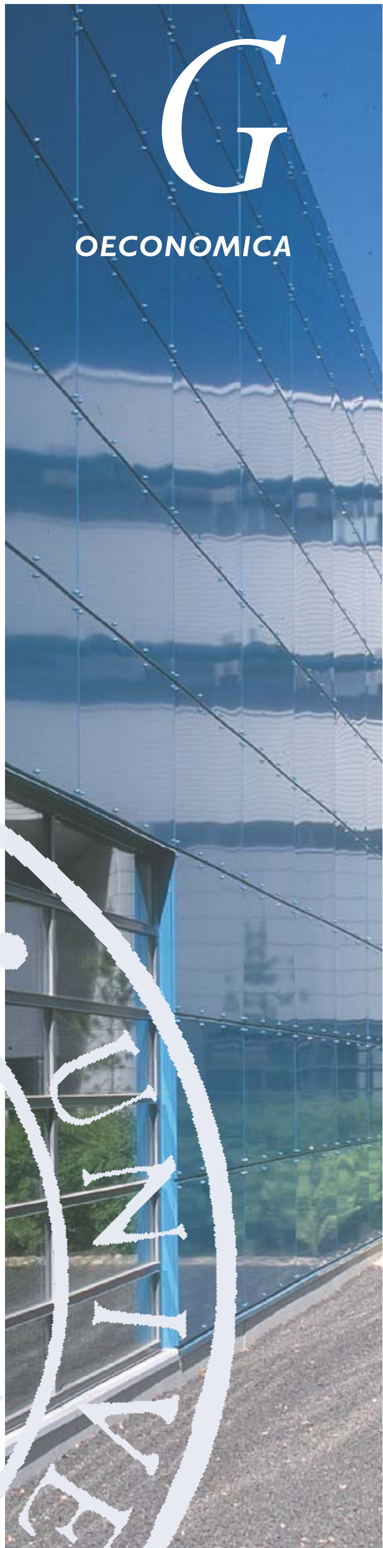
OULU 2014
G 69

ACTA UNIVERSITATIS OULUENSIS



Helinä Saarela

THE INFLUENCE OF SELF-PERCEIVED, SUBJECTIVE ATTRIBUTES ON INVESTMENT BEHAVIOR

*UNIVERSITY OF OULU GRADUATE SCHOOL;
UNIVERSITY OF OULU,
OULU BUSINESS SCHOOL,
DEPARTMENT OF FINANCE*

ACTA UNIVERSITATIS OULUENSIS
G Oeconomica 69

HELINÄ SAARELA

THE INFLUENCE OF SELF-PERCEIVED, SUBJECTIVE ATTRIBUTES ON INVESTMENT BEHAVIOR

Academic dissertation to be presented with the assent of The Doctoral Training Committee of Human Sciences, University of Oulu for public defence in the OP auditorium (L10), Linnanmaa, on 7 November 2014, at 12 noon

UNIVERSITY OF OULU, OULU 2014

Acta Univ. Oul. G 69, 2014

Supervised by
Professor Jukka Perttunen

Reviewed by
Professor Eero Pätäri
Professor Timo Rothovius

Opponent
Professor Markku Vieru

ISBN 978-952-62-0576-2 (Paperback)
ISBN 978-952-62-0577-9 (PDF)

ISSN 1455-2647 (Printed)
ISSN 1796-2269 (Online)

Cover Design
Raimo Ahonen

JUVENES PRINT
TAMPERE 2014

Saarela, Helinä, The influence of self-perceived, subjective attributes on investment behavior.
University of Oulu Graduate School; University of Oulu, Oulu Business School, Department of Finance
Acta Univ. Oul. G 69, 2014
University of Oulu, P.O. Box 8000, FI-90014 University of Oulu, Finland

Abstract

This doctoral thesis aims to contribute to investment behavior research by giving new information on the causes which generate differences in investment behavior. As causes to differences in behavior we focus on the influence of investors' self-perceived attitudes, evaluations and judgments. We refer to these investor characteristics as subjective attributes. We also test the power of demographic and socio-economic characteristics as causes of differences in investment behavior and refer to these as objective attributes. We approach investment behavior from three dimensions and construct empirical research around each dimension. We find the predictive power of subjective attributes to be strong, which makes it important to take them into account when modeling investment behavior.

Our data is collected from two different databases in which subjective and objective attributes are connected with actual investment behavior, i.e. investors' actual wealth levels and allocations. This is rare because only seldom can researchers link subjective attributes with actual behavior.

Our main contributions are the following: 1) Investor-specific risk-standing ability and other subjective attributes have a tight link with investor's actual risk-standing ability and portfolio choice. This confirms the meaning and importance of European Union regulations which require financial institutions to clarify these issues and in that way betters investor protection. 2) Subjective investor attributes as measures of financial sophistication can be visible as a propensity to withdraw from the stock market during severe market crises. We state that, in addition to its very positive effects, financial sophistication may induce the investor to make mistakes like total withdrawal from the stock market, realization of short- term losses, or exposure to timing problems of stock portfolio rebuilding. 3) Simple questions asked as claims work better as measures of overconfidence than more commonly used calibration-based techniques. Several measures of overconfidence explain trading activity. Trust in one's own market timing abilities shows as narrower diversification.

Our thesis has implications for regulation, financial institutions, financial literacy education and investors themselves.

Keywords: financial sophistication, overconfidence, portfolio choice, rebalancing, risk profile, subjective attributes

Saarela, Helinä, Itse miellettyjen, subjektiivisten ominaisuuksien vaikutus sijoitus-käyttäytymiseen.
Oulun yliopiston tutkijakoulu; Oulun yliopisto, Oulun yliopiston kauppakorkeakoulu, Rahoituksen yksikkö
Acta Univ. Oul. G 69, 2014
Oulun yliopisto, PL 8000, 90014 Oulun yliopisto

Tiivistelmä

Tämän tutkimuksen tavoitteena on antaa uutta tietoa syistä, jotka aiheuttavat eroja yksityishenkilöiden sijoituskäyttäytymisessä. Käyttäytymiserojen syissä keskitymme sijoittajien itse mieltämiin mielipiteisiin, arviointeihin ja käsityksiin. Nimeämme nämä tekijät sijoittajan subjektiivisiksi ominaisuuksiksi. Lisäksi testaamme demografisten ja sosioekonomisten ominaisuuksien vaikutusta sijoituskäyttäytymisen eroihin. Nimeämme nämä tekijät sijoittajan objektiivisiksi ominaisuuksiksi. Tarkastelemme sijoituskäyttäytymistä kolmesta lähestymiskulmasta rakentamalla empiirisen tutkimuksen jokaisen kulman ympärille. Tulostemme mukaan subjektiivisten ominaisuuksien vaikutus sijoituskäyttäytymiseen on merkittävä, joten ne on syytä ottaa huomioon käyttäytymisen mallintamisessa.

