Investor characteristics and trading behaviour: evidence from Finland

Author:
Zhang, Boqi

Publication Date:
2010

DOI:
https://doi.org/10.26190/unsworks/16098

INVESTOR CHARACTERISTICS AND TRADING BEHAVIOUR: EVIDENCE FROM FINLAND

Boqi Zhang

School of Banking and Finance
Australian School of Business
The University of New South Wales

A dissertation submitted to the University of New South Wales in partial fulfillment of the requirements for the degree of Master of Philosophy (MPhil) in Finance

2010

ORIGINALITY STATEMENT

I hereby declare that this submission is my own work and to the best of my knowledge it contains no materials previously published or written by another person, or substantial proportions of material which have been accepted for the award of any other degree or diploma at UNSW or any other educational institution, except where due acknowledgement is made in the thesis. Any contribution made to the research by others, with whom I have worked at UNSW or elsewhere, is explicitly acknowledged in the thesis. I also declare that the intellectual content of this thesis is the product of my own work, except to the extent that assistance from others in the project's design and conception or in style, presentation and linguistic expression is acknowledged.

Signed ……………………………..

Date ……………………………..

ABSTRACT

This thesis investigates the dynamics of trading behaviour and provides a comprehensive assessment of the overall performance of all Finnish retail and institutional investors over the years 1995 through 2004 using detailed transaction data on daily trades and investor identities. In contrast to prior published studies for Finland, this study reveals a significantly superior performance achieved by households over institutions in the longer run, either before or after the trading expenses. Despite much lower transaction costs, institutions trade several times as much as the most active household age group that reduces their net return as much as for households. I also find institutional trading is the key contributor to the volatility of Nokia share price.

This study further examines the trading performance of individual investors across gender and age bands and documents both males and females in their thirties are the best performing traders among their respective gender groups on either a gross or net basis. In term of gender, male groups show significantly higher turnover while females hold higher-risk stocks. Frequent trading reduces men’s net return more so than do women in all age groups. The life cycle hypothesis does not seem to apply to Finnish working males nearing retirement after Nokia price crashed in 2000. This age group of 60 to 69 were net buyers of Nokia shares, and hence does not indicate a movement out of a high-risk investment into cash or bonds.

I find strong evidence of correlated trading among household groups with young and middle-aged males sharing the highest cross correlations between their contemporaneous buy intensity. The level of correlated trading is surprisingly persistent and increases year by year. This finding suggests that profitable herding behaviour encourages more information sharing among households over time.

ACKNOWLEDGEMENTS

I would like to express my immense gratitude to my supervisor, Professor Peter Swan for his inspiring advice, enlightening discussions, constructive criticism and consistent support during the course towards the completion of this master dissertation.

I would like to acknowledge the financial support I received from Australian Research Council (ARC) grant funded scholarship from Professor Peter Swan whilst completing this Master research degree. I also wish to acknowledge the assistance that P. Joakim Westerholm has provided me with respect to interpreting the unique Finnish dataset on which I based this thesis.

I also wish to acknowledge the help and support I received from staff members and fellows at the School of Banking and Finance of Australian School of Business at the University of New South Wales, in particular, Mr. Vic Edwards, Ms. Shirley Webster, Ms. Stephanie Osborne, Huong Nguyen, Claudia Wee and Yuewen Xiao. Last but not least, I want to thanks my parents. I would not be where I am today without their support.

March 2010

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

CHAPTER 1: Introduction

1.1 Background of this Dissertation

High levels of trading activity on financial markets worldwide in the past decade are unprecedented. In order to meet these needs and achieve effective order execution, computer systems are frequently upgraded in the stock exchanges to handle larger trading volumes in a more accurate and controlled manner. Institutions traditionally play a key role in contribution to share turnover, but in recent years, an increasing number of households are involved in the stock market both directly and indirectly. This is due to the advent of online trading technology and emerging privatization of the social security and retirement plans linked to stocks, bonds and other elements of the market.

Together with trading volumes, there has often been more volatility in the form of stock market crashes in the past decade than some observers might have been expected. These have ended in the loss of billions of dollars and wealth destruction on a massive scale, notably the 1997 East Asian financial crisis, the high-tech bubble in late 90s and the 2007-2008 subprime crisis. Between 1 January and 11 October 2008, owners of stocks in U.S. corporations had suffered about $8 trillion in losses with other countries have averaged about 40%. Losses in the stock markets and housing value declines has placed further downward pressure on individual investors and caused serious social problems as many retirees and working people near retirement are unlikely to meet their expected investment returns for their retirement after the market crash, with many likely to run out of savings and wind up dependent on the age pension. This is particularly the case for countries, such as Australia, where superannuation is based on defined contribution saving, with no guarantees on the final payments. According to the IMF, Australian superannuation funds have about 80% of their assets allocated to equities and mutual funds (*The Australian*, 10 March 2009). After the beginning of 2007 subprime crisis, regulators all over the world propose reforms and promote changes to retirement regimes to reduce the heavy dependence on the share market and require superannuation fund to provide more advice and make safer investments for their members. Therefore, it is important to learn lessons from the past to help implement strategies to deal with financial crisis in the future as best as possible. In this study, I focus on investment performance and trading behavior of households in Finland who trade directly in the equity market[1] along with institutions during high-tech bubble period, from 1995 to 2004.

1.2 Motivation and Objective of this Dissertation

There are a large number of in-depth studies concerning the performance of equities managed by mutual funds[2]. Relatively little has been known about the trading characteristics of individual investors due to lack of high quality data available to researchers. The literature has been evolving rapidly in the past decade in order to exploit key issues concerning how and why investors trade on the stock market.

One of the most popular areas of interest is to compare the trading behaviour and investment performance between institutions and individuals for both short and long

[1] According to Kaustia and Knupfer (2009), direct stock ownership has been the primary means for stock market participation in Finland during 1995 to 2002. Also individuals have no influence on amounts of contributions or investment selection in government-sponsored pension plan.
[2] See, for example, Sharpe (1966), Jensen (1968), Grinblatt, Titman, and Wermers (1995), Carhart (1997), Daniel, Grinblatt, Titman, and Wermers (1997), Chen, Jegadeesh, and Wermers (2000).

term horizons[3]. Specific questions have been addressed in prior studies, for example, do institutions outperform individuals? Are institutions momentum investors who tend to buy winning stocks and sell losing stocks? Is contrarian trading strategy persistent for households? With increased availability of a set of demographic variables of households such as gender, birth date, language and postcode, another line of studies have been developed to answer more interesting questions about the role of gender in financial markets. By examining gender differences in trading behaviour, researchers aim to investigate its causes thoroughly, particularly with respect to understanding the decision-making processes. Relevant questions that have arises are, for example, whether male investors trade far more frequently, aggressively and hold more diversified portfolios than female investors and what are the drivers of household trades.

This thesis is focused on the analysis of trading behaviour and performance evaluation of various investor groups during the period of high-tech bubble in three stages. First, I examine the performance of two distinctive groups of investors: institutions and individuals through analysing their entire portfolios before and after trading costs. Secondly, I exploit the gender differences in trading behaviour among individual subgroups and its link to the life cycle hypothesis. Finally, focusing specifically on Nokia stock, I show the asymmetric impact of positive and negative trade imbalance on volatility and investigate which investor group may have raised the volatility and caused the collapse of its share price.

To gain a better understanding of trading behaviour, it is useful to analyse a dataset containing comprehensive and accurate trading history in a market that experiences

[3] See Choe, Kho, and Stulz (1999) for Korea, Grinblatt and Keloharju (2000, 2001) and Anderson, Swan and Westerholm (2009) for Finland, Jackson (2003) for Australia, Goetzmann and Massa (2002) and Griffin, Harris, and Topaloglu (2003) for the US market.

spectacular price rises and falls. The Finnish stock market is ideal for the research as Finland has a representative middle-size securities market, one of the most concentrated trading places in Europe. Nokia plays a very large role in the Helsinki Stock Exchange (HEX): it is by far the largest Finnish company[4], accounting for about a third of the market capitalization of the HEX as of 2007. As a technology company, Nokia's unique position in this industrialized country makes both domestic and foreign investors excited to explore investment opportunities to be gained from Nokia's company growth. Consequently, the development and collapse of its share price in the high-tech bubble is an important process to examine so as to understand the trading style of different investor classes.

1.3 Contribution of this Dissertation

The recent work by Anderson, Swan and Westerholm (2010) also reaches similar conclusion with respect to superior performance of households over foreign institutions for Finland based on the same ten-year sample period. In addition to the common topic also addressed by Anderson, Swan and Westerholm (2010), this thesis answers questions relating to the performance of groups broken down by age and gender within the household group. It also reveals whether institutions or individuals are primarily responsible for recent trends in trading volumes. The thesis recognises that the effects of the trading activity by each group of investors depend on the trading participation of other investor groups. Thus, the thesis explores the impact of trade imbalances on Nokia stock's return volatility for all twenty-nine investor classes that make up the entire

[4] In 2004 Nokia's share of the Finland's GDP was 3.5% and accounted for almost a quarter of Finland's exports in 2003.

market and further identifies whether net buy trades or net sell trades contribute more to stock price volatility. In short, the thesis addresses many issues concerning Finnish investors that have not been addressed by Anderson, Swan and Westerholm (2010).

This thesis contributes to the literature for the following reasons: first, the thesis utilize ten years of transaction data with all investors uniquely identified to provide new empirical evidences as to trading behaviour of all Finnish investors using improved methodology. The dataset is sourced from the central register of shareholdings for Finnish stocks in the Finnish Central Securities Depository (FCSD) whose data is the official record and covers approximately 99% of all companies listed in the HEX. It includes the trading activity of all market participants and hence monthly trading measures are possible to be calculated using daily portfolio return of different investor groups. On a broader level, the dataset allows me to aggregate individual and institutional investors as a group respectively to compare against each other regarding the performance and trading style. On a detailed basis, retail investors are also broken down depending on their gender and age [5] attributes into different aggregate demographic subportfolios while institutional investors are grouped by their business classes.

Second, this thesis thoroughly examines the gender and age differences on trading performances of all Finnish household investors over a lengthy sample of ten years. I constructed seven pairs of unique demographic subportfolios with different gender and age band (ranging from 20s to 80s) in order to find the evidence of life-cycle trading and gender effect on investment behaviour. An earlier paper, Ollila and Westerholm

[5] Detail of the grouping criteria based on gender and age are shown in Table 4.1.

(2003), utilises a small sample of 11,795 Finnish individual private investors randomly selected from the Finnish Central Securities Depository (FCSD) with demographic variables of gender and age included. The much longer dataset I work with has well over 400,000 individual investors that constitute the whole population of household group. As the grouping criteria is designed to divide Finnish households into different life stages between genders, this study attempts to obtain answers to the questions as to whether or not young investors are talented traders over the period of high-tech bubble; what impact major adverse market event such as the collapse of Nokia share price had on savings of workers approaching their retirement age[6] and retirees in Finland and how their trading behaviour have changed since the event. Thus, the data and the issues addressed are considerably different between this thesis and the earlier study.

Finally, the further implication of this study is to show what lessons we can learn from the classic trading activities taken by different investor groups at the time of Nokia bubble in Finland. The sample period begins with high-tech boom (late 1990s), passes through the period of bubble burst (early 2000s) and ends in 2004, covering 2,611 trading days. Note that the next year, namely 2005 is the time period when world equity markets are in the middle of another bullish run-up, caused by the booming subprime housing market in the US. It was later reversed by ongoing global financial crisis starting in the fall of 2007. I hope this thesis could shed some light on the similarities of equity trading pattern during the period of asset bubble on a market level.

The rest of the thesis proceeds as follows. Chapter 2 reviews related literature. Chapter 3 presents research hypothesis and methodology and Chapter 4 provides data

[6] The mandatory retirement age is 65 in Finland.

description and trading measures definitions. Chapter 5 presents my main results followed by discussion. Chapter 6 concludes the study.

CHAPTER 2 Literature Review

2.1 Individuals, Institutions and Trading Behaviour

Individuals tend to be viewed as noise traders in the context of Kyle (1985) while institutions are always thought of as sophisticated informed investors. Indeed, in earlier studies, most empirical evidences favour institutions but in recent years results become mixed as more studies show individuals gain more from trading and not naïve in making investment decisions.

With retail investor shareholdings only provided by few brokerage firms, rather than central security depository from the stock exchange which covers the whole population, households are usually separated into two categories in earlier studies, based on whether they manage their equity investments with or without the advice of a full-service broker. Barber and Odean (2000) first investigate the aggregate common stock performance of households at a large discount broker from 1991 to 1996. Several prior studies also try to provide evidence that individual investors lose from trade, while institutions profit. Barber and Odean (2000) propose that it is the cost of trading and the frequency of trading, not portfolio selections that explain the poor performance of households. Barber, Lee, Liu, and Odean (2009) use a unique and more complete Taiwan dataset to provide the same argument institutions benefit from trade and individuals lose. The results of Grinblatt and Keloharju (2000) for Finland suggest individual investors are naïve and unsophisticated relative to foreign institutional investors based on two year of data. However, recent research by Ivkovic and Weisbenner (2005) document the local holding of individual investors perform well while Ivkovic, Sialm, and Weisbenner (2008) document individuals with concentrated portfolios perform well. San (2007) support the superior performance of individuals in NYSE and Nasdaq-NM stocks during a relatively long period 1981-2004 and suggest institutions fail to profit due to bad timing of the momentum cycle. Interestingly, they show the significant outperformance of individuals is unique to the late 1990s bubble. Most recently, using the same Finnish database as Grinblatt and Keloharju (2000) but with eight-year extension, Anderson, Swan and Westerholm (2010) show performance findings of individual and institutional investors are reversed. Contrary to previous study, foreign institutional investors are less informed and outperformed by aggregate households at long horizons and can no longer be considered as the best performing investors in Finland during the high-tech bubble period. Their results support information disadvantage hypothesis in the Finnish market with respect to home bias.

In terms of trading strategy, there is also widespread agreement in the literature that individuals tend to be contrarian traders whereas institutions are momentum investors, both in the short term and the long term[7]. As individuals and institutions pursue the opposite strategies, trades of individuals are likely to be the counterparties to institutional trades and individuals are assumed to supply liquidity to meet institutions demand[8]. The other feature of trading style that some studies[9] claim to find evidence for is that individuals are prone to the "disposition effect" that causes them to sell profitable investments too early and hold onto losing investments for too long in the hope of a turn-around.

[7] For short term, Choe, Kho, and Stulz (1999) document this for Korean households, Grinblatt and Keloharju (2000, 2001) for individuals in Finland, Jackson (2003) for Australian individuals, Richards (2005) for individuals in six Asian markets, Goetzmann and Massa (2002) for individuals in a U.S. index fund, Griffin, Harris, and Topaloglu (2003) for individuals in Nasdaq stocks; for long term, see Westerholm (2007).

[8] See Kaniel, Saar, and Titman (2008).

[9] See Barber, Lee, Liu and Odean (2009), Cohn-Urbach and Westerholm (2007), Grinblatt and Keloharju (2000) and etc.

