of the analysis, i.e. robustness check. Finally, χ is the yearly dummy-variable. The regression equation used in each regression is more closely specified in the specific table providing the regression estimates. We are hoping to establish that earnings announcement trading performance increases with experience, but excess trading on the other hand decreases that effect.

4 Main results

Table 1 gives the descriptive statistics of the data. Panel A shows the statistics for all the day traders in the data, and Panel B for investors who have participated in at least one earnings announcement day trade. It is interesting to note that almost all the day traders in the data have also participated in at least one event trade, as the total number of day traders is 24 113 and the number of event day traders 20 500. This gives further proof on the claim that day traders are actually making bets about the direction of the market movement, as the market movement is at its greatest on earnings announcement days.

Approximately half of the day traders' trades are actual day trades. This indicates that these retail traders consistently try to outguess the market about the future direction. The assumptions we have made so far, are very well supported by this fact. Experience and previously experienced returns are most likely an important determinant in the behaviour of these investors. The basic statistics show that the event traders are quite similar to the "normal" day traders. However, one significant difference can be found. The proportion of female event traders is significantly smaller than the proportion of female day traders. This might imply that female traders are not as willing to take bets about the future market movements.

The average number of event trades is approximately 9 during the whole sample. Furthermore, on average these trades are executed around 5 events using 5 different stocks. The medians of the above-mentioned variables are 4, 2 and 3 respectively. This implies that event day traders are likely to make more than one day trade during the earnings announcement day. This is a further proof that the trading is extremely speculative and might also imply that psychological phenomenon such as greed and fear might drive the behaviour of these investors.

Table 1. Descriptive statistics.

	Mean	Median	Std. deviation	25% percentile	75% percentile
Panel A: All day traders N = 24113					
#of trades	185.61	82	290.39	24	216
# of stocks	16.58	11	16.45	5	23
# of day trades	93.30	31	176.01	8	99
Value of stock market buys	33733.97	10260	139383.75	4430	25390
Value of stock market sells	33768.23	10264.3	139227.46	4407	25380
Gender dummy	0.34	1	0.47	0	1
Panel B: Event day traders N = 20500					
# of trades	145.23	51	258.81	13	156
# of stocks	15.76	10	16.26	4	21
# of event trades	9.19	4	14.29	2	10
# of stocks around events	5.43	3	6.51	1	6
# events	5.10	2	8.66	1	5
Value of stock market buys	33823.53	8490	218222.15	3600	21744
Value of stock market sells	33390.55	8252.5	216272.54	3500	21105
Gender dummy	0.16	1	0.32	1	1

Table 1 gives descriptive statistics of the retail traders in the sample. Panel A shows the statistics for all the day traders in the sample. Number of trades/day trades tells the average number of trades/day trades per investor during the sample. Number of stocks is the average number of stocks in the portfolio. Value of market buys/sells cumulates the total market value of purchase/sell transactions. Gender dummy gets a value of 1 for women and 0 for men. Panel B shows the descriptive statistics for the day traders around earnings announcements. Some of the information remains unchanged, but number of event day trades refers to the number of day trades around earnings announcements. Correspondingly, the number of events gives the total number of earnings announcements the investors has traded on, while number of traded stocks around events tells the number of different stocks used in event trading.

Table 2 represents the results for the first logistic regression. Column 1 does not include either market or trading experience as a control variable, columns 2 and 3 add either one of them and finally column 4 includes both. The probability not to day trade in the second half decreases as the net return from the past event trades increases. This remains unchanged in all the specifications. Correspondingly previous event day trade activity has the same type of relationship with the dependent variable. The more investor has traded in the future, the less likely it is for her not to trade in the latter half of the sample.

Table 2. Results for logistic regression.