Tutkimusaineistomme muodostuu kahdesta erillisestä aineistosta, joissa kummassakin subjektiiviset ja objektiiviset ominaisuudet yhdistyvät todelliseen sijoituskäyttäytymiseen, eli sijoittajien olemassa oleviin varallisuusmääriin ja -jakaumiin. Tämä on poikkeuksellista, sillä subjektiivisia ominaisuuksia harvoin pystytään yhdistämään todelliseen sijoituskäyttäytymiseen.

Tutkimuksemme tärkeimmät kontribuutiot ovat seuraavat. 1) Sijoittajakohtaisella riskinsietokyvyllä ja muilla subjektiivisilla ominaisuuksilla on vahva yhteys sijoittajan todelliseen riskinsietokykyyn ja osakeriskin osuuteen. Tämä vahvistaa Euroopan Unionin määräysten merkityksellisyyttä: näiden asioiden selvittäminen on hyödyllistä sijoittajasuojan parantamiseksi. 2) Subjektiiviset ominaisuudet sijoittajien taloudellista oppineisuutta kuvaavina tekijöinä voivat näkyä taipumuksena vetäytyä osakemarkkinoilta voimakkaan kurssilaskun tilanteessa. Taloudellisen oppineisuuden yleisesti havaittujen positiivisten vaikutusten lisäksi oppineisuus voi myös johtaa sijoitusvirheisiin, kuten vetäytymiseen osakemarkkinoilta, lyhyen aikavälin tappioiden realisoimiseen ja salkun uudelleen rakentamisen mukanaan tuomaan ajoitusriskiin. 3) Yksinkertaiset väitemuodossa esitetyt kysymykset toimivat yliluottamuksen mittareina paremmin kuin enemmän käytetyt kalibrointipohjaiset mittarit. Useat yliluottamuksen mittarit selittävät kaupankäynnin aktiivisuutta. Luottamus omiin kykyihin ennustaa markkinaliikkeitä näkyy kapeampana salkun hajautuksena.

Tutkimuksellamme on merkitystä lainsäätäjille, finanssialan yrityksille, tahoille, jotka vastaavat sijoittajatietämyksen kouluttamisesta, sekä sijoittajille itselleen.

Asiasanat: osakepaino, rebalansointi, riskiprofiili, subjektiiviset ominaisuudet, taloudellinen oppineisuus, yliluottamus

Acknowledgements

To reach this moment, the home stretch of my doctoral studies, when I could write the acknowledgements, has been my dream for many years. Being a mother and a wife, having a demanding, full-time job and carrying out doctoral studies is a complicated equation to solve. But I made it! My heart is full of joy and satisfaction having reached my goal. But I would not have managed without the help and support of the following persons and institutions.

I am deeply grateful to my supervisor, Professor Jukka Perttunen of the University of Oulu, for guiding me through my studies. He has been patient and understanding with me and my many questions. Every time I came to his workroom, I left with valuable advice which helped me to proceed with my research. I am very grateful to D.Sc. Mirjam Lehenkari for her comments and support with regard to statistics. I am also very appreciative of my student colleagues D.Sc. Juha Joenväärä and M.Sc. Tuomo Haapalainen. Juha's lessons on mathematics and Tuomo's help with exercises were crucial in helping me pass the demanding courses in the Graduate School of Finance (GSF). I am very grateful to the whole faculty of the Graduate School of Finance. The faculty really fills its objective of promoting high quality doctoral education in finance in Finland by organizing advanced level doctoral courses, seminars, workshops and tutorials. The lessons in Helsinki have given me the possibility to receive a world-class education from leading professors in the field of finance. My thanks also go to my pre-examiners, Professor Eero Pätäri and Professor Timo Rothovius for reviewing my research and for their valuable remarks which helped me put the final touches to the dissertation.

Two institutions have allowed me to utilize their data as my research material. My deep thanks belong to OP-Pohjola Central Cooperative, Oulun OP and Helsingin OP which gave me investor questionnaire data, as well as investment portfolio data. I wish my empirical results have value to further promote OP-Pohjola Group's success in serving their customers. My deep thanks also go to the Finnish Shareholders' Association which gave me a license to collect information on their members through questionnaires. In particular, I wish to thank the chairman of Oulunseudun Osakesäästäjät, Antti Jylhä, who promoted the data gathering.

My friends and colleagues in Oulun OP as well as in other branches in OP-Pohjola Group deserve mention too. My friends have given me other things to think about than just my studies. My colleagues have enriched my dissertation with valuable comments based on their experience of investment behavior. My sister Päivikki needs to be thanked too. She gave me her home to stay in during the GSF courses in Helsinki.

To my father and deceased mother: I am deeply grateful for the balanced childhood and youth which you gave to us, your daughters and son. You spoke on behalf of education, you encouraged us, taught us sound values to guide us through life. You built the foundation on which my life is built.

Isälleni ja edesmenneelle äidilleni: Kiitos teille tasapainoisesta lapsuudesta ja nuoruudesta, jonka minulle, siskoilleni ja veljelleni annoitte. Korostitte koulutuksen merkitystä, kannustitte meitä, opetitte meille terveet arvot elämän tielle. Loitte elämälleni pohjan, joka kantaa minua läpi elämäni.

In addition to my name, the names of my family members would belong on the cover of my dissertation; my sons Juho and Markus as well as my husband Antti. I keep asking my sons if they have suffered from their mom's busy life with studies and duties in work. I also keep asking Antti how it has been to live with a wife who comes from work and starts working on her studies in the workroom at home. Mere words are not enough to say how I appreciate that all of you have supported me to reach my dream to go through the doctoral studies. Juho and Markus: I wish your mother's example helps you to reach for your dreams, no matter what those dreams are. You can be sure your mother will always stay by your side.