For trading patterns, substantial empirical studies[10] concentrate on institutional herding but do not show strong evidence of correlated trading across institutional investors, which occurs when active fund managers intentionally imitate or mimic the actions of competitors who are potentially better informed. Relatively little has been known about coordinated trading by individuals. Brad, Odean and Zhu (2009) demonstrate that the trading of individual investors is surprisingly systematic and shared psychological biases such as limited attention, the disposition effect and the representativeness heuristic appear to be possible coordinating factors. Furthermore, they find that the systematic trading of individual investors is driven by their own decisions in the form of market orders, rather than a passive reaction to the trading of institutions.

As to trading volume, secular decreases in trading cost due to technological advances and tick size reductions in the past decade are well known and have undoubtedly increased trading activities of both institutions and households. The introduction of new trading technology and lower trading costs have made it easier for institutions to execute automated algorithmic trading or split orders (Hendershott, Jones, and Menkveld, 2008) while online brokerage accounts have made trading easier for retail investors and increased their frequency of asset allocation. There have been previous studies of volume, many of which have focused on the link between volume and other variables such as return volatility. New research direction is to examine turnover issues, for example, Chordia, Roll and Subrahmanyam (2009) find turnover and serial dependence in large trades have increased the most for stocks with the greatest level of institutional holdings.

[10] See Lakonishok, Shleifer and Vishny (1992) for pension funds and Grinblatt, Titman and Wermers (1995) for mutual funds.

For trading motivations, retail investors may trade for reasons other than to increase profits. They could trade to meet liquidity demands, to move to more or less risky investments, to realize tax losses and to rebalance their portfolios. On the other hand, institutions may exhibit different trading patterns due to different motivations, such as fund management, market-making, proprietary trading and hedge trading.

2.2 Gender Difference and Life Cycle Hypothesis

Barber and Odean's (2001) finding that men trade 45% more than women in the United States is arguably the best known result regarding gender and a common belief in the field. In the context of emerging market, Feng and Seasholes (2008) study the investment behaviour of households in China with equal representation of men and women[11] using data provided by a Chinese national brokerage firm. They show the portfolio performances of males and females are not statistically different. There is significant difference in trading intensity between men and women before controlling for factors such as number of stocks held and number of trading rights but they find no significant difference after controlling for these factors.

From another point of view, some existing papers focus on the influences of gender on trading activity through overconfidence. Barber and Odean (2001) use gender as an instrument for overconfidence and suggest it is responsible for trading since portfolios of male exhibit greater turnover. Grinblatt and Keloharju (2008) propose gender, however, is linked to other attributes that might affect trading, in particular sensation seeking, which could account for some of the difference in trading activity between

[11] This is unlike the developed market. In the United States, men represent approximately 80% of investors.

genders. Using a different dataset from Finland with a set of control variables, they claim that investors who are most prone to sensation seeking and those who are most overconfident trade the most.

Life cycle hypothesis developed by Brumberg and Modigliani (1954) suggests that rational economic agents should smooth their consumption by appropriately investing and borrowing based on expectations about lifetime income. This has implications for the pattern of investment over the life of an investor: young people of low earning power should borrow to increase consumption; during the peak earning years of middle age they should save; and later in life they should divest to supplement whatever income they have to increase consumption. Grinblatt and Keloharju (2001) find young adults (post-1980 birth years) buy more relative to middle-age adults (born from 1946-1950) and investors begin net sales of stocks at a later age in life than expected from the life cycle hypothesis.[12]

2.3 Finnish Context

There are a few earlier and contemporaneous studies which employ the same Finnish dataset for different purposes during different time periods. This dataset categorizes in amazing detail the holding and transactions of the universe of participants trading on the HEX with negligible and rare exceptions. Using two year trades data on a daily basis from FCSD, Grinblatt and Keloharju (2000) show foreign investors tend to be momentum traders and domestic investors have contrarian behaviour and argue momentum is a behaviourally driven anomaly in which 'smart' investors take advantage of 'naive' investors in equilibrium. Grinblatt and Keloharju (2001) analyse all the

[12] Lindell (1998) notes that 90 percent of Finns retire before the mandatory retirement age of 65.

potential trade-motivating factors together to both avoid omitted variable biases and to understand the way these factors interact. Their paper also documents the relation between individual trades and future stock returns over a two-year period[13]. Kuuskoski and Westerholm (2003) take a different approach, instead of assessing mutual fund performance versus a benchmark, which is by comparing investment performance of retail investors to that of mutual fund in Finland for the period 1995 to 2000 and find small investors underperform mutual funds and medium size investors perform similarly to mutual funds before transaction cost and taxes but underperform after adjusting for transaction costs. Large investors outperform both before and after transaction cost and taxes. Cohn-Urbach and Westerholm (2007) show evidence that frequency of trading is negatively related to gross returns achieved by both individuals and institutions as well as net returns when transaction cost are considered. It reports substantial behavioural biases such as overconfidence, competence effect and disposition effect among Finnish retail investors. Anderson, Swan and Westerholm (2010) examines the home bias issue of international investor trading patterns in Finland and confirm the foreign investors consistently overweight the largest and most familiar stocks where they perceive their information disadvantage is the lowest. While they are superior performers and informed in the first two years of 1995-2004 period, they underperform and become uninformed over ten years. Most recently, using the same data, Kaustia and Knupfer (2009) test whether returns experienced by the existing Finnish individual investors in a given neighbourhood affect the likelihood of new investors to enter the stock market in the same neighbourhood.

[13]See Odean (1999), Barber and Odean (2000), Grinblatt and Keloharju (2000, 2001) for poor performance of individuals, however San (2007) finds positive excess returns in the two year following individual buying.

Gender and age similarities and differences in trading behaviour are also examined in the context of Finnish market. Perttunen and Tyynela (2003) analyse the trading activity and portfolio performance of Finnish households from July 1996 to June 2000 with accurate data and find men (young) trade more than women (old) and hurt their performance more than women (old) and thus support the behavioural model of overconfidence. Using a dataset recording 11,795 individual private investors from 1995 to 2000, Ollila and Westerholm (2003) investigate systematic differences in trading activity, diversification and portfolio value as measures of investor sophistication across individuals with different gender, age and language backgrounds. Given Nokia's high-capitalized dominance in HEX, they suggest that special caution must be taken when analysing trading activity in Finland. They argue high trading volume in the successful Nokia stock covering 1995 through 2000 can partially be due to portfolio rebalancing with the aim to improve diversification[14]. Therefore, counting all investors with high volume as overconfident, without considering other factors than trading activity, would be an oversimplification.

Comerton-Forde, O'Brien, and Westerholm (2007) use the intraday data ranging from 12 April 1999 to 26 May 2000 of the same database to explain the significant proportion of intraday patterns through strategic trading by informed and liquidity traders but their paper does not try to link the finding to the collapse of Nokia price bubble in the middle of 2000. They classify traders from their twenty-seven investor classes as either informed or liquidity traders based on their stocking picking ability through a regression model of subsequent stock performance against proportional change in ownership and nine other control variables.

[14] Portfolio with securities that have increased their weight must be rebalanced as diversification effects are lost.

Seru, Shumway, and Stoffman (2009) analyse trading performance at the individual level to determine whether and how Finnish investors learn from their trading experience. They find a substantial part of overall learning by trading is explained by the evidence that investors stop trading after realizing their poor ability. The rest become better at trading with experience.

2.4 Trading Direction and Volatility

Glosten, Jagannathan, and Runkle (1993) show positive and negative innovations to returns having different impacts on conditional volatility in their GJR-GARCH model. Positive unanticipated returns appear to result in a downward revision of the conditional volatility whereas negative unanticipated returns result in an upward revision of conditional volatility. The reaction of investors to the positive or negative news of a particular stock is the buying or selling behaviour which leads to the corresponding positive or negative unanticipated returns if the information about the stock is correct and accurate. Therefore the relation between trading direction and volatility needs to be examined, particularly in the period of asset price bubble during which asymmetric volatility contribution by both buyers and sellers are supposed to be fairly apparent.

CHAPTER 3: Research Methodology and Hypotheses

3.1 Investor Group Classification

All investors in Finland are categorized into two groups: individuals and institutions. In particular, among the pool of households, I construct seventeen subgroups of unique demographic portfolios grouped by age and gender with three subgroups missing either gender or age characteristics. Therefore the known fourteen subgroups lead to the seven pairs of household subgroups and each pair matches male with female ranging from the age level of 20s to 80s. For institutions, business sector is used to separate twelve subgroups including brokerage and finance firms, domestic financials, domestic private companies, domestic public companies, foreign companies, foreign individuals, nominee accounts and foreign banks, insurance companies, mutual fund, pension fund, governments and non-profit organizations. In total, the whole market is made up of twenty-nine aggregated investor groups in this study. The composition of investor types in this study is more detailed than that of Anderson, Swan and Westerholm (2010) and pays more attentions to individual investors with different demographic attributes than Comerton-Forde, O'Brien, and Westerholm (2007)[15] do.

3.2 Benchmark Index Construction

There are two value-weighted market indices available on Datastream as proxy for the entire Finnish market, namely OMX Helsinki index and OMX Helsinki Cap index[16]. Both are value-weighted accumulation indices of every stock listed on the HEX, except for the cap index, the weighting of any stock is limited to 10%. In addition, OMXH25 index is a market value-weighted index that consists of twenty-five most-traded stock

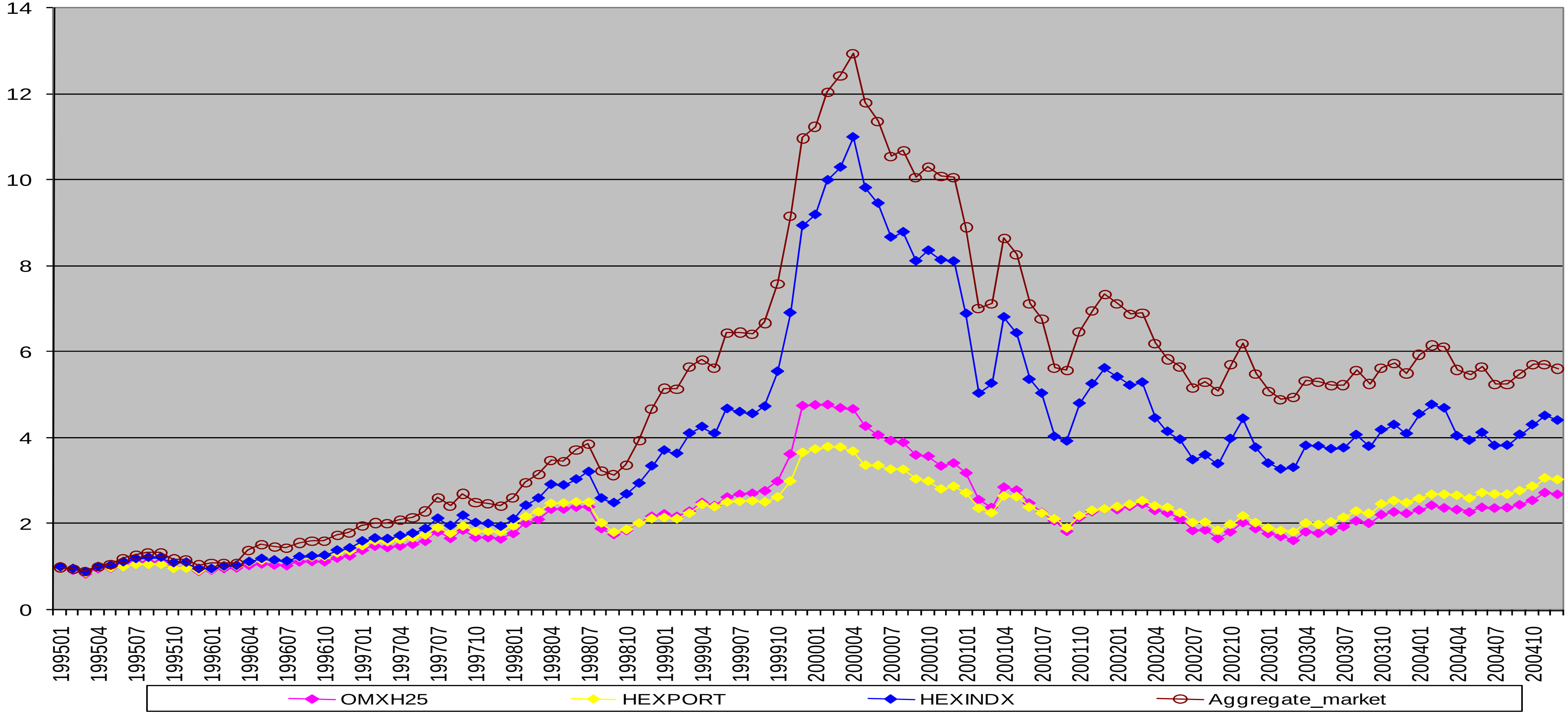
[15] The only four households categories in Comerton-Forde, O'Brien, and Westerholm (2007) are Farming households, Entrepreneur Households, Salary Earning households and other households.
[16] In Datastrem, OMX Helsinki index and OMX Helsinki Cap index refer to HEXINDX and HEXPORT.

classes[17]. Instead of using these indices, I construct the aggregate market index based on the original transaction data in the same way as for investor groups[18]. This is done by counting all investors as one person (one group) and aggregating all their trades. Figure 3.1 shows how these indices evolved over time in cumulative return index form. They all rose dramatically for the first five years of the sample period, reached the peak at middle 2000 and then declined sharply during the Nokia price crash in the second half of 2000 and oscillated until the end of 2004. Without the constraint of maximum weight of large stocks, the OMX Helsinki Cap index value is much above the OMX Helsinki index during most of the time period. As the real market portfolio rather than its proxy, the aggregate market index is the best benchmark in this study which includes all available traded stocks compared to other indices. With others being only price indices, the aggregate market index captures all the transactions in Finland dynamically.

[17] OMXH25 is not an accumulation index, whose price index is extracted from OMX Nordic Exchange website.
[18] Effectively I can check whether on a market level, the shares bought are equal to shares sold of any available single stock for daily level since transaction details of the entire market is given.

Figure 3.1: Cumulative Gross Return Performance of Different Market Indices

This figure shows a comparison of the cumulative return index among aggregate market portfolio and other market indices. All indices are rebased to 1 as in January 1995. Cumulative return index is an index which compounds monthly gross return r_i, defined as $\prod_{i=1}^{n}(1+r_i)$.



3.3 Hypothesis 1: *Institutional trading, rather than retail trading is the predominant cause of the increase in trading volume in the Finnish stock market.*

Compare to retail investors, institutions are able to trade more frequently and more cheaply. In the past decade, they substantially increase their trading activities due to lower tick sizes, decreased commissions and improvement in trading technology. Such behaviour may enable them to exploit private information more efficiently and effectively by trading more in recent years. The test here will examine which group are more responsible for the volume trend.

3.4 Hypothesis 2: *Institutions outperform households in the short term and underperform in the long run.*

As Anderson, Swan and Westerholm (2010) point out first, foreign investors are the most significant players in sixteen stocks of highest market capitalization in Finland as at 1 January 1995 since they have the largest holdings and are the most active buyers of these stocks in both the two-year and ten-year sample periods. Secondly they suffered the largest losses during the period 2001-2004 and continued to overweight these losing stocks. Combining these two facts (largest holdings and largest losses), in the context of this study, we are expected to see, over a more robust ten-year horizon, an inferior performance of aggregate institutional group including foreign investors compared to aggregate household group.