Specification	Logit(0 = at least one future event day trade, 1= no future event day trades)				Reference probability and probability changes
	(1)	(2)	(3)	(4)	
Probability of reference investor					17.10 %
PROFNR1	-3.09	-3.48	-2.77	-2.58	5.90 %
	-2.57	-2.86	-2.23	-2.09	
EAT	-11.79	-11.74	-12.18	-12.21	0.04 %
	-158.87	-158.28	-124.40	-124.32	
Market exp	no	no	yes	yes	
Trading exp	no	yes	no	yes	
Pseudo-R^2	0.45	0.46	0.46	0.46	
N	10250	10250	10250	10250	

Table 2 shows the results for the logistic regression. The sample period is divided into two halves. The first half has 2060 events last on April 20 2000 and the second half has 1165 events last on December 30 2002. The split is determined by placing equal number of investor/events in both periods. PROFNR1 is the weighted-cumulative net return from the past event trades. EAT is the number of earnings announcements traded on. Market experience tells the years of market experience and trading experience refers to the number of day trades during the sample. Unreported control variables are total value of event trades and year dummies for each year. T-values are below each regression coefficient and are based on robust standard errors.

To study the economic significance of the results, we show the changes in the probability associated with the changes in the explanatory variables. The probability changes are based on the Column 4 regression and are the products of the marginal effect of the explanatory variable and its standard deviation. For the return variable, a one standard deviation change from its mean implies a 5.9 percent point decrease in the probability not to event day trade in the future. This effect is economically significant, as the average investor probability not to participate is 17.10 percent. The effect of previous event trades is not economically significant as the probability change is only 0.04 percent.

Table 3 shows the results for the second logistic regression and duration analysis. The results of the regression are shown in Column 1 and Column 2 presents the results for the duration analysis. Higher net return from previous event day trades predicts a lower probability not to participate in the next event day trade for the same stock. This relation is statistically and economically significant as a one standard deviation increase in the earlier net return implies a 2.99 percentage unit decrease in the probability not to participate in the next earnings announcement day trade. We have controlled for market and trading experience, as well as market sophistication and total value of trading in this analysis.

Table 3. Results for logistic regression and duration model.

Specification	1		2	
Dependent variable	Next event		Time to next event	
	Coefficient	Prob. change	Coefficient	Prob. change
PROFNR1	-0.70	2.99 %	0.225	4.79 %
	-2.12		4.64	
Market experience	Yes		Yes	
Trading experience	Yes		Yes	
Market sophistication	Yes		Yes	
Value of trading	Yes		Yes	
N	9422		12972	

Table 3 gives the results for logistic regression and duration model. The dependent variable is the decision not to trade on the next earnings announcement for the particular stock and the time to next earnings announcement day trade. For each investor participating in at least two earnings announcement day trades, the time to next event is determined by the number of quarterly earnings announcements elapsed before the next day trade. The dependent variable is regressed on a set of explanatory variables using logistic regression in Column 1 and a duration model with an exponential duration distribution in Column 2. PROFNR1 is the weighted-cumulative net return from the past event trades. The control variables are market experience, trading experience, market sophistication and the total value of trading. T-values are presented below the regressions coefficients and are based on robust standard errors.

The duration regression shows that high past return is associated with an increase in the hazard rate. This implies that higher past return increases the investors' probability to participate in the future event trades. Correspondingly lower past return decreases the probability to do so. The effect is also economically significant as one-standard deviation increase in return implies about 4.79 percentage units higher rate of participation in the future. The number of observations is lower in logistic regression as for some events there are no observations for the next event.

Table 4. Cumulative proportion of day traders participating in later events.

	Cumulative proportion of day traders			
Number of events after postive or negative initial return	Positive initial return	Negative initial return	Difference between proportions	z-value
1	0.429	0.314	0.115	18.22
2	0.524	0.384	0.140	20.20
3	0.569	0.414	0.155	21.40
4	0.574	0.417	0.157	21.58
5	0.576	0.418	0.158	21.71
6	0.576	0.418	0.158	21.75
7	0.577	0.418	0.159	21.78
8	0.580	0.420	0.159	21.83
N	5445	3948		

Table 4 shows the proportion of investors participating in a subsequent event for the same stock conditional on having experienced either a negative or a positive return from the first event trade. The cumulative proportion of day traders refers to the number of investors who have made at least one day trade since the initial event trade divided by the number of investors and it is calculated for eight quartiles.