On summer holiday, Kempele, July 2014 Helinä Saarela

Contents

1 Introduction

1.1 Preface

The overall aim of our doctoral thesis is to provide new information on the causes which generate differences in investment behavior. As causes of differences in behavior we focus especially on the influence of investors' self-perceived attitudes, evaluations and judgments. As examples of those self-assessments we mention ability to withstand risk, investment experience, activeness in following economic events, and confidence level in own investment abilities. We consider those investor characteristics *subjective attributes* and test their power to explain investment behavior from various perspectives. By identifying those psychology-based subjective characteristics, and their influences on investment behavior, the focus can be placed on them. The importance of focusing on these characteristics stems from their predictive power as regards investors' portfolio choices and actions in their portfolios. Better understanding of the attributes that generate differences in investment behavior hold potential for understanding deviations from standard financial theories and for taking into account the comprehensive mix of attributes when developing behavioral models.

In addition to subjective attributes, we test the power of investors' demographic and socioeconomic variables to explain investment behavior. As examples of those variables we identify gender, age, education, income level and amount of total wealth. We use the definition *objective attributes* when we refer to these factors. Objective attributes are more commonly investigated than subjective ones because they can be measured more easily and accurately than subjective attributes. Classifying investor characteristics as subjective and objective attributes follows mainly the work of Dorn & Huberman (2005), Kapteyn & Teppa (2002, 2011) and Dohmen et al. (2005).

Although the importance of subjective attributes in understanding investment behavior has been acknowledged, research on the subject is fairly limited. The reason for this arises from a lack of proper data which contains self-assessments and has a connection to investors' actual portfolio choices. The data we use fills those important requirements. Our data is collected from two different databases. Firstly, we had the opportunity to use data that describes the clients of Finnish financial institution. Another dataset is based on a questionnaire for experienced Finnish investors which we made for our research. Both datasets contain a wide spectrum of investors' self-perceived attitudes and judgments, their actual portfolios, the breakdown of portfolios as well as their transactions within their portfolios. By using the data, we construct three empirical researches in order to test the power of subjective and objective attributes on investment behavior. We approach investment behavior from the following perspectives: 1) Influence of subjective and objective attributes on risk-taking behavior as shown through investors' portfolio choices, i.e. their risky shares, 2) Financial sophistication characteristics, measured by subjective and objective investor attributes, explaining rebalancing behavior with fund portfolios during the stock market crises, and 3) Confidence in own investment abilities – sometimes visible as overconfidence – explaining trading activity and diversification of common stock portfolios. As explanatory variables for trading activity and diversification we also test other subjective and objective attributes.

In Chapters 1.2–1.4 we familiarize the reader with the prior research on the influence of subjective and objective attributes on investment behavior with similar approaches than our empirical research problems. After going through the prior research, we introduce the overall purpose of our study as well as the research questions and background of the three empirical research chapters. We also discuss the reasons why it is important to investigate investment behavior. We then introduce the contributions of our study. Lastly we summarize the structure of the whole thesis.

1.2 The influence of subjective and objective attributes on portfolio choice

Portfolio choice is an investor-specific decision on the relative share of risky assets (= risky share) in relation to his total wealth[1]. When the investor chooses a higher risky share, he is prepared to stand higher fluctuations in his wealth. As compensation for these fluctuations he expects a higher return. The theory of portfolio choice (Markowitz 1952) explains heterogeneity in portfolio choice to be caused by different risk attitudes. Three questions rise from this: 1) How can we measure those risk attitudes? 2) What reasons cause the differences in risk attitudes and how are they visible through differences in portfolio choices? 3) Are there other variables which may explain portfolio choices?

There exists much empirical research on demographic and socioeconomic attributes and their influence on portfolio choice. For example, variation in portfolio choice can be linked to gender, age, education, family background, income level

[1] When we calculate the risky share we exclude the value of home from total wealth because home is not an investment instrument (see empirical research in Chapter 3)

and its safety, and amount of total wealth[2]. In our research we use the definition *objective attributes* when we refer to these variables. Risk-taking behavior is also shown to be linked to investors' *self-perceived subjective attributes*[3]; individuals have unique personal traits, opinions on risk taking as well as investment experience, and their interest in financial matters and the economy may differ. There is quite little empirical research on how subjective attributes affect portfolio choice. The reason for that is the lack of high-quality data. The influence of subjective preferences on risk-taking behavior is usually studied by questionnaires, experiments or by standard lottery questions. The questionnaires differ a lot and there is no commonly accepted question pattern for asking about preferences. The validity and reliability of such questionnaires has also been challenged (Grable & Lytton 2001). Investors might give inaccurate answers, "they might not mean what they say" or they might interpret the words and phrases in different ways (see for example Bertrand & Mullainathan 2001 or Manski 2004). The responses can be domain-specific and poorly correlated across different questionnaires. Moreover, a questionnaire may lose its validity with another population. The respondent may understand the word *risk* to signify only the possibility of value to decrease, not the possibility to increase. This can influence the respondent to answer too carefully to risk-related questions. Also, most typically the researcher does not have information on the investor's actual portfolio choice to test the subjective attributes against to actual investment decisions, to real-world behavior. Riley & Chow (1992) and Dorn & Huberman (2005) state that investors' *actual* wealth allocation reveals their risk preferences much better than hypothetical scenario questions. Manski (2004) points out that the reliability and validity of individuals' subjective expectations can be evaluated by contrasting those expectations to their realizations. Leaning on empirical evidence, Manski stresses that individuals respond accurately to questions which measure subjective attitudes concerning personally significant events.

In the following paragraphs we review the prior research on measurement techniques of risk attitudes as well as subjective and objective attributes which have been observed to affect risk-taking behavior and portfolio choice. We concentrate mainly on those prior findings in which the researcher has had a possibility to check the subjective attributes against actual investment decisions. Furthermore, we consider tools which are constructed to measure risk attitudes.