3.5 Hypothesis 3: *Males behave significantly differently from females of the same age band across various monthly trading measures before and after transaction cost.*

Males are expected to be confident (not necessarily overconfident) in their trading skills and turn over their portfolios more often and aggressively than females, consequently more transaction costs are generated. I carry out Wilcoxon rank-sum test and independent t test[19] to test the mean difference in all trading measures between the male and female households group at the same age band, both before and after transaction cost. The trading measures obtained are the gross and net return, CAPM beta, realized beta, realized volatility, portfolio size and turnover. A variety of performance evaluation methods are also implemented including Jensen's alpha, Sharpe ratio and Treynor ratio.

3.6 Hypothesis 4: *The trading of different individual investor groups on Nokia shares is correlated contemporaneously and is persistent.*

As social animals, it is not easy for investors to stick to an opinion that differs markedly from that of the majority. People generally prefer to have their opinion validated by those of others in the group and thus tend not to trade independently. This test attempts to find evidence about the extent to which individual trading is correlated. Brad, Odean and Zhu (2009) document highly correlated and persistent systematic trading of individuals. This is also a necessary condition for the trading biases of individuals to affect asset prices as the trades of any particular individual are likely to be small.

[19] The Wilcoxon rank-sum test is a nonparametric alternative to the independent t-test which is based solely on the order in which the observations from the two samples fall. Wilcoxon rank-sum test is still valid for data from any distribution, whether normal or not, and is much less sensitive to extreme values than t-test.

Contemporaneous correlation matrix of buying intensity denoted as $BI_{i,t}$ (percentage of trades that are buys) among fourteen individual investor subgroups[20] are calculated in each year. Buying intensity is defined as follows:

$$BI_{i,t} = \frac{b_{i,t}}{b_{i,t} + s_{i,t}} \quad , \tag{3.1}$$

where $b_{i,t}$ is the number of buy shares of Nokia on day t by investor group i, $s_{i,t}$ is the number of sell shares of Nokia on day t by investor group i.

In each year, the maximum correlation of each group's buy intensity to the remaining investor groups' buy intensity[21] is recorded as a measure of highest correlated trading level that investor group have achieved. Then a yearly ranking index is developed for the correlated trading among individual subgroups based on the yearly maximum correlation. Thirdly, the calculation of cross-section ranking correlation is performed between two adjacent years across fourteen investor subgroups to check for the persistence of correlated trading. The rank correlation coefficient measures the correspondence between different rankings on the same set of all fourteen subgroups.[22]

3.7 Hypothesis 5: *Buy trades and sell trades of same investor groups contribute differently to the volatility of Nokia share price over the course of its bubble.*

[20] The three unknown gender and age groups are eliminated.
[21] I pick up the maximum value from the 13 correlations with the rest of the groups each year.

[22] An increasing rank correlation coefficient implies increasing agreement between rankings. The coefficient is inside the interval [-1, 1] and assumes the value: -1 if the disagreement between the two rankings is perfect, one ranking is the reverse of the other; 0 if the rankings are completely independent; 1 if the agreement between the two rankings is perfect, the two rankings are the same.

This test examines the asymmetric impact of positive and negative trade imbalance on volatility. In the spirit of Glosten-Jagannathan-Runkle GARCH (GJR-GARCH) model in Glosten, Jagannathanm, and Runkle (1993) who separate the effect of negative news shocks from positive ones on volatility, I investigate the impact of trading imbalance on volatility trying to separate buy and sell trades (positive and negative trading imbalance). It is not reasonable to control for twenty-nine investor groups based on the previous grouping criteria due to potential multicollinearity issues. Therefore, five new aggregate groups are formed: aggregate males, aggregate females, domestic institutions, foreign banks and other institutions. I run the following time-series regression of monthly realized volatility of Nokia share price on its 1-month lag and monthly trade imbalance of the five aggregate investor groups over 10-year period.

$$RVOL_t = a_0 + (a_1 + b_1 D_1)\left|TIB_{1,t}\right| + (a_2 + b_2 D_2)\left|TIB_{2,t}\right| + \ldots + (a_5 + b_5 D_5)\left|TIB_{5,t}\right| + RVOL_{t-1} + \varepsilon_t \text{ , (3.2)}$$

where $D_i = \begin{cases} 1 & TIB_i < 0 \\ 0 & TIB_i \geq 0 \end{cases}$ is the dummy for positive and negative imbalance, the scaled trade imbalance denoted by $TIB_{i,t}$ is defined as:

$$TIB_{i,t} = \frac{b_{i,t} - s_{i,t}}{b_{i,t} + s_{i,t}} \text{ ,} \qquad (3.3)$$

where $b_{i,t}$ is the number of buy shares of Nokia on day t by investor group i , $s_{i,t}$ is the number of sell shares of Nokia on day t by investor group i .

It controls for the monthly trade imbalances of other investor groups. This means $a_i + b_i D_i$ is the investor group i 's trade imbalance contribution to the volatility of Nokia price return after taking out the effect of the remaining four groups.

Coefficient b_i measures the effect of negative imbalance therefore a_i , $a_i + b_i$ is the investor group i 's corresponding positive and negative imbalance contribution to the realized volatility of Nokia price after taking out the effect of the remaining four groups and volatility lag. A positive b_i indicates when investor group i makes net sell of Nokia share, the volatility goes up by more than that of net buy and vice versa for negative b_i . A significant coefficient b_i is strong evidence of asymmetric impact.

CHAPTER 4: Data and Measures

4.1 Data Description

The highly detailed data provided by FCSD contains a record of the opening balance of shares owned by each investor on 1 January 1995, and then a record of every transaction thereafter to 30 December 2004, which includes the high-tech boom and bubble burst periods, in late 1990s and early 2000s. A trader identification code is allocated to every investor on the market and each trade they make is then followed by a transaction identification code, so it is possible to follow the trading activity of every investor on this market over the 10-year period from 1995 to 2004. The other important information in the dataset is investor's business sector, ownership type, legal status, year of birth[23], gender and post code. I am also provided with specific information about stock splits, rights issue, dividends and etc. To trade on HEX, Finnish institutions, companies and individuals must register with FCSD and be given a unique account, even if they trade through multiple brokers. Foreign investors may choose to trade through one nominee account, which may have multiple foreign investors and are registered through financial institutions. The dataset is also capable to classify each investor into one of twenty-nine investor classes based on their business sector, legal type, ownership type[24], age and gender. The details of grouping criteria on age band and gender are show in Table 4.1.

[23] The age records are measured at 2000.
[24] Ownership type separates domestic and foreign investor.

Table 4.1: Households Grouping Criteria and Number of Transactions

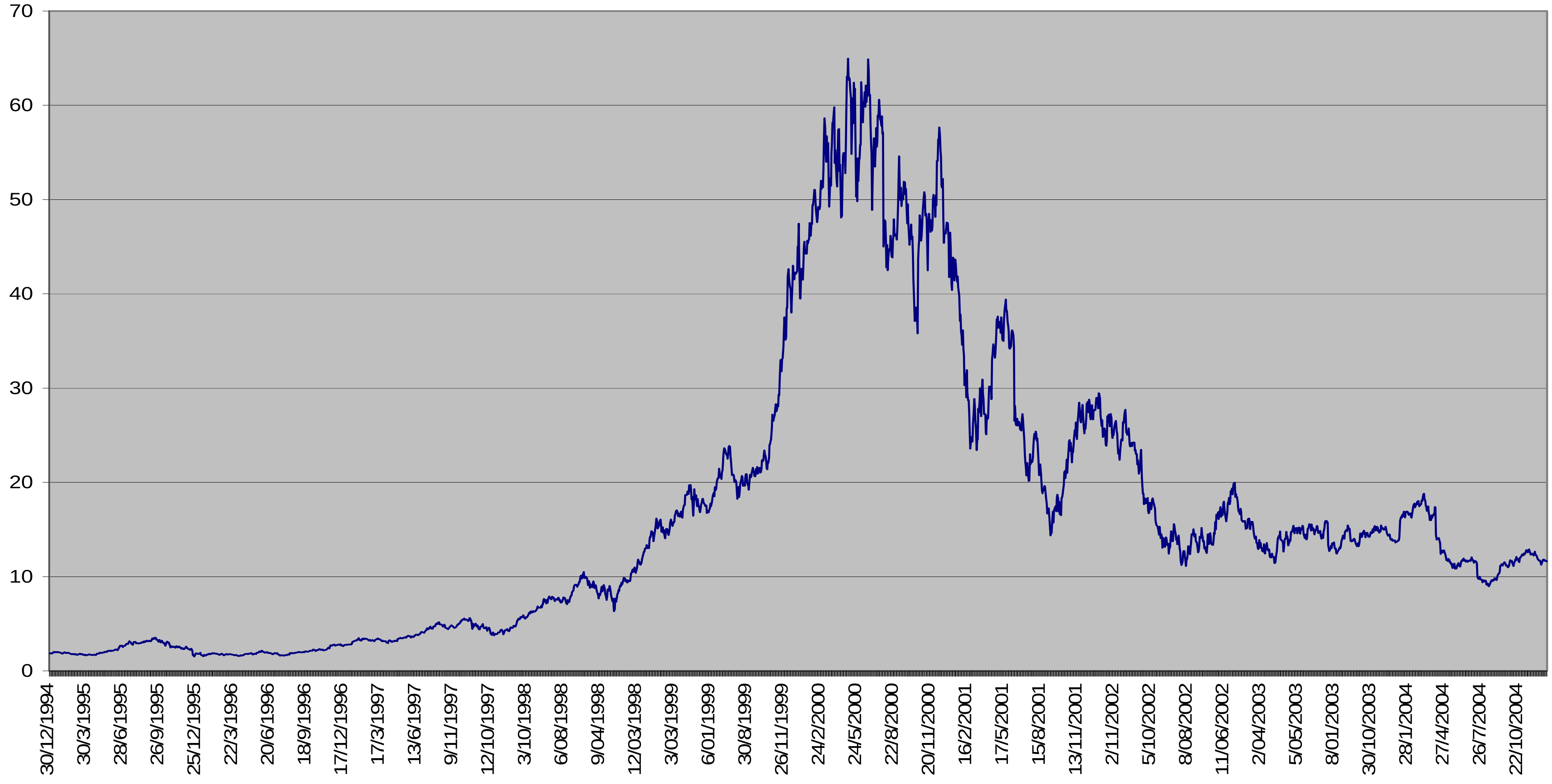
This table gives the criteria used to group household portfolios. The portfolios are divided by age and gender of individual investors. The number of transactions is counted over the 10-year period.

Gender Criteria	Age Band Criteria	Trader ID	Gender ID	Age Band ID	No of Transactions
0 = Unknown	0 = Unknown	1	0	0	24,431
1 = Male	1 = 21 – 30	2	1	0	423,323
2 = Female	2 = 31 – 40	3	1	1	1,389,640
	3 = 41 – 50	4	1	2	2,527,442
	4 = 51 – 60	5	1	3	2,509,306
	5 = 61 – 70	6	1	4	2,705,217
	6 = 71 – 80	7	1	5	1,311,804
	7 = 81 – 90	8	1	6	565,031
		9	1	7	245,945
		10	2	0	297,041
		11	2	1	387,805
		12	2	2	614,230
		13	2	3	776,365
		14	2	4	1,066,836
		15	2	5	636,761
		16	2	6	422,407
		17	2	7	245,216

As the stock of the largest market capitalization in the HEX, Nokia’s stock price was extremely volatile over the course of the sample period as illustrated in Figure 4.1 and thus dramatically affects all portfolios formed in this study which is the unique nature of this single share price bubble and makes Finnish market the perfect one for undertaking trading behaviour research. It will be shown later that all portfolios, either individuals or institutions, peak at the same time as Nokia total return index does.

Figure 4.1: Nokia Price over 10-Year Period

This figure presents Nokia's daily share price from 01/01/1995 to 31/12/2004, stock splits and dividends are adjusted.



4.2 Measure Definition

4.2.1 Portfolio returns

I improve the frequency of portfolio returns from monthly level to daily level to obtain the monthly performance measures including the Sharpe ratio. Therefore, the standard deviation of daily return of each group is able to be captured over every month across ten years. Given detailed information of this unique dataset, the exact number of daily observation over each month can be identified and then applied to multiply the above daily standard deviations to get monthly standard deviations for each group. Therefore, it is possible to carry out the calculation of monthly Sharpe ratio and Treynor ratios. Monthly realized volatility and realized beta are also able to be calculated with daily returns.

To calculate daily returns, I aggregate transactions over all stocks whose information is available for each investor group every trading day. Following Cohn-Urbach and Westerholm (2007), I apply the following formulae which can be used to calculate the returns of each investor group for every day/month of the sample period. Two returns are calculated here, daily/monthly gross return and daily/monthly log gross return. The first one is used to construct the cumulative return index[25]. Daily/Monthly gross return is defined as:

$$R_i^1 = \frac{(Close - Open) + (Sale - Purchase) + Dividend}{Open + Purchase} \ , \qquad (4.1)$$

[25] According to monthly gross simple return r_i that I calculate, cumulative return index is an index rebased to 1 as in January 1995, defined as $\prod_{i=1}^{n}(1+r_i)$.

or

$$R_i^1 = \frac{\left(Close + Sale + Dividend\right) - (Open + Purchase)}{Open + Purchase} \quad , \tag{4.2}$$

Daily/Monthly log gross return is defined as:

$$R_i^2 = \log\left(\frac{Close + Sale + Dividend}{Open + Purchase}\right) , \tag{4.3}$$

where *Close* is the closing position, the dollar value of the portfolio at the end of the i th day/month (uses Datastream's unadjusted closing prices), *Open* is the opening position, the dollar value of the portfolio at the beginning of the i th day/month, *Purchase* is the total purchase costs, the total amounts used to buy shares during the i th day/month, *Sale* is the total sale proceeds, the total amounts from the sale of any shares during the i th day/month, *Dividend* is the total dividends received, the total amounts received in dividends for the i th day/month.

This equation allowed me to calculate the daily/monthly return for each investor group using only these five values (opening and closing portfolio values, total sale proceeds, total purchase cost and total dividends received). To calculate opening and closing portfolio values, a program was written to keep track of each group's portfolio at the start and end of each day/month using the opening balances of shares and any subsequent transactions executed by each group. I then multiply the holdings of each investor by the market value of each share to calculate the closing portfolio value for each investor group. This same value is then used as the next day/month's opening portfolio value. The proceeds from each sale and cost of each purchase are calculated by multiplying the number of shares traded by the transaction price at each trading time.

Both of these quantities were recorded in the trade data. I then added these values together for every purchase or sale, in order to calculate the total proceeds from sales or total costs of purchases for each investor group in each day/month.

This approach is more precise when measuring the return performances and trading activities of investors as I take both purchase cost and sale proceeds for all stocks into account. Most of the US mutual fund studies only use at best quarterly stock holding records and consequently miss trades that may occur within the quarter. In this study, the dataset maintains a record of the initial stock holdings of every Finnish investor registered by 1 January 1995 that enables me to form portfolios of all the stocks each investor group hold, in reality, over the full ten years, rather than a single stock or the whole market[26]. This means the outperformance results of aggregate individuals' portfolios compared to institutions found in the study are more robust than San (2007), who has only results which applies on average, for the stock level.