Table 4 presents the results for the effect of personal experience on future earnings announcement day trades. The first two columns show the proportion of first-time event traders participating in the future event trades conditional on experiencing either positive or negative return in their first event trade. Of those investors who experience a positive first-event return approximately 43 percent participate in the next earnings announcement day trade. The corresponding figure for experiencing a negative return is 31.4 percent. The difference is statistically significant with a z-value of 18.22. The table shows that the difference between the groups increases as we take into account a larger number of events. This shows that initially experienced returns have a huge effect on future trading behaviour.

Table 5 reports the results for the final regression analysis. We study the effect of market experience, trading experience and market sophistication/trade diversification on event day trading returns. Market experience is positively related to event day trading returns for all day trades, complete day trades, partial day trades as well as for the return of the remaining day trade position. Trading experience has negative effect on the event day trading return, especially for partial day trades. This may imply that excess trading is actually harmful for trading performance as noted by e.g. Barber & Odean (2001) earlier. Those who trade a lot, perhaps too much, make a significant number of predictions about the future market movement. Thus, it is natural that the number of wrong hits is higher, which shows as a large number of partial day trades. Day traders are known not to close their day trade position completely if the return is negative. Finally trade diversification has also a negative effect on event day trading returns implying that some of the higher trading returns may be caused by information advantage. As the number of traded stocks increases the investor cannot have as much information on ten stocks as on one particular stock.

Table 5. Effect of experience on trading performance.

	All trades		Complete trades		Partial trades		Remaining position	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Intercept	0.011	0.005	0.005	0.011	0.0003	0.0001	(-0.024)	(-0.024)
	(10.04)	(6.73)	(7.17)	(9.34)	(0.36)	(0.14)	(-12.89)	(-11.67)
EXP	0.001	0.002	0.001	0.001	0.001	0.002	0.001	0.0014
	(2.56)	(4.07)	(5.64)	(1.51)	(5.9)	(4.02)	(2.22)	(1.08)
EXPsq/1000		-0.001		-0.004		-0.001		-0.002
		(-1.41)		(-0.34)		(-1.31)		(-0.11)
DT	0.0003	-0.001	-0.001	0.002	-0.001	-0.001	-0.003	-0.003
	(0.12)	(-3.42)	(-3.39)	(0.1)	-(4.30)	-(4.32)	(0.4013)	(-0.84)
NSS	-0.012	-0.005	-0.005	-0.012	0.001	0.001	0.029	0.029
	(-2.31)	(-1.66)	(-1.67)	(-2.32)	(0.36)	(0.37)	(3.57)	(3.57)
N	20500	20500	13000	13000	4536	4536	2964	2964
Year fixed	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ind.fixed	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 5 reports the estimates of regression of the form

$$\textit{Trading return}_{i,t} = \alpha_i + \beta_1 \textit{ Experience}_{i,t} + \beta_2 \textit{ Experience\^{}2}_{i,t} + \gamma_t + \varepsilon_{i,t},$$

where *Experience* is measured by market experience (EXP), trading experience (DT) or market experience in different stocks (NSS). Experience^2 is the square of the market experience variable .The dependent variable is the net return of a particular event trade, for all event day trades, complete event day trades, partial event day and for the remaining day trade position respectively. We also include year dummies as well as individual intercepts in each of the regressions. The figures below the regression estimates are the t-statistics associated with the specific estimate.

5 Conclusion

We have studied the relationship between previously experienced event trade returns and future trading activity. Furthermore, we provide evidence that experience is an important determinant of day trading returns. The results have implications for the investor performance literature as well as investor learning literature. Some of the themes have also contribution on a general level on the reinforcement literature.

We have data on 20500 Finnish retail day traders participating in more than 3000 events during 1995-2002. We find an inverse relationship between previously experienced returns and future trading activity. This can be seen as punishment-avoiding behaviour in operant conditions which can be seen as a special case of reinforcement.