[2] See references in Chapter 1.2.2

[3] See references in Chapter 1.2.1

1.2.1 Subjective attributes and their measurement

By using a standard lottery question the investor is asked to make a choice between certain and uncertain outcome. His answer defines his certainty equivalent. Investors with concave utility function choose a certainty equivalent below the expected value of uncertain outcome (Weber & Milliman 1997). Barsky *et al.* (1997) use this technique to investigate the risk tolerance and financial risk-taking behavior among the participants of the U.S. Health and Retirement Study. The respondents respond to a hypothetical gamble that concerns the safety of their lifetime income. The answers reveal risk preferences, which enables the calculation of risk aversions. Barsky *et al.* find risk tolerance to have a link with stock ownership: among those households where the primary respondent gives the most risk-tolerant response, the risky share is 4.1% higher than in those households where the primary respondent gives the least risk-tolerant response.

Dorn & Huberman's (2005) research is another example in which the respondents' risk attitudes were checked against their actual risky shares. Dorn & Huberman use German discount brokerage data of 947 respondents and enrich it with a questionnaire examining various self-perceived subjective characteristics. The respondents assess their risk attitude by using a four-point scale, estimate their knowledge on financial instruments and investment experience as well as evaluate their overall confidence in their ability to make right decisions. To obtain information on actual investments, the respondents are asked to give the value of their total wealth and its share of risk-free and risky instruments. Dorn & Huberman find investment experience, knowledge of financial instruments and confidence in own skills to predict lower risk aversion. Also, the actual risky share is higher with experienced investors who perceive their investment knowledge to be high, who have a strong confidence in their abilities as an investor and who are less risk averse.

Kapteyn & Teppa (2002, 2011) formulate a questionnaire where they ask subjective questions on hypothetical choices concerning lifetime income stream, personal investment strategies, saving motives and precautionary savings. They collect the responses by using a pc-inquiry among the Dutch population and then merge it with Center Savings Survey (CSS) data which includes information on the respondents' assets, liabilities, demographics and subjective variables. They use the same method as Barsky *et al.* (1997) by asking the respondents to decide about their preferences on the safety of lifetime income. Furthermore, by naming the questions to ad hoc–questions, they ask the respondents to evaluate their investment strategies and saving motives in an informal way by using a 7-point scale. Kapteyn & Teppa find subjective ad hoc-questions on risk and return attitudes to be more powerful in explaining risky shares than the more theory-based, but complicated, lottery-type risk tolerance measures.

Dohmen *et al.* (2005) use German data in which the respondents' risk attitudes are collected in different ways. The first method is to evaluate the respondents' attitudes towards risk taking in general (an 11-point scale where 11=least risk averse). Secondly, they ask domain-specific questions concerning willingness to take risks in financial matters, car driving, career, health as well as sports and leisure. The final question is a lottery type one: "which share of a windfall gain of 100,000 euros would the investor invest in an asset whose return is +100% or -50% with equal probability". They do not use other subjective variables as explanatory variables on risk attitudes but rely instead on objective variables. They find higher risk standing attitudes measured by the general risk-taking question to be negatively correlated with age and female gender and positively correlated with respondent's height and parents' education. This general risk-taking question is the best predictor of risk attitude in average. The best predictor in a given context is a question that is constructed to the existing context. Furthermore, the authors find risk attitude to be strongly correlated across different life contexts. This result gives support to the standard assumption that behavior is a personal trait which is evidenced in different contexts.

Halko et al. (2011) use Dohmen *et al.'s* (2005) 11-point scale test of general risk-taking to investigate the link between gender and risk attitudes in different domains of life. In addition to Dohmen *et al.'s* method they ask the respondents' willingness to invest in a hypothetical risky asset and employ a traditional lottery question to reveal the respondents' certainty equivalents. Their data consists of 335 Finnish respondents: investors, investment advisors and students. The respondents also reveal their actual risky shares. Halko et al. find Dohmen *et al's* 11-point scale risk attitude test to be the strongest predictor of actual risky shares; the hypothetical asset and traditional lottery question do not explain the risky share. Like Dohmen et al., Halko *et al.'s* results confirm the permanence of risk attitude in different life contexts; they find the respondents' general and financial risk-taking attitudes to correlate strongly with each other and with the risky share. Halko *et al.* (2011) also use another Finnish dataset (taken from the same database that we use) and find the risk attitudes measured by simple questions on risk and return (5-point scale risk profile) to be linked with actual risky shares. Financial knowledge, which they measure by investors' self-perceived experience in investment issues, is an important variable explaining risky shares.

Grable & Lytton (1999) have no possibility to compare the risk preferences to actual portfolio choices. Instead, their main aim is to present a financial risk-tolerance instrument which would show a high degree of reliability and validity. By reviewing academic publications, they identify more than 100 items which measure risk-taking behavior. They drop the amount of items to 13 pieces by going through several steps to test that the items really measure risk tolerance and nothing else, by analyzing their correlations, and by confirming that the different items capture the same levels of risk tolerance. These items measure either one or several dimensions of financial risk tolerance: a guaranty versus gamble, general risk-taking propensity, a choice between a sure loss or gain, investment experience, investment knowledge, comfort level when making risky choices, willingness to speculate, evaluation of the choice compared to some reference point, and respondent's knowledge and temperament when taking risks. Grable & Lytton (2003) test the validity of their 13-item instrument with actual investment decisions in an Internet-based survey. The respondents also tell their total wealth level and its breakdown. Grable & Lytton find a clear correlation between the 13-item instrument and the risky share of the respondents' portfolios. The validity and reliability of Grable and Lytton's tool is acknowledged by other researchers too, see for example, Yang (2004), Gillian *et al.* (2010), Lucarelli & Brighetti (2010). Their tool is freely available via an online website hosted by Rutgers University (http://njaes.rutgers.edu/money/riskquiz/).

Hallahan *et al.* (2004) analyze Australian data which they pick from an investment advisory's database (www.riskprofiling.com, FinaMetrica). The FinaMetrica system is widely used among investment advisors in many countries. When the respondent answers the system's 25 questions through a computer-based questionnaire, the system generates a personal risk tolerance score (RTS) on a scale from 1 to 100. Before the respondent sees his own RTS he has to evaluate which score he imagines he will get. Hallahan *et al.* compare the self-evaluated RTSs and actual RTSs and find that respondents on average underestimate their risk tolerance. The respondents' self-evaluation is approximately 4.12 + 83.8% of their actual RTS. Also, when filling the RTS questionnaire, the respondents choose the most suitable portfolio to their own needs from a selection of different combinations of high, medium and low risk/return portfolios. Hallahan *et al.* find the respondents to have a tendency to choose a portfolio which is consistent with their personal RTS score. They use demographic variables as explanatory variables and find male gender, higher income classes and higher wealth to be positively related with risk tolerance.