4.2.2 Transaction Costs, Net Return and Turnover

Since transaction costs are not included in the dataset, I need to make an assumption about the average level of cost of trading incurred by investors. Households and institutions need to be considered separately, given the large differences in transaction cost. During the sample period, trading methods in HEX shifted from primarily broker-executed phone trading to a substantial proportion of trades being executed through online discount brokerages, with little broker involvement in the trade. Therefore the cost of trading for individuals, especially in small quantities, would experience a regime

[26] During the ten-year period, up to 123 stocks have been traded on the HEX based on the database in this study.

change and fall substantially over the sample period. Institutions tend to have much lower transaction cost, since their trades are large and have long-term relationship with brokers. Some existing studies have provided estimates of trading cost for both investor classes[27]. Therefore, this study applies trading cost of 0.2% into the estimates of institutional net returns and 1.5% for individual net returns:

Daily/Monthly net simple returns for Institutions:

$$R_i^1 = \frac{(Close + Sale + Dividend) - (Open + Purchase) - 0.002(Purchase + Sale)}{Open + Purchase} \quad , \qquad (4.4)$$

Or net log return:

$$R_i^2 = \log\left(\frac{(Close + Sale + Dividend) - 0.002(Purchase + Sale)}{Open + Purchase}\right) \quad , \qquad (4.5)$$

Daily/Monthly net simple returns for Individuals:

$$R_i^1 = \frac{(Close + Sale + Dividend) - (Open + Purchase) - 0.015(Purchase + Sale)}{Open + Purchase} \quad , \qquad (4.6)$$

Or net log return:

$$R_i^2 = \log\left(\frac{(Close + Sale + Dividend) - 0.015(Purchase + Sale)}{Open + Purchase}\right) \quad , \qquad (4.7)$$

[27] See Barber and Odean (2000) for individuals, Keim and Madhavan (1997,1998), Stoll (1995) for institutions.

where trading value is calculated as the sum of purchase cost and sale proceeds.

Turnover is calculated based on the definition introduced by Barber and Odean (2001). I calculate the monthly portfolio turnover for each aggregate investor group as one-half the monthly sales turnover plus one-half the monthly purchase turnover. Sell turnover for investor group h in month t is calculated as $\sum_{i=1}^{S_{ht}} p_{i,t} \min(1, \frac{S_{it}}{H_{it}})$, where S_{it} is the number of shares in security i sold during the month, $p_{i,t}$ is the value of stock held at the beginning of month t scaled by the total value of stock holdings, and H_{it} is the number of shares of security i held at the beginning of month t. Buy turnover is calculated as $\sum_{i=1}^{S_{ht}} p_{i,t+1} \min(1, \frac{B_{it}}{H_{i,t+1}})$, where B_{it} is the number of shares of security i bought during the month.

4.2.3 Realized Volatility, Realized Beta, Sharpe Ratio and Treynor Ratio

To compute monthly realized measures from daily return, I apply the following formula, where realized variance of the portfolio of investor group i in month t is defined as $\sum_{j=1}^{N_i} r_{i,j,t}^2$ (realized volatility is squared root of realized variance) and realized beta for stock i in month t is:

$$\beta_{i,t} = \frac{\text{cov}(r_{i,t}, r_{m,t})}{\text{var}(r_{m,t})} = \frac{\sum_{j=1}^{N_t} r_{i,j,t} r_{m,j,t}}{\sum_{j=1}^{N_i} r_{m,j,t}^2} , \tag{4.8}$$

where $r_{i,j,t}$ is the log return of investor group i on day j of month t, $r_{m,j,t}$ is the log return of aggregate market on day j of month t, and N_t is the number of days into which month t is partitioned, $\operatorname{cov}(r_{i,t}, r_{m,t})$ is the monthly realized covariance of $r_{i,j,t}$ and $r_{m,j,t}$, $\operatorname{var}(r_{m,t})$ is the monthly realized variance of $r_{m,j,t}$.

The Sharpe ratio S_i and the Treynor ratio T_i are defined below:

$$S_{i,t} = \frac{r_{i,t} - r_{f,t}}{\sigma_{i,t}} \quad , \qquad T_{i,t} = \frac{r_{i,t} - r_{f,t}}{\beta_{i,t}} \quad , \tag{4.9}$$

where $r_{i,t}$ is the log return of investor group i in month t, $r_{f,t}$ is the risk free rate in month t, $\beta_{i,t}$ is the beta coefficient of investor group i estimated from CAPM in month t, $\sigma_{i,t}$ is the standard deviation of investor group i in month t, which is obtained by multiplying the daily standard deviation with the squared root of exact number of daily observation over month t to get monthly standard deviation for each group

$$\sigma_{i,t} = \sqrt{\mathrm{var}_{i,t}} = \sqrt{n_{i,t}\,\overline{\mathrm{var}}_{i,t}} = \sqrt{n_{i,t}}\ \overline{\sigma}_{i,t} \tag{4.10}$$

$\overline{\mathrm{var}}_{i,t}$ is the daily variance in month t, and $\overline{\sigma}_{i,t}$ is the daily standard deviation of investor group i in month t, defined as

$$\overline{\sigma}^2_{i,t} = \frac{1}{n_{i,t}} \sum_{j=1}^{n_{i,t}} \left(r_{j,i} - \mu\right)^2 . \tag{4.11}$$

It can be shown that the monthly variance is close to the monthly realized variance $\sum_{j=1}^{N_i} r^2_{i,j,t}$, as the mean of daily returns during the month should be close to zero. Therefore monthly standard deviation should also be close to the monthly realized volatility.

CHAPTER 5: Results

5.1 Institutions Trading versus Individuals Trading

Table 5.1 reports the summary results of monthly gross trading measures of the three aggregate groups: household, institution and market. The trading measures include gross return, CAPM beta and realized beta, standard deviation of the return and realized volatility, portfolio size, turnover, Jensen's alpha, Sharpe ratio and Treynor ratio.

From the table, aggregate households achieve average monthly return of 2.05% while aggregate institutions earn 1.43%. The aggregate market index yields 1.47%. This compares with the indices provided by Datastream and OMX Nordic Exchange website, namely HEXINDX, HEXPORT and OMXH25 which gain average monthly log gross returns of 1.24%, 0.93% and 0.83% respectively. The different results between indices are expected since the aggregate market index and HEXINDX do not have the maximum weight limit. Therefore, the weight of Nokia is not capped in these two indices while it is capped in HEXPORT and OMXH25. Aggregate household has average monthly standard deviation of 9.82% and realized volatility of 9.78%, lower than that of aggregate institutions (12.94% and 12.87% respectively) who take on more risks. The other trading measures of households are: average monthly alpha value of 0.03% (3bp) and average monthly turnover of 2.6%, or 31.2% annually while institutions achieve alpha of -0.34bp and turnover of 29.3%, or 351.6% annually. It is shown later that the most frequent male and female group turn their portfolio over 98.35% and 31.71% respectively. Therefore institutions as a whole still trade 3.6 times as much as the most active household age group and this supports the notion that the turnover trend is driven more by institutions rather than retail investors.

Table 5.1: Descriptive Statistics of Monthly Gross Trading Measures of Different Aggregate Groups

This table provides summary results of monthly trading measures of aggregate households, institution and market before transaction cost. The gross trading measure includes standard deviation of log return (Gross_std), log return (Log_gross_return), Sharpe ratio and alpha, CAPM beta (Beta), Treynor ratio, realized beta and realized volatility, aggregate portfolio holding, turnover, buy turnover and sell turnover. All statistics are 119-month average across 10 years. (N=119 is the number of month observations during the 10 years)

	Household	Institution	Market
N	119	119	119
Gross_std			
Mean	0.098191	0.129391	0.126084
Median	0.065001	0.08815	0.085619
Min	0.020894	0.030906	0.029548
Max	1.278872	1.668331	1.644626
StdDev	0.145846	0.197078	0.192568
Log_gross_return			
Mean	0.020457	0.01425	0.014708
Median	0.019534	0.012047	0.012146
Min	-0.22273	-0.25264	-0.25096
Max	0.258293	0.2263	0.229594
StdDev	0.07927	0.081805	0.081213
Sharpe_ratio			
Mean	0.349314	0.19548	0.209259
Median	0.181786	0.058152	0.057569
Min	-2.07333	-1.72909	-1.75347
Max	3.841472	2.75986	2.883986
StdDev	1.111874	0.898833	0.916093
Alpha			
Mean	0.00029	-3.4E-05	0
Median	0.000246	-2.7E-05	0
Min	-0.0099	-0.00064	0
Max	0.004696	0.000815	0
StdDev	0.00151	0.000144	0

	Household	Institution	Market
N	119	119	119
Beta			
Mean	0.729166	1.027894	1
Median	0.711071	1.027631	1
Min	0.331845	0.926631	1
Max	1.866319	1.070719	1
StdDev	0.154275	0.016426	0
Treynor_ratio			
Mean	0.025192	0.011057	0.011807
Median	0.019323	0.009665	0.01007
Min	-0.33247	-0.25044	-0.25485
Max	0.377514	0.219988	0.226562
StdDev	0.112079	0.079935	0.081299
Realized_beta			
Mean	0.732227	1.027533	1
Median	0.721739	1.026934	1
Min	0.391738	0.940138	1
Max	1.702376	1.069693	1
StdDev	0.142685	0.01546	0
Realized_volatility			
Mean	0.097807	0.128739	0.125463
Median	0.064132	0.088481	0.08532
Min	0.022278	0.03165	0.030339
Max	1.246517	1.626125	1.603012
StdDev	0.142032	0.191882	0.187492

	Household	Institution	Market
N	119	119	119
Aggregate_portfolio_holding			
Mean	1.11e+10	1.25e+11	1.36e+11
Median	1.1e+10	1.18e+11	1.29e+11
Min	2.34e+09	1.58e+10	1.82e+10
Max	2.86e+10	3.94e+11	4.21e+11
StdDev	6.17e+09	9.18e+10	9.79e+10
Turnover			
Mean	0.026447	0.293046	0.270433
Median	0.024975	0.267635	0.249285
Min	0.007284	0.085201	0.075161
Max	0.056911	0.777227	0.744442
StdDev	0.010244	0.144415	0.137167
Buy_turnover			
Mean	0.023832	0.289725	0.267094
Median	0.023139	0.267392	0.246686
Min	0.005576	0.050542	0.044751
Max	0.053046	0.772885	0.740302
StdDev	0.010106	0.143517	0.136075
Sell_turnover			
Mean	0.029062	0.296368	0.273771
Median	0.026591	0.268843	0.249725
Min	0.008992	0.098897	0.088147
Max	0.076021	0.781568	0.748582
StdDev	0.012452	0.148629	0.141294

In order to see whether or not these differences are statistically significant, Table 5.2 provides results of both an independent t test and Wilcoxon rank sum test of the trading measures between aggregate households and institutions.

From the table, except for volatility, the results of the two tests are consistent. Both tests confirm that households earn significant higher alpha than institutions but not significant return, although the return difference is 7.44% annually. Therefore, households outperform institutions significantly in a market-adjusted manner. The evidence on higher portfolio betas of institutions by the tests also supports this finding, both in terms of CAPM beta and realized beta. The return of institutions is compensated by their risk-taking actions but once adjusted, they underperform significantly.

Table 5.3 reports the summary results of monthly net trading measures of the aggregate households and institutions. Net monthly return of households falls to 1.97% from gross return of 2.05%, down 0.08%, or 0.96% lower annually. Institutions achieve net monthly returns (1.34%) that are 0.09% less than gross monthly return (1.43%), or 1.08% annually. Interestingly, the huge trading volume of institutions reduces their net return nearly as much as do households even though institutions have a much lower transaction cost of 0.2% compared to households’ 1.5%. The similar magnitude in reductions in returns between the two groups is also observed in Cohn-Urbach and Westerholm (2007).

Table 5.2: Independent T Test and Wilcoxon Rank Sum Test for Aggregate Households and Institutions

This table reports the independent t-test and Wilcoxon rank-sum test of difference in selected monthly trading measures between aggregate households and institutions. The test results of average monthly log return, average monthly standard deviation (Std), average monthly beta, average monthly alpha, average monthly realized beta and average monthly realized volatility between the two aggregate groups are presented. P-values are in square brackets. *denotes significance on 10% level, **denotes significance on 5% level and ***denotes significance on 1% level.

Log return	Household	0.0205		*Std*	Household	0.0982
	Institution	0.0143			Institution	0.1294
	Difference	0.0062			Difference	-0.031
Independent t-test p-value		[0.5528]		Independent t-test p-value		[0.1664]
Wilcoxon rank-sum test p-value		[0.4708]		Wilcoxon rank-sum test p-value		[0.0003]***
Beta	Household	0.7292		*Alpha*	Household	0.0003
	Institution	1.0279			Institution	-3.40E-05
	Difference	-0.299			Difference	0.0003
Independent t-test p-value		[<.0001]***		Independent t-test p-value		[0.0209]**
Wilcoxon rank-sum test p-value		[<.0001]***		Wilcoxon rank-sum test p-value		[<.0001]***
Realized beta	Household	0.7322		*Realized volatility*	Household	0.0978
	Institution	1.0275			Institution	0.1287
	Difference	-0.295			Difference	-0.031
Independent t-test p-value		[<.0001]***		Independent t-test p-value		[0.1588]
Wilcoxon rank-sum test p-value		[<.0001]***		Wilcoxon rank-sum test p-value		[0.0003]***

Table 5.3: Descriptive Statistics of Monthly Net Trading Measures of Different Aggregate Groups

This table provides summary results of monthly trading measures of aggregate households and institutions after transaction cost. All statistics are 119-month average across 10 years. (N=119 is the number of month observations over the 10 years) The net measures include monthly standard deviation of log net return (Net_std), average monthly log net return (Net_log_return), average monthly Sharpe ratio (Net_Sharpe_ratio), average monthly alpha (Net_alpha), average monthly CAPM beta (Net_beta), average monthly Treynor ratio (Net_Treynor_ratio), average monthly realized beta (Net_realized_beta) and average monthly realized volatility (Net_realized_volatility).

	Household	Institution	Market			Household	Institution	Market
N	119	119	119		N	119	119	119
Net_std					***Net_beta***			
Mean	0.098195	0.129394	0.126086		**Mean**	0.729208	1.027891	1
Median	0.064995	0.088191	0.085656		**Median**	0.711052	1.027632	1
Min	0.020907	0.030912	0.029542		**Min**	0.331679	0.926679	1
Max	1.27886	1.668355	1.644648		**Max**	1.86572	1.070733	1
StdDev	0.145842	0.197079	0.192569		**StdDev**	0.154202	0.01642	0
Net_log_return					***Net_Treynor_ratio***			
Mean	0.019694	0.013381	0.013847		**Mean**	0.024095	0.010212	0.010946
Median	0.01921	0.010358	0.011419		**Median**	0.01895	0.008028	0.008872
Min	-0.2239	-0.25384	-0.25216		**Min**	-0.33421	-0.25161	-0.25605
Max	0.257177	0.225837	0.229149		**Max**	0.375514	0.219526	0.226117
StdDev	0.079286	0.081877	0.081283		**StdDev**	0.11207	0.080002	0.081367
Net_Sharpe_ratio					***Net_realized_beta***			
Mean	0.336719	0.184694	0.198261		**Mean**	0.732143	1.027543	1
Median	0.166889	0.050659	0.050036		**Median**	0.721279	1.026947	1
Min	-2.08272	-1.73786	-1.76232		**Min**	0.390962	0.940047	1
Max	3.821436	2.743928	2.867511		**Max**	1.703442	1.069828	1
StdDev	1.10996	0.898701	0.915847		**StdDev**	0.142789	0.015472	0
Net_alpha					***Net_realized_volatility***			
Mean	0.00029	-3.4e-05	0		**Mean**	0.097798	0.128733	0.125457
Median	0.000242	-2.7e-05	0		**Median**	0.064105	0.088483	0.085285
Min	-0.00984	-0.00064	0		**Min**	0.022232	0.031545	0.030234
Max	0.004693	0.000811	0		**Max**	1.246506	1.626147	1.603032
StdDev	0.001506	0.000143	0		**StdDev**	0.142033	0.191886	0.187497

Figure 5.1 presents the cumulative gross return index of three aggregate groups: household, institution and market. Figure 5.2 presents cumulative net return index of aggregate household, aggregate institution and Nokia total return index.