Furthermore, we find that positive returns decrease the likelihood not to participate in day trading during next earnings announcement day. This finding is also consistent with the punishment-avoiding behaviour. Positive experienced return also decrease investor's time to next event trade implying that positive experience, in form of positive return, is an important determinant of future actions.

Finally, we test for the long-term effect of initially experienced returns. Some behaviourists argue that punishment is a primary process and thus not a long-term phenomenon. Our results show the opposite. After 8 quartiles after experiencing a positive or negative event trade return, there is a statistically and economically significant difference in the behaviour of the investors. Significantly higher proportion of investors who experienced positive first event trade return decide to event trade during the next two years.

REFERENCES:

Arthur, B. V. (1991). Designing economic agents that act like human agents: A behavioural approach to bounded rationality. American Economic Review 81, 353-359.

Baer, D. & Wolf, M. (1970). The entry into natural communities of reinforcement. In R. ulrich, T. Stachnik, & J. Mabry (eds.), Control of human behavior (Vol.2, pp. 319-324). Gleenview, IL: Scott, Foresman.

Barber, B.M. & Odean, T. (2001). Boys will be boys: gender, overconfidence, and common stock investment. The Quarterly Journal of Economics 116(2), 261-292.

Barberis, N., Shleifer, A. & Vishny, R. (1998). A model of investor sentiment. Journal of Financial Economics 49, 307-343.

Bereby-Meyer, Y. & Roth, A. (2006). The speed of learning in noisy games: Partial reinforcement and the sustainability of cooperation. American Economic Review 96, 1029-1042.

Camerer, C. & Ho, T-H. (1999). Experience-weighted attraction learning in normal form games. Econometrica 67, 827-874.

Charness, G. & Levin, D. (2005). When optimal choices feel wrong: A laboratory studt of Bayesin updating, complexity and affect. American Economic Review 95, 1300-1309.

Cross, J. (1973). A stochastic learning model of economic behaviour. Quarterly Journal of Economics, 87, 239-266.

De Bondt, W. & Thaler, R. (1985). Does the stock market overreact? Journal of Finance, 40(3), 793-805.

Dhar, R. & Zhu, N. (2006). Up close and personal? An individual level analysis of the disposition effect. Management Science 52, 726-740.

Dinsmoor (2004). The etymology of basic concepts in the experimental analysis of behavior. Journal of the Experimental Analysis of Behavior, 82 (3): 311-316.

Feng, L. & Seasholes, M. (2005). Do investor sophistication and trading experience eliminate behavioural biases in financial markets? Review of Finance 9, 305-351.

Ferster, C. (1967). Arbitrary and Natural Reinforcement 1967, The Psychological Record, 22, 1-16

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

Huettel, S., Mack, P. & McCarthy, G. (2002). Perceiving patterns in random series: Dynamic processing of sequence in prefrontal cortex. Nature Neuroscience 5, 485-490.

Kaustia, M. & Knüpfer, S. (2008). Do investors overweigh personal experience. Evidence from IPO subscriptions. Journal of Finance 63(6), 2679-2702.

Knutson, B. & Peterson, R. (2004). Neurally reconstructing expected utility. Games and Economic behaviour 52, 305-315.

Linnainmaa, J. (2005). The individual day trader. University of California, Berkeley, working paper.

Linnainmaa, J. (2006). Learning from experience. Working paper, University of Chicago.

List, John A. (2003). Does Market Experience Eliminate Market Anomalies? Quarterly Journal of Economics (2003), 118(1), 41-71.

Nicolosi, G., Peng, L. & Zhu, N. (2009). Do Individual Investors Learn from Their Trade Experience? Journal of Financial Markets (forthcoming).

Roth, A. & Erev, I. (1995). Learning in extensive-form games: Experimental data and simple dynamic models in the intermediate term. Games and Economic Behaviour 8, 164-212-

Seru, A., Shumway, T. & Stoffmann, N. (2009) Learning by Trading. Available at SSRN: http://ssrn.com/abstract=891694.

Skinner, B. (1974). About Behaviorism. Knopf, New York.

Talouselämä (2004). Kilpailuta välittäjäsi. 8.11.2004.