Probably the most well-known risk attitude measurement tool is the Survey of Consumer Finances (SCF) single-question method (see the question in Chapter 2.1). When answering the question, the respondent reveals his attitude on risk taking and return target on a four-point scale. The SCF data does not include the breakdown of the respondent's wealth, which precludes checking the risk attitude against the respondent's actual investment decisions (Bucks *et al.* 2009, Grable & Lytton 2001). Furthermore, the SCF method relies on only this single question about risk. Grable & Lytton (2001, 2003) point out that the SCF question does not measure the multidimensional nature of risk tolerance like their own 13-item tool. Chen & Finke (1996) use the same argument. Despite its weaknesses, the SCF data, or at least the same question measuring risk preferences, is very commonly used in financial research. (See, for example, Sung & Hanna 1996, Hanna & Lindamood 2004, Wang & Hanna 2007, Bucks *et al.* 2009)

1.2.2 Objective attributes

Gender is seen to influence risk-taking behavior[4]. Men are more prone to take investment risks than women, and are more likely to invest a bigger share of their wealth in risky instruments. The risky share is seen to increase with age[5]. Yet, after retirement the share of risky assets is seen to fall. Guiso *et al.* (1996) find the share of risky assets to be at its lowest level with young people and reaching its highest level at age 61. Ameriks & Zeldes (2004) find the share of risky assets to reach its peak between age 49 and 58. The above-referenced researchers point out that the potential reason for decreasing risk tolerance after retirement compared to younger people is the lower capability to withstand stock market volatility because of shorter investment period. Another reason might be the need to maintain the current life standards in retirement by using a part of accumulated wealth for consumption.

Marital status is seen to influence risk taking but the results are mixed. Agnew *et al.* (2003) and Grable (2000) find the risky share to be higher for married investors. In contrast, Hallahan *et al.* (2004) find evidence that single investors are more risk tolerant than couples. Bernasek & Shwiff (2001) argue that the investment portfolio of a couple may reflect the spouses' combined risk preferences.

---

[4] See, for example, Powell & Ansic (1997), Bodie & Crane (1997), Grable (2000), Campbell & Viceira (2002), Agnew *et al*. (2003), Hallahan *et al*. (2004), Dohmen *et al*. (2005)

[5] See Riley & Chow (1992), Agnew *et al.* (2003), Donkers *et al.* (2001), Kapteyn & Teppa (2002), Dohmen *et al.* (2005

Proportion of risky investments is shown to rise with income level[6]. A typical explanation for this phenomenon is the fact that bad investment decisions have fewer ramifications for high income investors than for low income investors. Similarly with income level, risk taking and higher education are found to have a positive correlation[7]. Participation in risky assets is seen to increase with wealth level, and the scale of investment instruments typically increases with wealth[8]. Quadrini (2000) and Carroll (2000) point out that private business ownership is very common in the highest wealth levels. Their explanation for this is capital market imperfections and the cost of external financing, which necessitates large self-financing.

Heaton & Lucas (2000a, 2000b) use the term background risk to describe the uninsurable risk that affects risk tolerance and portfolio choice. The potential reasons for varying background risk rise from differences in human capital, labor income volatility, real estate market fluctuations, ownership of employer company's stocks and participation in private businesses. Guiso & Paiella (2008) investigate the background risk of Italian investors by calculating their quantitative measure of risk aversion and comparing it to their income uncertainty. Their results give support to the notion of background risk; income uncertainty and borrowing constraints have a negative effect on risk-taking behavior.

Lusardi *et al.* (2009) construct two financial sophistication indexes by measuring investors' basic and advanced knowledge of the economy, for example, understanding the influences of inflation, interest calculation, functions of stock market and differences between bonds and stocks. They find a positive link between financial sophistication and retirement planning. Rooij *et al.* (2011) use the same indexes and find them to be positively correlated with stock market participation. Also Calvet *et al.* (2009b) and Peress (2004, 2011) find financial sophistication measured by wealth, income, education and financial experience to be positively correlated with a risky share. Guiso & Japelli (2005) use the term "financial awareness" when analyzing respondents' knowledge of various investment instruments and ownership of these instruments. They find financial awareness to be positively correlated with socioeconomic variables which increase the probability of financial market participation: education, wealth, income and year of birth. Financial awareness is also positively correlated with long-term bank relations, intensity of social interaction and national newspaper readership

[6] See Riley & Chow (1992), Haliassos & Bertaut (1995)

[7] See Haliassos & Bertaut (1995), Grable (2000) and Donkers et al. (2001) and Guiso et al. (2002)

[8] See, for example, Peress (2004, 2011), Guiso et al. (2009) or Carroll (2000)

in the area where the investor lives. The social learning concerning investment opportunities is engendered by peers who are already informed.

1.3 Drivers of trading and rebalancing

The reasons behind trading with the risky portfolio can be a willingness to take into account stock market value fluctuations and to modify the portfolio against such movements, i.e. to *rebalance* the risky portfolio. During the stock market downturn, rebalancing can be seen as a propensity to buy to resist the decline of the portfolio's market value, to maintain the desired risky share, or to take advantage of low market prices. Alternatively, rebalancing can show as a selling propensity stemming from, for example, unwillingness to stand the decline of the portfolio's value. During the stock market upturn, the arguments for rebalancing are the opposite. The terms trading and rebalancing cannot be precisely separated from each other because trading is how rebalancing is conducted. Also, we cannot be sure about whether the investor at hand thinks he is trading in order to rebalance his portfolio or whether he trades for some other reason.

The research on rebalancing behavior during stock market up- or downturns is quite scarce. Typically the research concentrates on trading activity in general without linking it to the stock market situation. Also, usually the research focuses on common stocks but not mutual funds. The role of mutual funds in individual investors' risky portfolios is large, which underscores the importance of their investigation. One reason for the scarcity of research on rebalancing behavior is the lack of proper data. For the data to be good quality it should include the possibility to single out the active rebalancing decisions from the passive changes in the portfolio caused by market value fluctuations. The investor's total wealth should be divided into asset classes to analyze his portfolio construction as a whole. Oftentimes the data contains only a part of the investor's portfolio, for example his common stock ownership. Investor characteristics should be included as well to be able to investigate the link between such characteristics and rebalancing.