In Figure 5.1, the aggregate institution has a very close cumulative return path to the aggregate market due to dominating market capitalization of the institutions compared to individuals shown in Table 5.1 (ten times that of individuals'). The outperformance of institutions over individuals holds for most of the two-year sample as do Anderson, Swan and Westerholm (2010) and Grinblatt and Keloharju (2001). In addition, the gap is very small between the two groups before 2000 and wide substantially afterwards, while narrows in 2001 and widens again towards the tails. This result suggests the household group experiences a better performance over the institution group after 2000. In Figure 5.2, the net performance does not change the pattern observed in Figure 5.1 though both aggregate groups reduce their performance by the amount of transaction cost incurred. Moreover, the Nokia total return index has a similar but more exaggerated shape and its deviation from both groups is the widest in the middle of 2000. The highly positive correlation between the Nokia index and two groups display the great influence of Nokia holdings on their overall performance.

Figure 5.1: Cumulative Gross Return Performance of Different Aggregate Groups

This figure shows a comparison of the cumulative return index among aggregate individual, aggregate institution and aggregate market before transaction cost. All indices are rebased to 1 as of January 1995. Cumulative return index is an index which compounds monthly gross return r_i, defined as $\prod_{i=1}^{n}(1+r_i)$.

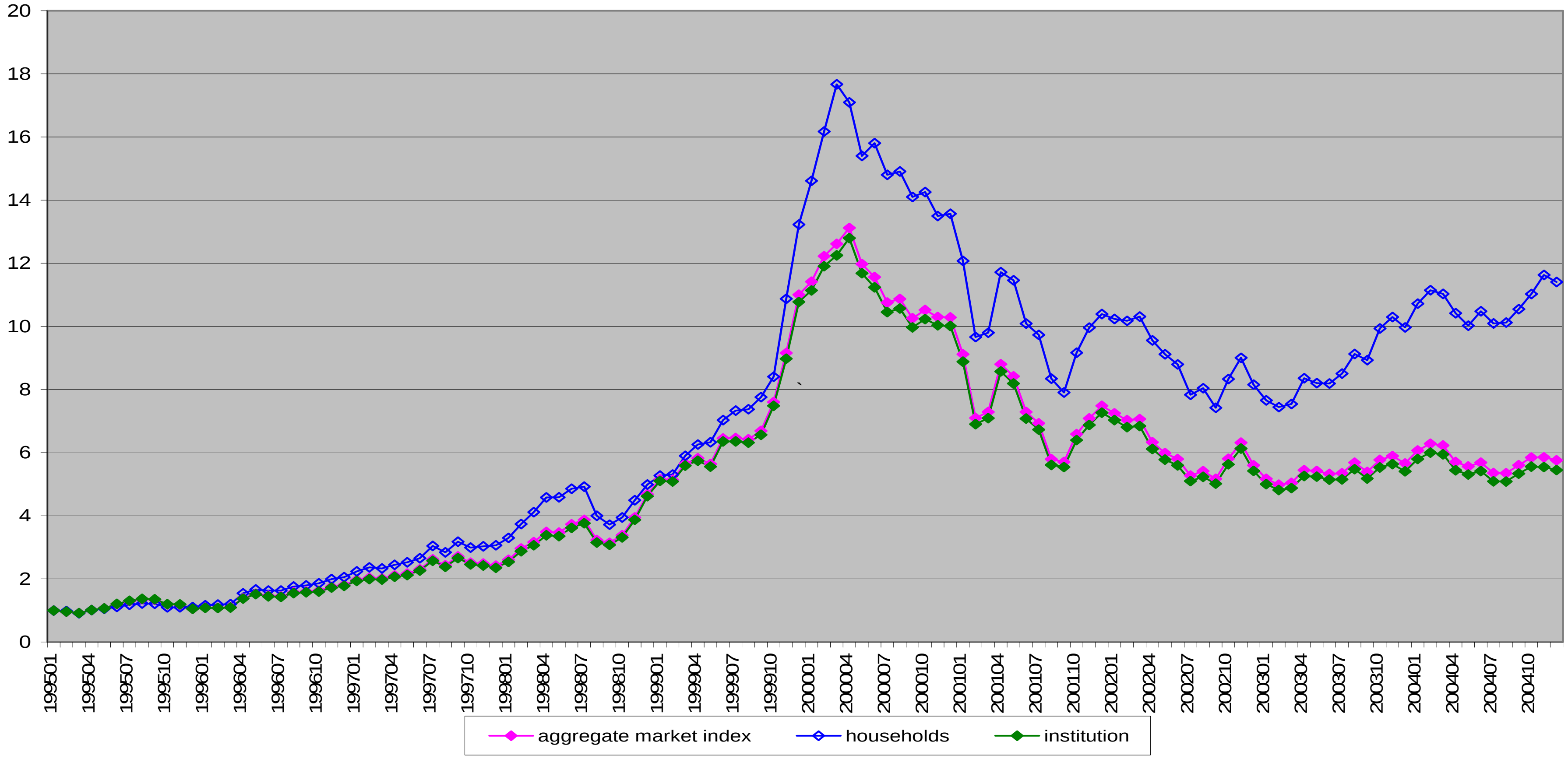
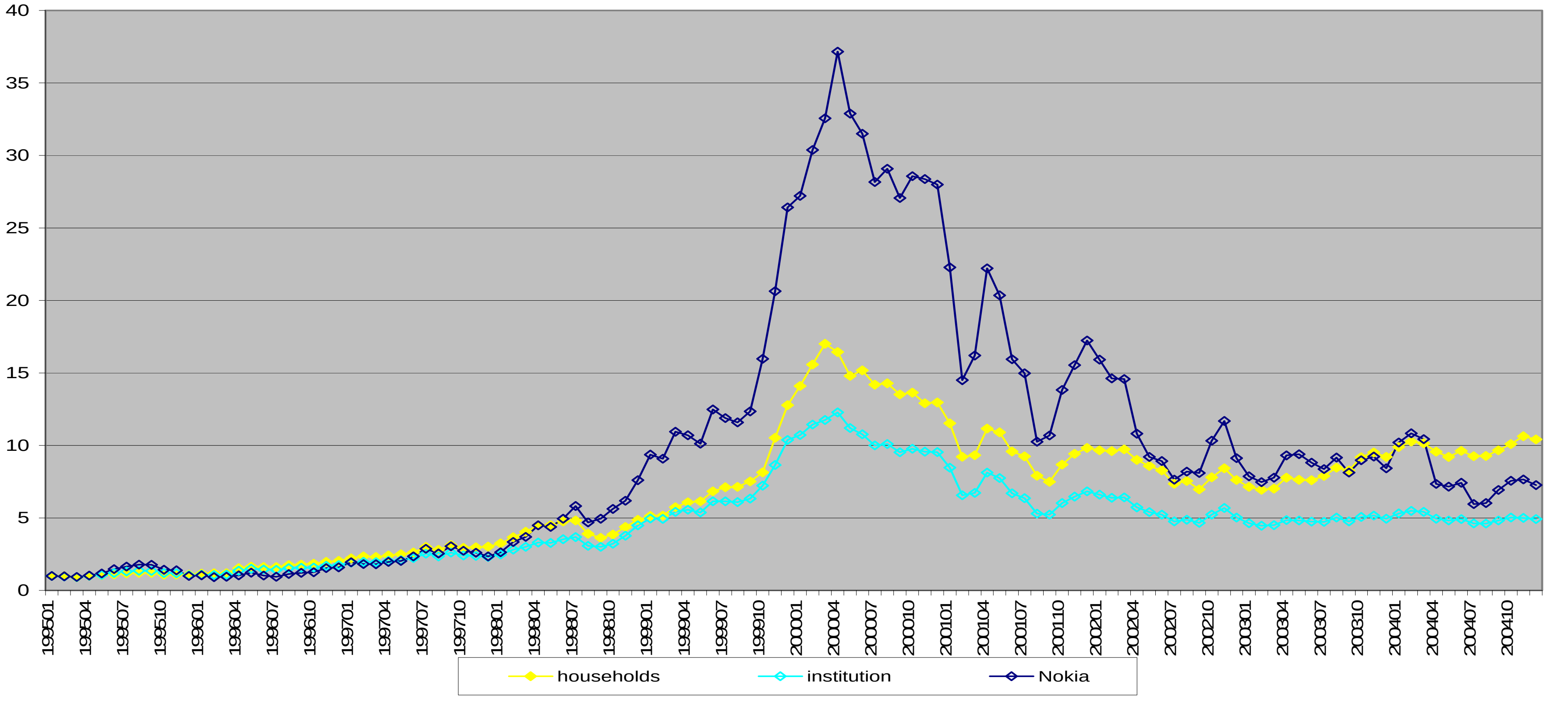


Figure 5.2: Cumulative Net Return Performance of Different Aggregate Groups and Nokia Index

This figure shows a comparison of the cumulative return index among aggregate individual, aggregate institution after transaction cost and Nokia return index. All indices are rebased to 1 as in January 1995. Cumulative return index is an index that compounds monthly gross return r_i, defined as $\prod_{i=1}^{n}(1+r_i)$.



5.2 Males versus Females

Table 5.4 provides summary results of monthly gross trading measures of fourteen demographic portfolios grouped by age and gender of individuals before accounting for transaction cost. The trading measures are the same as in Table 5.1. The age records are measured as of 2000.

Males born between 1960 and 1970 (30s) belong to the most aggressive trading group who earns the highest average monthly return of 2.76% among all male investor subgroups while it also has the highest average monthly standard deviation of 11.32% and average monthly realized volatility of 11.3%. The return measure is also supported by their highest average monthly alpha value of 0.07% (7bp) and highest average monthly turnover of 8.2%, or 98.35% annually. This frequent trading evidence (investors in their 30s trade the most) is consistent with Grinblatt and Keloharju (2008) who suggest age is inversely related to number of trades per year for most ages except for the very young (20s) who moves from college years to early career years. Ollila and Westerholm (2003) also document investors in the age group (26-45) trade the most. However the excessive trading of 30s males does not lead them to the best performance measured by average monthly Sharpe ratio and Treynor ratio which suggests their risk-adjusted performance is not good enough to be at the top ranking, though the second highest among all age groups of males. The 50- to 59-year old male investor group owns the largest size of equity assets with an average aggregate monthly portfolio value of nearly two billion euros. This is expected as they are supposed to be richer than the rest of the age groups. Also males experience a positive relationship between age and aggregate portfolio size before retirement and a negative relationship after retirement.

This fact could be due to life cycling trading as older investors once past earning years are unwilling to bet their retirement saving on risky stocks and start to sell them.

The same pattern is repeated among female investors with 30 year old women yielding the highest return of 2.44%, highest alpha of 0.06% (6bp) and highest turnover of 2.64% (31.71% annually). Similarly, female investors in their 50s have the largest equity assets with an average aggregate monthly portfolio value of nearly one billion euros.

Turning to statistical test of the gender effect in trading, and starting from the mean result in Table 5.4, the differences are apparent in turnover and aggregate portfolio size for most ages except for 70s and 80s as old investors should be reasonably homogeneous in their trading decisions, irrespective of gender. Instead of comparing aggregate males with aggregate females, the results are more convincing as the table shows males turn their portfolio over far more frequently and hold much larger-size aggregate portfolios than females across all age bands consistently. Table 5.5 reports results of both independent t test and Wilcoxon rank sum test of the remaining trading measures between male and female of the same age band.

On average females hold higher-risk stocks in their portfolio than males as they have significant higher portfolio betas both in terms of CAPM beta and realized beta[28]. The only exception is the age of thirties. Furthermore, average beta for all age groups is less than 1 which means stocks hold by either men or women are less sensitive to market swings. However, no significant difference in gross return and performance measures is

[28] Ollila and Westerholm (2003) also document male are more diversified than women.

documented between males and females across the same age band from 20s to 80s. Similarly, Feng and Seaholes conclude performance across gender is economically and statistically indistinguishable in China.

Table 5.6 reports the summary results of monthly net trading measures of the above fourteen demographic portfolios. Table 5.7 shows the gender comparison of turnover and return difference between gross and net return of these portfolios. The best performers are still the investors in their thirties. Net monthly return of men in their 30s falls to 2.54% from gross return of 2.76%, 0.22% lower, or 2.68% lower annually. The huge turnover rate (8.2%) hurt their performance the most among all-age male subgroups. Women in their 30s achieve net monthly returns (2.36%) that are 0.08% less than gross monthly return (2.44%), or 0.92% annually. In terms of gender difference, trading reduces men's return more so than do women in all age groups and this is consistent with Barber and Odean (2001). However, it does not imply the most aggressive male investors are overconfident as they still achieve higher net return than the same age women.

Table 5.4: Descriptive Statistics of Monthly Gross Trading Measures of Demographic Portfolios

This table provides summary results of monthly trading measures of fourteen demographic portfolios before transaction cost. The fourteen portfolios are grouped by age and gender of individual investors. Panel A lists standard deviation of log return, log return, Sharpe ratio and alpha; Panel B lists CAPM beta, Treynor ratio, realized beta and realized volatility; Panel C lists the aggregate portfolio holding, turnover, buy turnover and sell turnover. All statistics are 10-year averages.

Panel A

Gender	**Male**							**Female**						
Trader_id	3	4	5	6	7	8	9	11	12	13	14	15	16	17
Age	20	30	40	50	60	70	80	20	30	40	50	60	70	80
N	119	119	119	119	119	119	119	119	119	119	119	119	119	119
	Month_gross_std							***Month_gross_std***						
Mean	0.1021	0.1132	0.1026	0.0938	0.0927	0.0983	0.1029	0.1036	0.0961	0.1004	0.1036	0.0993	0.1028	0.1113
Median	0.0636	0.0646	0.0635	0.0627	0.0614	0.0668	0.0661	0.0677	0.066	0.0679	0.07	0.0675	0.0673	0.0716
Min	0.0212	0.0234	0.0231	0.0197	0.0183	0.0234	0.0237	0.0226	0.0223	0.0225	0.0231	0.0209	0.0231	0.0258
Max	1.2154	1.5522	1.0468	1.2653	1.2275	1.4199	1.573	1.3834	1.1395	1.3279	1.4269	1.3793	1.4969	1.5801
StdDev	0.1554	0.1779	0.1438	0.1394	0.1386	0.1555	0.17	0.1605	0.1325	0.1484	0.1584	0.1518	0.1656	0.1806
	Monthly_log_gross_return							***Monthly_log_gross_return***						
Mean	0.0232	0.0276	0.0252	0.0207	0.0193	0.0171	0.0106	0.0224	0.0244	0.0233	0.0205	0.0193	0.0169	0.0108
Median	0.0284	0.0344	0.0315	0.0223	0.0215	0.0191	0.0085	0.0239	0.0328	0.028	0.0215	0.0237	0.0209	0.0162
Min	-0.272	-0.314	-0.233	-0.22	-0.235	-0.217	-0.215	-0.255	-0.231	-0.217	-0.224	-0.21	-0.23	-0.259
Max	0.2755	0.6442	0.2704	0.2306	0.2688	0.2909	0.272	0.3179	0.2654	0.2716	0.2499	0.267	0.2762	0.2543
StdDev	0.0835	0.1094	0.0858	0.0767	0.0745	0.0777	0.0778	0.0824	0.0825	0.0801	0.0812	0.0782	0.0785	0.0836
	Monthly_sharpe_ratio							***Monthly_Sharpe_ratio***						
Mean	0.3731	0.3823	0.4052	0.3702	0.3379	0.2869	0.1854	0.3616	0.4007	0.3796	0.3332	0.3173	0.2942	0.1998
Median	0.2621	0.3674	0.3765	0.234	0.1543	0.1603	0.0528	0.1881	0.3058	0.2809	0.1887	0.1654	0.2024	0.0967
Min	-2.07	-1.738	-2.081	-2.144	-2.03	-1.915	-1.951	-2.045	-2.455	-2.33	-2.238	-2.08	-2.233	-2.253
Max	3.8014	3.5866	3.9151	3.9956	3.6677	3.5744	3.5725	3.8403	3.6358	3.8516	3.7881	3.576	3.6294	3.5114
StdDev	1.0872	1.0846	1.1206	1.1592	1.0987	1.0796	1.0732	1.093	1.1281	1.0932	1.1068	1.0829	1.0767	1.0944
	Monthly_alpha							***Monthly_alpha***						
Mean	0.0005	0.0007	0.0002	0.0003	0.0003	0.0002	-1e-04	0.0005	0.0006	0.0005	0.0003	0.0003	0.0002	-1e-04
Median	0.0003	0.0005	0.0005	0.0004	0.0002	0.0002	-9e-05	0.0004	0.0004	0.0003	0.0003	0.0002	3e-05	-5e-05
Min	-0.005	-0.013	-0.047	-0.015	-0.003	-0.002	-0.003	-0.003	-0.006	-0.002	-0.003	-0.002	-0.002	-0.003
Max	0.0073	0.0233	0.0123	0.0057	0.0052	0.0038	0.0019	0.0062	0.0068	0.0056	0.0049	0.005	0.003	0.0035
StdDev	0.0019	0.0035	0.0051	0.0019	0.0012	0.0009	0.0009	0.0014	0.0018	0.0012	0.001	0.001	0.0009	0.0011

Panel B														
Gender	Male							Female						
Trader_id	3	4	5	6	7	8	9	11	12	13	14	15	16	17
Age	20	30	40	50	60	70	80	20	30	40	50	60	70	80
N	119	119	119	119	119	119	119	119	119	119	119	119	119	119
	Monthly_beta							***Monthly_beta***						
Mean	0.7192	0.6989	0.7171	0.7007	0.6677	0.7358	0.7627	0.7493	0.6963	0.757	0.7751	0.7495	0.7609	0.8193
Median	0.7155	0.6671	0.6448	0.6734	0.6556	0.7317	0.7633	0.7504	0.6867	0.7477	0.7738	0.7444	0.7618	0.8388
Min	0.2897	0.2385	0.1965	0.32	0.2414	0.305	0.3759	0.3461	0.2971	0.3352	0.3598	0.382	0.3834	0.3819
Max	1.3685	1.6793	5.5661	2.7945	1.0778	1.1986	1.4961	1.2847	1.7468	1.6209	1.3253	1.3575	1.2572	1.2956
StdDev	0.1418	0.2017	0.4789	0.2231	0.1272	0.1147	0.1252	0.1245	0.1608	0.1357	0.1121	0.1294	0.1225	0.1237
	Monthly_Treynor_ratio							***Monthly_Treynor_ratio***						
Mean	0.0342	0.0354	0.0412	0.0286	0.0272	0.0204	0.011	0.0302	0.0352	0.0284	0.0243	0.0231	0.0204	0.0126
Median	0.0313	0.039	0.0397	0.0269	0.0248	0.0175	0.007	0.0287	0.0382	0.0341	0.0248	0.0253	0.0223	0.0142
Min	-0.296	-0.586	-0.469	-0.312	-0.313	-0.308	-0.302	-0.295	-0.303	-0.302	-0.296	-0.297	-0.334	-0.285
Max	0.6867	0.7802	1.3633	0.3671	0.4034	0.2968	0.3167	0.4712	0.5532	0.3595	0.3405	0.3277	0.3843	0.3978
StdDev	0.1313	0.1679	0.1769	0.1148	0.1146	0.1064	0.1041	0.118	0.1281	0.109	0.1083	0.107	0.1089	0.1088
	Monthly_realized_beta							***Monthly_realized_beta***						
Mean	0.7246	0.7101	0.7169	0.7044	0.6711	0.7378	0.7626	0.7524	0.7034	0.7606	0.7784	0.7518	0.7622	0.8202
Median	0.7278	0.6822	0.6513	0.6814	0.6624	0.7369	0.7648	0.7494	0.6918	0.7514	0.7803	0.7386	0.7619	0.8372
Min	0.4234	0.3088	0.3056	0.3754	0.197	0.3485	0.3916	0.4357	0.3968	0.3766	0.3958	0.4156	0.3986	0.4328
Max	1.2818	1.7241	4.7874	2.5437	1.0764	1.1982	1.4964	1.2859	1.7496	1.6231	1.3266	1.3573	1.2572	1.2963
StdDev	0.1319	0.2021	0.4086	0.2013	0.1263	0.1129	0.1248	0.1201	0.1578	0.1337	0.1105	0.1278	0.1197	0.1235
	Monthly_realized_volatility							***Monthly_realized_volatility***						
Mean	0.1018	0.113	0.1023	0.0936	0.0923	0.0977	0.1022	0.1031	0.0959	0.1	0.1031	0.0988	0.1022	0.1105
Median	0.0644	0.0638	0.0626	0.0624	0.0608	0.0671	0.0671	0.067	0.0657	0.0678	0.0693	0.0686	0.0676	0.0724
Min	0.0236	0.0259	0.0247	0.0208	0.0191	0.0238	0.0249	0.0243	0.0239	0.0242	0.0244	0.0237	0.0239	0.0259
Max	1.1847	1.5139	1.0213	1.2332	1.1964	1.384	1.5332	1.3484	1.1108	1.2943	1.3908	1.3445	1.4591	1.5402
StdDev	0.1514	0.1739	0.1402	0.1357	0.135	0.1515	0.1656	0.1564	0.1291	0.1445	0.1542	0.1478	0.1612	0.1759

Panel C														
Gender	**Male**							**Female**						
Trader_id	3	4	5	6	7	8	9	11	12	13	14	15	16	17
Age	20	30	40	50	60	70	80	20	30	40	50	60	70	80
N	119	119	119	119	119	119	119	119	119	119	119	119	119	119
	Monthly_aggregate_portfolio_holding							***Monthly_aggregate_portfolio_holding***						
Mean	3e+08	8e+08	1e+09	2e+09	1e+09	8e+08	4e+08	2e+08	3e+08	5e+08	1e+09	6e+08	7e+08	4e+08
Median	3e+08	7e+08	1e+09	2e+09	1e+09	8e+08	4e+08	2e+08	3e+08	5e+08	1e+09	6e+08	7e+08	3e+08
Min	6e+07	9e+07	2e+08	4e+08	3e+08	2e+08	2e+08	5e+07	6e+07	9e+07	2e+08	1e+08	2e+08	2e+08
Max	9e+08	4e+09	4e+09	4e+09	3e+09	2e+09	1e+09	5e+08	8e+08	1e+09	2e+09	1e+09	2e+09	1e+09
StdDev	2e+08	8e+08	8e+08	1e+09	6e+08	4e+08	2e+08	1e+08	2e+08	3e+08	5e+08	3e+08	4e+08	2e+08
	Monthly_turnover							***Monthly_turnover***						
Mean	0.0595	0.082	0.0481	0.0288	0.0222	0.0109	0.0067	0.0143	0.0264	0.0226	0.0135	0.0102	0.0062	0.0049
Median	0.0548	0.0755	0.0489	0.0275	0.021	0.0101	0.0056	0.0114	0.0233	0.0208	0.0124	0.0091	0.0051	0.0032
Min	0.0037	0.0219	0.0166	0.0095	0.0066	0.0032	0.002	0.0032	0.0114	0.0107	0.0048	0.0044	0.0018	0.0011
Max	0.2088	0.1975	0.0937	0.0558	0.0508	0.0385	0.0384	0.1123	0.1067	0.0514	0.0441	0.0384	0.0334	0.0889
StdDev	0.0394	0.0397	0.0177	0.0096	0.0087	0.005	0.0043	0.0128	0.0129	0.0082	0.0054	0.0048	0.0043	0.0085
	Monthly_buy_turnover							***Monthly_buy_turnover***						
Mean	0.0557	0.0777	0.0449	0.0267	0.0203	0.0091	0.0047	0.0107	0.0222	0.0193	0.0111	0.0078	0.0039	0.0018
Median	0.0512	0.069	0.0453	0.0259	0.0193	0.0084	0.004	0.0092	0.0205	0.0186	0.0106	0.0071	0.0034	0.0014
Min	0.0026	0.0161	0.0116	0.0067	0.006	0.003	0.0011	0.0008	0.0064	0.0059	0.0037	0.002	0.0013	0.0005
Max	0.2139	0.2011	0.1007	0.0572	0.0483	0.0183	0.0143	0.1074	0.0981	0.0476	0.0217	0.016	0.0115	0.0096
StdDev	0.039	0.0419	0.0184	0.0098	0.0082	0.0036	0.0028	0.011	0.0111	0.0067	0.004	0.0029	0.0018	0.0015
	Monthly_sell_turnover							***Monthly_sell_turnover***						
Mean	0.0633	0.0862	0.0513	0.0308	0.024	0.0127	0.0086	0.0179	0.0306	0.026	0.0159	0.0127	0.0085	0.0081
Median	0.0582	0.0809	0.0484	0.0278	0.021	0.0103	0.007	0.0136	0.0255	0.0233	0.0135	0.0107	0.0064	0.0049
Min	0.0048	0.0264	0.0185	0.0116	0.0072	0.0031	0.0019	0.0031	0.011	0.0109	0.0058	0.0032	0.0015	0.0015
Max	0.2045	0.1939	0.1241	0.0794	0.0738	0.0637	0.0697	0.1402	0.1153	0.0768	0.0691	0.0662	0.0591	0.1769
StdDev	0.0423	0.0399	0.0196	0.0117	0.0115	0.0079	0.0077	0.0177	0.0172	0.0117	0.0084	0.0081	0.0076	0.017

Table 5.5: Independent T Test and Wilcoxon Rank Sum Test for Gender Differences of Same Age Band

This table reports the independent t-test and Wilcoxon rank-sum test of difference in certain trading measures between males and females of same age band. P-values are in square brackets. *denotes significance on 10% level, **denotes significance on 5% level and ***denotes significance on 1% level.

Age_band		21-30	31-40	41-50	51-60	61-70	71-80	81-90
Averge monthly log return	Male	0.0232215	0.0276364	0.0251616	0.0207092	0.0192938	0.0171005	0.0105821
	Female	0.022359	0.0243563	0.0233376	0.0204576	0.0192699	0.0169143	0.010795
	Difference	0.0008625	0.0032801	0.0018241	0.0002516	2.399E-05	0.0001862	-0.000213
Independent t-test p-value		[0.9362]	[0.7942]	[0.8655]	[0.9804]	[0.9981]	[0.9853]	[0.9838]
Wilcoxon rank-sum test p-value		[0.988]	[0.994]	[0.997]	[0.9835]	[0.931]	[0.9385]	[0.8773]
Age_band		21-30	31-40	41-50	51-60	61-70	71-80	81-90
Averge monthly realized beta	Male	0.7246284	0.7101337	0.7169145	0.704384	0.671055	0.7377652	0.7625782
	Female	0.7523611	0.7034049	0.7605558	0.7784406	0.7517526	0.7622175	0.820216
	Difference	-0.027733	0.0067288	-0.043641	-0.074057	-0.080698	-0.024452	-0.057638
Independent t-test p-value		[0.0911]	[0.7749]	[0.2693]	[0.0005]***	[<.0001]***	[0.1065]	[<.0001]***
Wilcoxon rank-sum test p-value		[0.028]**	[0.817]	[<.0001]***	[<.0001]***	[<.0001]***	[0.062]	[<.0001]***
Age_band		21-30	31-40	41-50	51-60	61-70	71-80	81-90
Averge monthly beta	Male	0.719184	0.6989483	0.7171063	0.7006647	0.667663	0.7357702	0.7627145
	Female	0.7493156	0.6963221	0.7569686	0.7751443	0.7494609	0.7608545	0.8193393
	Difference	-0.030132	0.0026262	-0.039862	-0.07448	-0.081798	-0.025084	-0.056625
Independent t-test p-value		[0.0829]	[0.9116]	[0.3832]	[0.0013]***	[<.0001]***	[0.1044]	[0.0005]***
Wilcoxon rank-sum test p-value		[0.021]**	[0.68]	[<.0001]***	[<.0001]***	[<.0001]***	[0.053]*	[<.0001]***

Table 5.6: Descriptive Statistics of Monthly Net Trading Measures of Demographic Portfolios

This table provides summary results of monthly trading measures of fourteen demographic portfolios after transaction cost. The fourteen portfolios are grouped by age and gender of individual investors. Panel A lists standard deviation of log return *(Month_net_std)*, log return, sharpe ratio and alpha; Panel B lists CAPM beta, treynor ratio, realized beta and realized volatility. All statistics are 10-year average.