When considering common trading behavior, research finds evidence of, for example, larger propensity for men to trade, below-average annual returns when trading very actively, overconfidence in own skills causing active trading or investors' competence characteristics (e.g., education, income and portfolio size) affecting trading frequency (Barber & Odean 2001, 2002, Graham *et al.* 2009). Also, heterogeneity in stock market participation caused by differing sources of income, fixed per period participation or transaction costs, or information barriers are seen to influence stock market participation and trading behavior (Vissing-Jorgensen 2002, Guiso & Jappelli 2006). Because the above-referenced research does not concentrate on the link between rebalancing behavior and stock market situation, they fit with our research on rebalancing quite poorly. Next we review the research that does have a link with stock market up- or downturns.

Calvet *et al.* (2009a) investigate rebalancing behavior by using Swedish tax records data. Their data contains the distributions of total wealth of Swedish citizens, which allows calculation of investor-level fluctuations in risky shares. The research period covers the technology boom and the bear market after the boom 1999–2002. Calvet *et al.* find that, on average, households tend to resist passive market value fluctuations by offsetting about half of negative returns through active rebalancing, i.e. through trading. Rebalancing behavior is motivated by the returns of households' portfolios. Individuals with returns below the index returns buy risky assets from individuals with above average returns. Investors with higher initial risky shares reduce their risk exposure by engaging in selling transactions more aggressively than other investors. The other characteristics which affect rebalancing behavior are education, total wealth, income level and diversification of portfolio. Calvet *et al.* associate these investor characteristics as measures of financial sophistication. Investors of these types are more willing to maintain their risky shares by buying more risky assets despite the market decline (2009a, 2009b). Calvet *et al.* (2009a) find also that the behavior of more educated and wealthy households differs from the average Swedish behavior as regards exit decisions. More educated and wealthier households holding better diversified portfolios are less likely to totally exit the stock market. The same holds among investors with higher risky shares. Positive mutual fund returns reduce exit probability, but positive returns on directly held stocks increase it. With directly owned stocks the authors cite the disposition effect where the investor is prone to sell winner stocks but holds loser stocks. With mutual funds Calvet *et al.* point to the belief of differing skills among fund managers: when the fund is losing value, the investor is prone to think it is badly managed and therefore he sells it.

Using Finnish data, Grinblatt & Keloharju (2000) also find positive returns on directly held stocks to increase the selling propensity if the seller is an individual investor, which they categorize as a less sophisticated investor than an institutional investor. Those categorized as more sophisticated, i.e. institutional investors, react in the opposite way by selling stocks with bad returns and buying stocks with superior returns. By following this strategy they achieve higher performance than less sophisticated investors. Dorn & Huberman (2005) measure investors' sophistication by using their subjective characteristics: self-perceived investment experience and knowledge about financial instruments. They also measure investors' actual investment knowledge. When they link sophistication characteristics to portfolio turnover (they investigate trading activity in general, i.e. without linking it to passive market changes) they find mixed results. Experienced and wealthier investors trade less but those with high actual knowledge about financial instruments trade more. Self-perceived knowledge, higher education, and income level have no statistical significance.

Bilias *et al.'s* (2010) PSID (Panel Study of Income Dynamics) data does not allow the possibility to separate active rebalancing behavior from market value fluctuations. Therefore, they gather information on trading behavior in upswing and downswing periods via interviews. Their data covers the stock market boom during the latter part of the 1990s and the bear market in the early 2000s among U.S. citizens. The households are asked about frequency, direction and value of their stock transactions since the previous interview. The definition of "stocks" refers of directly owned stocks, stock funds and investment trusts held in stock instruments. Bilias *et al.* find that both in upswing and downswing periods more than half of households do not make transactions with their stocks. When they break the downswing into sub-periods, 1999 – 2001 and 2001 – 2003, the share of no-transactions households slightly increases in the latter period to 71%. In both upswing and downswing periods households are more prone to buy only than to sell only. Then again, as the downswing period is prolonged, the share of buyers decreases from 18% to 11%. Higher education, income level or net financial wealth encourages trading. Education and net financial wealth increase buying propensity as the downswing is prolonged. Having more children not only discourages stock market participation but also discourages trading. The authors further their research by using SCF data (Survey of Consumer Finance) in which the stock owners cover only brokerage account owners, i.e. fund and investment trust owners are not considered. They find that stock index drops increase the probability of trading more than index increases, but their research does not examine the direction of trade.

The financial crisis of 2008 – 2009 and its conversion into a European Union government deficit crisis has given birth to empirical research focusing on its consequences on households, corporations, governments, expectations on return and risk and on regulation of financial markets (see, for example, Ivashina & Scharfstein 2010, Duchin *et al.* 2010, Campello et al. 2011 and Hudomiet et al. 2011). However, research on individual investors' rebalancing behavior is scarce.

We assume the reason to be once again a lack of data including actual portfolios or the possibility to separate active rebalancing behavior from market value fluctuations. Bucher-Koenen & Ziegelmeyer (2011) use German data to analyze the rebalancing behavior in financial crisis. They ask the investors what they have done with those assets whose value has decreased. Of 458 respondents 75% answer they have kept those assets, 13% report they have sold all the assets and 11.6% report they have sold some. Investors with low financial sophistication realized their risky portfolios more often than investors with higher sophistication. Investors older than 66 years were more likely to sell their risky assets than younger investors. Income uncertainty or unemployment did not factor as significant reasons to sell the portfolio. Bucher-Koenen & Ziegelmeyer conclude that the non-participation or withdrawing from the stock market of financially illiterate people can increase differences in wealth distribution. Withdrawing investors are not willing to return to the stock market because of bad experiences. That deters them from taking part in market recoveries. Thus, the crisis can have long-term and harmful effects on individuals' well-being.

Guiso *et al.* (2013) collect risk aversions[9] of clients in an Italian bank just before the financial crisis in 2007 and again, with the same clients, after the huge stock market crash in 2009. They find risk aversions to increase among all risk-aversion classes during this time period. Using experimental data they find the emotion of fear to increase risk aversion. Hoffmann *et al.* (2011) measure the monthly changes of Dutch investors' views by using simple questions on return expectations, risk attitudes and risk perceptions. The data covers a period from April 2008 to March 2009 and is linked with information on investors' trading behavior and performance within their brokerage accounts. As the crisis evolves, the data shows significant fluctuations in views, with return expectations being the most volatile ones. They find this development to be linked with trading; the higher the investors' return expectations or upward revisions of expectations or their risk tolerance, the more likely they are to trade and have higher buy-sell ratios. On the other hand, investors with higher levels of risk perception or upward revisions of risk perceptions trade also, but their buy-sell ratios are lower. The most successful investors trade less, and when trading, have lower buy-sell ratios, take less risk and are not overconfident about their investment skills, as measured by trading derivatives. Hoffman *et al.* make a conclusion that achieving success before and during a market decline leads some investors to become overconfident about their

[9] They use a standard lottery question as well as risk attitude question with three-level scale.

skills. Overconfidence makes them less risk averse in the following months, causing increasing trading volume. However, their investment performance does not persist as the crisis continues. In their later research with the same data, Hoffmann *et al.* (2013) find return expectations, risk tolerance and risk perception to quickly return to pre-crisis levels. The fluctuation of perceptions influences the investors' trading behavior but they do not stop trading or do not sell their portfolios. Instead, some investors utilize the low stock prices to enter the stock market.

Like Hoffmann *et al.* (2011, 2013), Roszkowski & Davey (2010) gather panel data about investors' risk tolerance and risk perceptions. They find risk tolerance to remain quite stable prior during and after a financial crisis. When examining risk perception, the results are different: 75 % perceive the stock market as much riskier than prior to the crisis. Roszkowski & Davey emphasize that the terms risk tolerance and risk perception should be distinguished and measured separately. Also Mellan (2009) discusses the same theme.

1.4 Confidence in own investor abilities: sometimes overconfidence with harmful effects

Researchers in various sciences have observed that individuals have a tendency to be too confident about the precision of their own knowledge. This happens especially with difficult tasks and when the feedback is slow and noisy (Griffin & Tversky 1992, Odean 1998). Investment in the stock market is an example of this kind of task. The phenomenon caused by overly strong confidence in one's own investor abilities is here referred to as *overconfidence*. In Chapter 1.4.1 we introduce the common manifestations of overconfidence, illusion of knowledge, illusion of control, self-attribution bias and miscalibration, as well as review the prior research on the phenomenon. Also, we present investor characteristics that may explain overconfidence. In Chapter 1.4.2 we consider the potential consequences of overconfidence; researchers point out that false confidence in one's own abilities can lead investors to trade too actively or to diversify their portfolios too narrowly. Lastly, we offer other potential reasons for active trading and poor diversification.

1.4.1 Manifestations of overconfidence and factors explaining it

Investors have a tendency to suffer from 1) *illusion of knowledge*. They can see themselves as knowledgeable about financial securities or perceive themselves to have more investment knowledge than peers have. They are too optimistic about the precision of their own knowledge and give too little attention to information which does not support their own views (Odean 1998). Barber & Odean (2002) see this as a result of the vast amount of information which is available, especially to online traders. Investors erroneously rely on information and use too much time gathering and utilizing it. This drives them to trade too actively. Dorn & Huberman (2005) state that investors, who perceive themselves as more knowledgeable than others are more commonly male, better educated, wealthier and have higher income levels.

Langer (1975) defines 2) *illusion of control* as a tendency to overestimate control over outcomes: the investor can estimate the probability of his personal success to be higher than objective probability predicts. Confidence in one's own success is strengthened by the familiarity of the task, personal involvement in the task, and competition with others. Odean (1998) investigates investors who switch from phone-based trading to online trading. Odean concludes that online investors may feel that placing orders personally improves the chances of successful trading, i.e. investors may erroneously think that personal involvement influences the outcome of trading. This illusion of control enhances investors' trading activity. De Bondt (1998) suggests that investors can suffer from a "false belief in universal liquidity". By universal liquidity they mean investors' false belief over control of risk: investors may erroneously believe they can control the risk by forecasting the price fluctuations correctly and assume that they can hedge their portfolios by selling quickly. The same belief can drive also them to under-diversify their portfolios.

Investors may also suffer from 3) *self-attribution bias*: they can estimate that success is a result of their own skills but that failure is due to some external factors (Dorn & Huberman 2005). Gervais & Odean (2001) define the self-attribution bias as a process in which the investor associates his success with his own ability and ignores the fact that positive returns are simultaneously enjoyed by the whole market. Falsely seeing his success as the result of his own ability causes him to become overconfident and to accelerate his trading. Daniel *et al.* (1998) link the self-attribution bias to processing of private and public information. Investors overestimate the precision of their private information and do not properly take account of information that contrasts with their own. Correction of information happens over time as more public information arrives. This learning causes excess volatility, short-term momentum, and long-term reversals of stock returns. Statman *et al.* (2006) find support for the idea that positive market returns increase investors' confidence via biased self-attribution. This, in turn, accelerates their market-wide and security-specific trading activity. The phenomenon is more pronounced with stocks with smaller market capitalization. When market returns decrease, the investors' overconfidence level diminishes.

People may suffer from systematic 4) *miscalibration*. This means that they are overconfident about the accuracy of their knowledge and they are prone to set overly tight confidence intervals. De Bondt (1998) asks U.S. investors to give their best return prediction and a lower and upper bound of return prediction such that they are 90% certain that the closing price of the DJIA (Dow Jones Industrial Average index, containing 30 large U.S. companies) will be within those bounds. They also ask investors to make the same estimate for the stock which has the largest share of their own stock portfolio. De Bondt finds that the respondents set too narrow confidence intervals with respect to historical volatility and that they give a more optimistic return prediction for their own portfolio than for the market portfolio. Glaser & Weber (2007) ask investors to state the upper and lower bound of 90% confidence intervals for five questions concerning knowledge of general economics and financial issues. When the correct answer lies outside the bounds, Glaser & Weber deem it a surprise. The mean percentage of surprises is 75%, i.e. much larger than 10%. Another way to measure miscalibration is to ask the respondents to evaluate the probability that they answered the questions at hand correctly. As with confidence intervals, the probabilities are generally too high.[10]

Researchers have identified several investor characteristics which may explain manifestations of overconfidence. Griffin & Tversky (1992) state: "When predictability is very low, however, experts may be more prone to overconfidence than novices". The findings that investment experience can cause overconfidence support this idea. Deaves *et al.* (2010) find greater experience to correlate with overconfidence. Investors learn as their experience increases. Their confidence intervals widen when their investments fail. On the other hand, their intervals narrow when they success. Barber & Odean (2001) argue that online traders are already more overconfident than average people when they switch from phone-based trading to online trading. The investors' confidence in their own abilities increased because of their investment experience and profitable trades. The overconfident investors are typically men, quite young and have high income levels.