Panel A

Gender	Male							Female						
Trader_id	3	4	5	6	7	8	9	11	12	13	14	15	16	17
Age	20	30	40	50	60	70	80	20	30	40	50	60	70	80
N	119	119	119	119	119	119	119	119	119	119	119	119	119	119
	Month_net_std							***Month_net_std***						
Mean	0.1021	0.1132	0.1026	0.0938	0.0927	0.0983	0.1029	0.1036	0.0961	0.1004	0.1036	0.0993	0.1028	0.1113
Median	0.0638	0.0646	0.0635	0.0627	0.0614	0.0668	0.0661	0.0678	0.066	0.0679	0.07	0.0675	0.0673	0.0716
Min	0.0213	0.0234	0.0232	0.0197	0.0183	0.0234	0.0237	0.0227	0.0223	0.0225	0.0231	0.0209	0.0231	0.0258
Max	1.2154	1.5522	1.0468	1.2653	1.2275	1.4199	1.5729	1.3834	1.1395	1.3279	1.4269	1.3793	1.4969	1.5801
StdDev	0.1554	0.1779	0.1438	0.1394	0.1386	0.1555	0.17	0.1605	0.1325	0.1484	0.1584	0.1518	0.1656	0.1806
	Monthly_log_net_return							***Monthly_log_net_return***						
Mean	0.0216	0.0254	0.0238	0.0199	0.0186	0.0168	0.0104	0.0219	0.0236	0.0227	0.0201	0.019	0.0167	0.0106
Median	0.0267	0.0314	0.0307	0.0219	0.021	0.0187	0.0084	0.0238	0.0319	0.0271	0.0212	0.0234	0.0205	0.0161
Min	-0.273	-0.317	-0.235	-0.22	-0.235	-0.217	-0.215	-0.255	-0.232	-0.218	-0.224	-0.21	-0.23	-0.259
Max	0.2751	0.6421	0.2695	0.2302	0.2685	0.2907	0.2719	0.3177	0.2645	0.2707	0.2497	0.2668	0.2761	0.2543
StdDev	0.0837	0.1096	0.0859	0.0767	0.0745	0.0776	0.0778	0.0825	0.0825	0.08	0.0811	0.0782	0.0784	0.0836
	Monthly_Sharpe_ratio							***Monthly_Sharpe_ratio***						
Mean	0.3476	0.347	0.3835	0.3561	0.327	0.2814	0.1819	0.3552	0.3877	0.3692	0.3269	0.3123	0.2912	0.1976
Median	0.2456	0.36	0.3644	0.2149	0.1471	0.1562	0.0525	0.1825	0.2966	0.274	0.1864	0.1638	0.1995	0.0964
Min	-2.079	-1.759	-2.099	-2.155	-2.035	-1.917	-1.952	-2.048	-2.462	-2.335	-2.241	-2.082	-2.233	-2.256
Max	3.7762	3.5277	3.8706	3.9696	3.6434	3.5608	3.5655	3.8309	3.6063	3.832	3.7768	3.5668	3.6236	3.5091
StdDev	1.0875	1.0838	1.1173	1.1566	1.0958	1.0778	1.0722	1.0924	1.1256	1.0906	1.1053	1.0813	1.0755	1.0941
	Monthly_alpha							***Monthly_alpha***						
Mean	0.0005	0.0007	0.0002	0.0003	0.0003	0.0002	-1e-04	0.0005	0.0006	0.0005	0.0004	0.0003	0.0002	-6e-05
Median	0.0003	0.0004	0.0005	0.0004	0.0003	0.0002	-6e-05	0.0004	0.0004	0.0003	0.0003	0.0002	6e-05	-1e-05
Min	-0.005	-0.013	-0.047	-0.015	-0.003	-0.002	-0.003	-0.003	-0.006	-0.002	-0.003	-0.002	-0.002	-0.003
Max	0.0072	0.0232	0.0123	0.0057	0.0052	0.0038	0.0019	0.0062	0.0068	0.0056	0.0049	0.005	0.0031	0.0035
StdDev	0.0019	0.0035	0.0051	0.0019	0.0012	0.0009	0.0009	0.0014	0.0018	0.0012	0.001	0.001	0.0009	0.0011

Panel B														
Gender	**Male**							**Female**						
Trader_id	3	4	5	6	7	8	9	11	12	13	14	15	16	17
Age	20	30	40	50	60	70	80	20	30	40	50	60	70	80
N	119	119	119	119	119	119	119	119	119	119	119	119	119	119
	Monthly_beta							***Monthly_beta***						
Mean	0.7193	0.699	0.7171	0.7007	0.6677	0.7358	0.7627	0.7494	0.6964	0.757	0.7752	0.7495	0.7609	0.8194
Median	0.7162	0.6681	0.645	0.6735	0.6556	0.7317	0.7632	0.7504	0.6864	0.7476	0.7742	0.7444	0.7618	0.8386
Min	0.2893	0.2377	0.1965	0.32	0.2415	0.3056	0.3759	0.3457	0.2966	0.335	0.3596	0.382	0.3834	0.3818
Max	1.3675	1.6812	5.5639	2.7936	1.0776	1.198	1.4958	1.2847	1.7467	1.6208	1.3253	1.3568	1.2568	1.2951
StdDev	0.1417	0.2017	0.4787	0.223	0.1272	0.1146	0.1251	0.1245	0.1607	0.1357	0.1121	0.1294	0.1225	0.1237
	Monthly Treynor_ratio							***Monthly_Treynor_ratio***						
Mean	0.0318	0.0319	0.0391	0.0274	0.0262	0.02	0.0108	0.0296	0.0341	0.0275	0.0238	0.0227	0.0201	0.0124
Median	0.0293	0.0363	0.0388	0.0258	0.0237	0.0171	0.0068	0.0285	0.0374	0.0336	0.0243	0.0246	0.0221	0.0141
Min	-0.301	-0.591	-0.473	-0.313	-0.315	-0.309	-0.303	-0.296	-0.304	-0.303	-0.297	-0.297	-0.334	-0.285
Max	0.6846	0.7733	1.3581	0.3646	0.4018	0.2966	0.3165	0.4705	0.5521	0.3584	0.34	0.3274	0.3842	0.3976
StdDev	0.1314	0.168	0.1767	0.1148	0.1145	0.1063	0.1041	0.118	0.1281	0.109	0.1082	0.107	0.1088	0.1088
	Monthly_realized_beta							***Monthly_realized_beta***						
Mean	0.7245	0.7098	0.7167	0.7043	0.6709	0.7377	0.7627	0.7523	0.7032	0.7604	0.7784	0.7517	0.7622	0.8203
Median	0.7282	0.6792	0.6513	0.6809	0.6621	0.7369	0.7654	0.7487	0.6916	0.7512	0.7802	0.7382	0.7612	0.8371
Min	0.4219	0.3063	0.3037	0.3746	0.1964	0.3477	0.3917	0.4349	0.3956	0.376	0.3954	0.4153	0.3986	0.4327
Max	1.2808	1.7248	4.7926	2.5457	1.0762	1.1975	1.4961	1.2856	1.7489	1.6225	1.3263	1.3565	1.2567	1.2957
StdDev	0.132	0.2022	0.4091	0.2015	0.1264	0.113	0.1248	0.1201	0.1578	0.1337	0.1106	0.1279	0.1198	0.1235
	Monthly_realized_volatility							***Monthly_realized_volatility***						
Mean	0.1018	0.113	0.1023	0.0935	0.0923	0.0977	0.1022	0.1031	0.0959	0.1	0.1031	0.0988	0.1022	0.1105
Median	0.0644	0.0638	0.0625	0.0624	0.0608	0.0671	0.0671	0.0671	0.0657	0.0678	0.0693	0.0686	0.0676	0.0724
Min	0.0235	0.0257	0.0245	0.0207	0.0191	0.0238	0.0249	0.0243	0.0239	0.0242	0.0244	0.0237	0.0239	0.0259
Max	1.1847	1.5139	1.0213	1.2332	1.1964	1.384	1.5332	1.3484	1.1108	1.2943	1.3908	1.3445	1.4591	1.5402
StdDev	0.1514	0.1739	0.1402	0.1357	0.135	0.1515	0.1656	0.1564	0.1291	0.1445	0.1542	0.1478	0.1612	0.1759

Table 5.7: Comparison of Turnover and Gross-Net Return Differences of Demographic Portfolios

This table provides gender comparison of monthly turnover and monthly return difference between gross and net basis (*Monthly_diff_log_return*). The fourteen portfolios are grouped by age and gender of individual investors. Monthly portfolio turnover is calculated as one half monthly sales turnover $\sum_{i=1}^{S_{ht}} p_{i,t} \min(1, \frac{S_{it}}{H_{it}})$ plus one half monthly purchase turnover $\sum_{i=1}^{S_{ht}} p_{i,t+1} \min(1, \frac{B_{it}}{H_{i,t+1}})$ where S_{it} is the number of shares in security i sold during the month, B_{it} is the number of shares of security i bought during the month. $p_{i,t}$ is the value of stock held at the beginning of month t scaled by the total value of stock holdings, and H_{it} is the number of shares of security i held at the beginning of month t.

Gender	Male							Female						
Trader_id	3	4	5	6	7	8	9	11	12	13	14	15	16	17
Age	20	30	40	50	60	70	80	20	30	40	50	60	70	80
N	119	119	119	119	119	119	119	119	119	119	119	119	119	119
	Monthly_turnover							***Monthly_turnover***						
Mean	5.95%	8.20%	4.81%	2.88%	2.22%	1.09%	0.67%	1.43%	2.64%	2.26%	1.35%	1.02%	0.62%	0.49%
Median	5.48%	7.55%	4.89%	2.75%	2.10%	1.01%	0.56%	1.14%	2.33%	2.08%	1.24%	0.91%	0.51%	0.32%
Min	0.37%	2.19%	1.66%	0.95%	0.66%	0.32%	0.20%	0.32%	1.14%	1.07%	0.48%	0.44%	0.18%	0.11%
Max	20.88%	19.75%	9.37%	5.58%	5.08%	3.85%	3.84%	11.23%	10.67%	5.14%	4.41%	3.84%	3.34%	8.89%
StdDev	0.0394	0.0397	0.0177	0.0096	0.0087	0.005	0.0043	0.0128	0.0129	0.0082	0.0054	0.0048	0.0043	0.0085
	Monthly_diff_log_return							***Monthly_diff_log_return***						
Mean	0.16%	0.22%	0.14%	0.08%	0.06%	0.03%	0.02%	0.04%	0.08%	0.07%	0.04%	0.03%	0.02%	0.01%
Median	0.16%	0.30%	0.08%	0.04%	0.06%	0.04%	0.01%	0.02%	0.09%	0.08%	0.03%	0.03%	0.03%	0.01%
Min	0.11%	0.38%	0.21%	0.08%	0.06%	0.04%	0.02%	0.02%	0.05%	0.08%	0.05%	0.03%	0.01%	0.01%
Max	0.04%	0.21%	0.09%	0.04%	0.04%	0.02%	0.01%	0.01%	0.09%	0.09%	0.02%	0.02%	0.01%	0.01%
StdDev	-0.0002	-0.0002	-2e-05	1e-06	3e-05	3e-05	1e-05	-4e-05	-1e-05	3e-05	3e-05	3e-05	3e-05	-3e-06

5.3 Buy Intensity and Trader imbalance

5.3.1 Buy Intensity among Households

In this section, I examine whether individual investors tend to choose their investment options by observing the decisions of others around them. The average yearly correlation matrix of daily buy intensity among fourteen demographic groups in Panel A of Table 5.8 shows the level of all contemporaneous correlations is quite high which suggests trading decisions are not independent across individual investors. Young males (30s) and middle-aged males (40s and 50s) have the highest cross correlations with 10-year average ranging from 66.52% to 70.32% compared to the remaining groups and their correlations increase over time[29]. This is similar to the level of contemporaneous correlation results provided by Barber, Odean and Zhu (2009), around 70 percent. In Panel B, these three groups are also placed in the top three based on the 10-year average maximum correlation of buy intensity of each group to that of the remaining groups with little deviation in rankings. Ranking correlation in Panel C shows the ranking upon maximum correlation of buy intensity is surprisingly persistent across years.

This evidence might explain why they are the best performers over 10 years in Section 5.2 as they might share some common valuable information not available to other groups. Kaustia and Knupfer (2009) argue people are more likely to discuss their stock market experiences with others when they have experienced good returns. Since Finnish male investors find it profitable to mimic the trades of their male peers and are more likely to talk about decisions that have produced good outcomes, the information continues to spread over and the level of correlated trading is expected to increase over

[29] Yearly correlation result is not presented in this study.

time. The other possible factors that could contribute to this pattern might be similarity of trading skills and growing trading experiences among these male subgroups.

Table 5.8: Average Yearly Contemporaneous Correlation Matrix of Demographic Portfolios

This table provides average contemporaneous correlation matrix of fourteen demographic portfolios, average maximum correlation of buy intensity *(Average_Buy_Ratio_Max_Corr)*, average ranking and ranking correlation between two consecutive years. The fourteen portfolios are grouped by age and gender of individual investors. Panel A lists average contemporaneous correlation matrix, all statistics are 10-year averages; Panel B lists average maximum correlation of buy intensity and average ranking; Panel C lists ranking correlation between two consecutive years. *denotes significance on 10% level, **denotes significance on 5% level and ***denotes significance on 1% level.

Panel A

		Trader_id	3	4	5	6	7	8	9	11	12	13	14	15	16	17
		Gender	M	M	M	M	M	M	M	F	F	F	F	F	F	F
Trader_id	Gender	Age	20	30	40	50	60	70	80	20	30	40	50	60	70	80
3	M	20	1	0.593	0.5943	0.6031	0.5457	0.4375	0.2732	0.4381	0.4681	0.4921	0.5215	0.461	0.3668	0.2376
4	M	30	0.593	1	0.6801	0.6652	0.5859	0.4748	0.2805	0.4338	0.4963	0.5375	0.5279	0.4779	0.3855	0.2342
5	M	40	0.5943	0.6801	1	0.7032	0.6318	0.5149	0.3219	0.4543	0.5211	0.5751	0.5835	0.5132	0.4049	0.2691
6	M	50	0.6031	0.6652	0.7032	1	0.6724	0.5417	0.3626	0.4915	0.5405	0.5994	0.6399	0.5537	0.4323	0.2757
7	M	60	0.5457	0.5859	0.6318	0.6724	1	0.5203	0.3472	0.4865	0.5181	0.5264	0.5675	0.525	0.4091	0.2544
8	M	70	0.4375	0.4748	0.5149	0.5417	0.5203	1	0.3163	0.4298	0.4455	0.458	0.487	0.4968	0.4049	0.2398
9	M	80	0.2732	0.2805	0.3219	0.3626	0.3472	0.3163	1	0.3103	0.2982	0.2989	0.3331	0.3121	0.3	0.2297
11	F	20	0.4381	0.4338	0.4543	0.4915	0.4865	0.4298	0.3103	1	0.4291	0.4375	0.4836	0.4327	0.3779	0.2404
12	F	30	0.4681	0.4963	0.5211	0.5405	0.5181	0.4455	0.2982	0.4291	1	0.4856	0.5017	0.468	0.3668	0.2565
13	F	40	0.4921	0.5375	0.5751	0.5994	0.5264	0.458	0.2989	0.4375	0.4856	1	0.5266	0.4781	0.3873	0.2679
14	F	50	0.5215	0.5279	0.5835	0.6399	0.5675	0.487	0.3331	0.4836	0.5017	0.5266	1	0.5124	0.4228	0.281
15	F	60	0.461	0.4779	0.5132	0.5537	0.525	0.4968	0.3121	0.4327	0.468	0.4781	0.5124	1	0.415	0.2694
16	F	70	0.3668	0.3855	0.4049	0.4323	0.4091	0.4049	0.3	0.3779	0.3668	0.3873	0.4228	0.415	1	0.2139
17	F	80	0.2376	0.2342	0.2691	0.2757	0.2544	0.2398	0.2297	0.2404	0.2565	0.2679	0.281	0.2694	0.2139	1

Panel B

Trader_id	Gender	Age	N	Average_Buy_Ratio_Max_Corr	Rank_Mean	Rank_StdDev	Rank_Min	Rank_Max	Overall Ranking
3	M	20	10	0.638475349	5.9	3.247221034	1	11	6
4	M	30	10	0.698135083	2.9	1.595131482	1	6	3
5	M	40	10	0.71044142	1.8	1.398411798	1	5	2
6	M	50	10	0.715038952	1.6	0.966091783	1	3	1
7	M	60	10	0.674017901	4.4	1.173787791	3	7	4
8	M	70	10	0.557639043	9	2	6	11	9
9	M	80	10	0.396127637	12.9	1.449137675	9	14	13
11	F	20	10	0.530189767	10.4	1.264911064	9	12	11
12	F	30	10	0.563869722	9.3	1.567021236	8	13	10
13	F	40	10	0.610746736	6.9	1.728840331	4	10	7
14	F	50	10	0.648229455	5.2	2.097617696	1	8	5
15	F	60	10	0.574610407	8	2.260776661	4	12	8
16	F	70	10	0.46369968	11.6	0.516397779	11	12	12
17	F	80	10	0.334890536	13.7	0.483045892	13	14	14

Panel C

Year	Previous Year	Rank Correlation
1995	n.a.	n.a.
1996	1995	0.686257299 [0.0067]***
1997	1996	0.783176093 [0.0009]***
1998	1997	0.903937947 [<.0001]***
1999	1998	0.82875895 [0.0002]***
2000	1999	0.928997613 [<.0001]***
2001	2000	0.846137946 [0.0001]***
2002	2001	0.975729558 [<.0001]***
2003	2002	0.92834427 [<.0001]***
2004	2003	0.907360165 [<.0001]***

Old investor groups are ranked at the bottom of the index on average as they are considered to be less involved in the information sharing among other age groups and therefore make trading decision independently. However, the correlated trading pattern is relatively lower for middle-aged females, about 50% compared to 68% of middle-aged males. This might account for the performance difference between the two highest return earning groups of different gender though not significant as documented previously in this study.

5.3.2 Trade Imbalance and Volatility

Table 5.9 reports result of both independent t test and Wilcoxon rank sum test of the difference in monthly trade imbalances for all twenty-nine subgroups before and beyond 2000. Before January 2000, the trade imbalances of all age groups across gender are negative which means net selling for all demographic subgroups. Most of the results between the two tests are consistent. The differences in means of monthly trade imbalances are all significant across male groups except for 80s. For female groups, only 70s and 80s groups do not show significances. The difference are all negative across 14 portfolios meaning after the crash all demographic groups tend to sell less Nokia stocks than before. Trade imbalances of 30s-60s male groups even turn positive which implies net buying of Nokia stock. 60s males are the most eager investors to buy Nokia shares in the second five-year period with the trade imbalance of 0.0253. In terms of old investors, trading behaviour of 70s males change quite substantially from trade imbalance of -0.168 to -0.016. Their female counterparties hardly change their trading style after crash.

Consistent with the existing literature, these results confirm the contrarian behaviour of individual investors who buy low after Nokia stock price crash and sell high before crash. More interestingly, compared to other age groups, male investors near retirement prefer to buy Nokia share rather than a life-cycle approach to investing, where investments are switched from equities to cash and bonds. This unusual behaviour is unique to the Nokia price bubble as high-tech crisis changed the way working individuals allocate their savings for retirement plans. The original plans which involving transfer stock assets to cash would result in substantial realized loss. The other explanation might be the role of men in the family, 60s males are desperate to turn around their investments in the difficult times as the main income earner and therefore trade aggressively on the Nokia share price hoping for a rebound.

Turning to impact on volatility, there are multicollinearity issues given the highly correlated trading activities among household group. Table 5.10 shows the regression results of impact of trading imbalance on realized volatility. Sell trades of aggregate males and domestic institutions have more impact on the volatility than their buy trades and it is significantly negative. For institutional investors, domestic financials are the traders who contribute the most to the volatility. They increase volatility when they are net buyers of Nokia shares (0.27053) and reduce volatility much more when they are net sellers (-1.14508). Other institutions are the only traders who reduce the volatility significantly when they generate negative trading imbalance. For household groups, aggregate females hardly move the volatility while aggregate males exhibit relatively bigger impact.

Table 5.9: Independent T Test and Wilcoxon Rank Sum Test for Bubble Impact on Trade Imbalance

This table reports the independent t-test and Wilcoxon rank-sum test of difference in trade imbalance among all age groups including both male and female before and after 2000 when Nokia price crashed. Both are 5-year period: 1995-1999 and 2000-2004. P-values are in square brackets. *denotes significance on 10% level, **denotes significance on 5% level and ***denotes significance on 1% level. Panel A lists all age groups for males; Panel B lists all age groups for females.

Panel A

	Gender	**Male**						
	Trader_id	3	4	5	6	7	8	9
	Age	20	30	40	50	60	70	80
Average monthly trade imbalance	Before 2000	-0.126	-0.073	-0.117	-0.113	-0.117	-0.168	-0.32
	After 2000	-0.009	0.0014	0.0057	-8.80E-04	0.0253	-0.016	-0.266
	Difference	-0.117	-0.075	-0.122	-0.112	-0.142	-0.152	-0.054
Independent t-test p-value		[0.0070]***	[0.0057]***	[0.0005]***	[0.0093]***	[0.0070]***	[0.0230]**	[0.5548]
Wilcoxon rank-sum test p-value		[0.1100]	[0.0139]**	[0.0010]***	[0.0150]**	[0.0273]**	[0.0269]**	[0.6125]

Panel B

	Gender	**Female**						
	Trader_id	11	12	13	14	15	16	17
	Age	20	30	40	50	60	70	80
Average monthly trade imbalance	Before 2000	-0.369	-0.125	-0.167	-0.217	-0.241	-0.293	-0.454
	After 2000	-0.092	-0.02	-0.044	-0.049	-0.044	-0.244	-0.318
	Difference	-0.276	-0.105	-0.123	-0.168	-0.197	-0.049	-0.135
Independent t-test p-value		[0.0002]***	[0.0081]***	[0.0064]***	[0.0039]***	[0.0008]***	[0.4992]	[0.1253]
Wilcoxon rank-sum test p-value		[<.0001]***	[0.0229]**	[0.0252]**	[0.0041]***	[0.0014]***	[0.4513]	[0.0384]**

Table 5.10: Regression Results of Trading Imbalance Impact on Volatility

This table reports results of time series regression with the dependent variable being monthly realized volatility of daily return of Nokia share, independent variable being various investor groups including both households and institutions. P-values are in square brackets. *denotes significance on 10% level, **denotes significance on 5% level and ***denotes significance on 1% level. The intercept is a_0 in the regression, *Month_rvol_lag* is the coefficient of lagged realized volatility $RVOL_{t-1}$, a is the coefficient of positive trading imbalance and b is the coefficient of negative trading imbalance. *Buy_trades_effect* is the volatility contribution by positive trading imbalance which is a and *Sell_trades_effect* is the volatility contribution by negative trading imbalance which is $a+b$.

$$RVOL_t = a_0 + (a_1 + b_1 D_1)\left|TIB_{1,t}\right| + (a_2 + b_2 D_2)\left|TIB_{2,t}\right| + ... + (a_5 + b_5 D_5)\left|TIB_{5,t}\right| + RVOL_{t-1} + \varepsilon_t$$

Intercept	0.10214			
	[<.0001]***			
Month_rvol_lag	0.34638			
	[0.0002]**			
R-square	0.3422			
adj R-square	0.2745			
	a	b	Buy trades effect	Sell trades effect
Aggregate Male (1)	0.14551	-0.26226	0.14551	-0.11675
	[0.1057]	[0.0162]**		
Aggregate Female (2)	0.01941	0.01157	0.01941	0.03098
	[0.8338]	[0.9026]		
Domestic Institutions (3)	0.27053	-1.41561	0.27053	-1.14508
	[0.4851]	[0.0828]*		
Foreign Banks (4)	0.14416	-0.70275	0.14416	-0.55859
	[0.6133]	[0.2501]		
Other Institutions (5)	-0.27064	0.18937	-0.27064	-0.08127
	[0.0521]*	[0.216]		

CHAPTER 6: Summary and Conclusion

This thesis analyses the trading behaviour of individuals and institutions using detailed trading data and examine the overall performance of different investors groups who make up of all market participants. The results show households demonstrate a significant higher alpha than institutions, both gross and net transaction cost. In addition, an increase in institutions trading is a key contributor to trading volume trends as they trade several times as much as the most active household age group.

This study also investigate the trading performance of demographic portfolios across all ages and finds both males and females in their 30s are the most frequent traders among their respective gender groups who earn the highest average monthly return and highest alpha on either a gross or net basis. In term of gender difference in trading, male groups show significantly higher turnover and larger aggregate portfolio size while females hold higher-risk stocks in their portfolio. The strong evidence of correlated trading is also revealed among households groups.

This work opens up two interesting issues to be examined in future research. First, microstructure data with quotes information may further explain the trading behaviour of market participants in Finland. Second, analysing other markets besides equity might give more insights as we just saw price movements of different asset classes in global financial markets are positively correlated in an integrated manner during the crisis.

.

REFERENCES

Anderson, K., Swan, P., Westerholm, J., 2010. Are households more sophisticated investors than delegated monitor? New Evidence from Finland, Working paper. Australian School of Business, University of New South Wales.

Barber, B., Odean, T., 2000. Trading is hazardous to your wealth: The common stock investment performance of individual investors. Journal of Finance 55, 773-806.

Barber, B., Odean, T., 2001. Boys will be boys: Gender, overconfidence, and common stock investment. Quarterly Journal of Economics 116, 261-292.

Barber, B., Lee, Y., Liu Y., Odean, T., 2009. Just how much do individual investors lose by trading? Review of Financial Studies, 22, 609-632.

Barber, B., Odean, T., Zhu, N., 2009. Systematic noise. Journal of Financial Markets, 12 ,547-569.

Blake, C., Elton, E., Gruber, M., 2007. Monthly holdings data and the selection of superior mutual funds. Working paper, NYU.

Brumberg, R., Modigliani, F., 1954. Utility analysis and the consumption function: An interpretation of cross-section data: in K.Kurihara, ed.: Post Keynesian Economics.

Carhart, M., 1997. On persistence in mutual fund performance. Journal of Finance, 52, 57-82.

Chen, H., Jegadeesh, N., Wermers, R., 2000. Journal of Financial and Quantitative Analysis, 35, 343-368.

Choe, H., Kho B., Stulz, R., 1999. Do foreign investors destabilize stock markets? The Korean experience in 1997. Journal of Financial Economics 54, 227–264.

Chordia, T., Roll, R., Subrahmanyam, A., 2009. Why has trading volume increased? AFA 2010 Atlanta Meetings Paper.

Cohn-Urbach, B., Westerholm, J., 2007. Trading frequency, investor returns and behavioural biases. Working paper, University of Sydney.

Comerton-Forde, C., O’Brien, M., Westerholm, J., 2007. An empirical analysis of strategic behaviour models. Australian Journal of Management, 32, 181-203.

Daniel, K., Grinblatt, M., Titman, S., Wermers, R., 1997. Measuring mutual fund performance with characteristic-based benchmarks. Journal of Finance, 52, 1035-1058.

Fama, F., French, K., 1992. The cross-section of expected stock returns. Journal of Finance, 47,427-465.

Fama F., French, K., 1993. Common risk factors in the returns on bonds and stocks. Journal of Financial Economics, 33, 3-53.

Feng, L., Seasholes, M., 2008. Individual investors and gender similarities in an emerging stock market. Pacific-Basin Finance Journal, 16, 44-60

Goetzmann, W., Massa, M., 2002. Daily momentum and contrarian behaviour of index fund investors. Journal of Financial and Quantitative Analysis 37,375–390.

Griffin, J., Harris, J., Topaloglu, S., 2003. The dynamics of institutional and individual trading. Journal of Finance 58, 2285–2320.

Grinblatt, M., Titman, S., Wermers, R., 1995. Momentum investment strategies, portfolio performance, and herding: A study of mutual fund behaviour. American Economic Review, 85, 1088-1105.

Grinblatt, M., Keloharju, M., 2000. The investment behaviour and performance of various investor types: A study of Finland's unique dataset. Journal of Financial Economics 55, 43-67.

Grinblatt, M., Keloharju, M., 2001. What makes investors trade? Journal of Finance 56, 589-616.

Grinblatt, M., Keloharju, M., 2009. Sensation seeking, overconfidence and trading activity. Journal of Finance 64, 549-578.

Glosten, L., Jagannathan, R., Runkle, D., 1993. On the relation between the expected value and the volatility of the nominal excess return on stocks. Staff Report 157, Federal Reserve Bank of Minneapolis.

Hendershott, T., Jones, C., Menkveld, A., 2008. Does algorithmic trading improve liquidity? Working paper, Columbia University.

Ivkovich, Z., Weisbenner, S., 2005. Local Does as Local Is: Information Content of the Geography of Individual Investors' Common Stock Investments. Journal of Finance LX, 267-306.

Ivkovich, Z., Sialm, C., Weisbenner, S., 2008. Portfolio concentration and the performance of individual investors. Journal of Financial and Quantitative Analysis, 43, 613-656.

Jackson, A., 2003. The aggregate behaviour of individual investors. Working paper, London Business School.

Jensen, M., 1968. The performance of mutual funds in the period 1945-1964. Journal of Finance 23, 389-416.

Kahneman, D., Madhavan, A., 1997. Transaction costs and investment style: An inter-exchange analysis of institutional equity trades. Journal of Financial Economics, 46, 265-292.

Kahneman, D., Madhavan, A., 1998. The cost of institutional equity trades. Financial Analysts Journal, 54, 50-69.

Kaniel, R., Saar, G., Titman, S., 2008. Individual investor trading and stock returns. Journal of Finance, 63, 273-310.

Kaustia, M., Knupfer, S., 2009. Learning from the outcomes of others: Stock market experiences of local peers and new investors' market entry. EFA 2009 Bergen Meetings Paper.

Kuuskoski, M., Westerholm, J., 2003. Do direct stock market investments outperform mutual fund? A study of Finnish retail investors and mutual fund. Finnish Journal of Business Economics, 2, 197-212.

Kyle, A., 1985. Continuous auctions and insider trading. Econometrica, 53, 1315–1336.

Lakonishok, J., Shleifer, A., Vishny, R., 1992. The impact of institutional trading on stock prices. Journal of Financial Economics, 32, 22-43.

Lindell, C., 1998. Pensions are not the solution to the unemployment problem. Central Pension Security Institute Reports 1998 10, Helsinki.

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

Ollila, M., Westerholm, J., 2003. Impact of gender, age and language on investment strategy. Finnish Journal of Business Economics, 2, 179-196.

Perttunen, J., Tyynela, M., 2003. Trading behaviour of Finnish households: activity, performance and overconfidence. Finnish Journal of Business Economics, 2, 179-196.

Richards, A., 2005. Big fish in small ponds: The trading behaviour of foreign investors in Asian emerging equity markets. Journal of Financial and Quantitative Analysis 40, 1–27.

San, G., 2007. Who gains more by trading – individuals or institutions? Working paper, Hebrew University of Jerusalem.

Seru, A., Shumway, T., Stoffman, N., 2009. Learning By Trading. Review of Financial Studies, forthcoming.

Sharpe, W., 1966. Mutual fund performance. Journal of Business, 39, 119-138.

Stoll, H., 1995. The importance of equity trading costs: Evidence from securities firms' revenues. Global Equity Markets: Technological, Competitive, and Regulatory Challenges. R.Schwartz. ed. New York, New York University Salomon Center.