In addition to experience, information gathering and time spent on it are also seen as characteristic of overconfidence. Guiso & Jappelli (2006) hypothesize that

[10] See also Russo & Schoemaker (1992), Klayman & Soll (1999), Soll & Klayman (2004), Deaves *et al*. (2010)

overconfident investors purchase more information than rational investors because they spuriously assume the value of the information is higher than it in fact is. They find that investors who spend 2 – 4 hours per week acquiring financial information have 27% lower Sharpe ratios than those who do not spend time gathering information. The negative correlation between Sharpe ratio and information is strong for overconfident investors i.e. males and investors who have high self-perceived financial knowledge. Also, the authors find that overconfident investors are less willing to delegate financial decisions to other people.

The effect of gender is mixed in the existing research. Biais *et al.* (2005) find a gender effect when they use miscalibration as a measure for overconfidence and regress it with trading performance. In a group of least-miscalibrated investors, men earn higher profits than women, but men who belong to the most miscalibrated investor category earn more negative profits than women. Using Finnish data, Grinblatt & Keloharju (2009) find men to trade more actively than women. They link trading activity to sensation-seeking behavior and to the proxy of overconfidence, two phenomena which can be more visible among men. The authors measure individuals' level of sensation seeking by using speeding tickets as indicators, and they measure overconfidence as forms of claim. Among both genders sensation seeking is positively correlated with trading activity. The same is true as regards the measure of overconfidence and trading activity among men (overconfidence is not measured among women because it is gathered among men who enlist in the army). Although sensation seeking is positively correlated with male gender, it does not explain gender differences in trading activity. Glaser & Weber (2007) do not find gender effect when they use three alternative measures of overconfidence. Gender is also used as a straight measure of overconfidence, see, for example, Barber & Odean (2001).

There are findings that entrepreneurs have stronger confidence in their abilities than average people. This can lead to overconfidence, see for example Cooper *et al.* (1998) or Bernando & Welch (2001). On the other hand, working in the public sector may indicate willingness to have a stable surrounding, which may be reflected in investing and risk-taking levels (see, for example, Selcuk *et al.* 2010).

Dorn & Huberman (2005) use the term "financial sophistication" and measure it through investment experience and knowledge about financial assets. To measure self-perceived financial knowledge, they ask German online investors how well they could explain 11 financial instruments to an imaginary friend. Also, they test the respondents' actual financial knowledge with true/false questions concerning financial knowledge and by asking the respondents to rank asset categories according to their riskiness. And thirdly, they ask the respondents to estimate their financial knowledge relative to peers. They use these financial sophistication variables as explanatory variables and find that self-perceived knowledge relative to peers explains the self-attribution bias and illusion of control. Dorn & Huberman conclude that relative knowledge could be used as a straight overconfidence measure. They also link relative knowledge, self-attribution bias and illusion of control to risk aversion. The more knowledgeable the investor thinks himself to be relative to peers, or the more he imagines his investment success to result from his own abilities (self-attribution bias), the more risk tolerant he perceives himself to be. Guiso & Japelli (2009) use the term "financial literacy". They test actual and self-perceived financial knowledge and find the factors to only weakly correlate. They state that relying on investors' self-assessments about financial knowledge is problematic because investors have a propensity to be overconfident about their knowledge.

1.4.2 Reasons for over-active trading and under-diversification: due to overconfidence or something else?

There are two main issues which are typically assumed to be consequences of overconfidence: too much trading and under-diversification of portfolio. Overconfidence literature assumes that investors are overly reliant on information, especially their own information, and give too little attention to public information. This results in differences in opinions which induce overly active trading. Overconfident investors overestimate expected profits and engage in trades where the profits are insufficient to cover the costs of trading. Through excessive trading the investors lower their expected utility. This is in contrast to rational investors who purchase information and trade only when doing so increases their expected utility (Odean 1998, Daniel *et al.* 1998).

Odean (1999) tests brokerage account owners' potential overconfidence in the precision of own information on the U.S. stock market. He measures whether the stocks the investors buy outperform the stocks they sell after the transaction costs have been subtracted. Odean finds the stocks the investors buy to underperform the ones they sell, indicating that investors rely too much on their own information and misinterpret other information. Barber & Odean (2002) analyze investors who switch from phone-trading to online trading. By examining the six-year returns prior to switching online, they find the switchers to have been outperforming the market and the average investor with the same portfolio size. Barber & Odean argue the strong performance had made these investors overconfident and thus to suffer from self-attribution bias. After going online, they have access to a large quantity of information. They spend much time with information and may have too optimistic beliefs concerning its usefulness. They may feel that personally placing their orders improves returns. Barber and Odean find that investors accelerate their trading after going online. Also, the number of speculative trades the investors engage in nearly doubles. For these investors, active trading results in performance that no longer outperforms the market or the average investor. In their prior research (Barber & Odean 2000) the authors find the same results: the returns of overconfident investors who trade the most actively are below the market return and average investor.

Glaser & Weber (2007) set questions to online investors by asking about their knowledge of finance and general economics. They measure investors' miscalibration on stock market forecasts by using the confidence-interval technique. They also test the better-than-average effect through questions concerning the investors' investment skills and performance relative to others. By connecting this questionnaire-based information with investors' actual stock market transactions, they find the better-than-average effect to have a significant and positive effect on trading activity. The miscalibration effect was viewed as non-significant. The other variables which explain trading are portfolio size and warrant trading. Glaser & Weber do not find a link between investment performance and overconfidence. Contrary to Glaser & Weber, Biais *et al.* (2005) find miscalibration to lower trading performance. Dorn & Huberman (2005) test the influence of self-attribution bias and illusion of control on trading activity and do not find them to correlate with intensity of trade. They measure the investors' self-perceived investment knowledge relative to other investors but do not use it as a measure of overconfidence. They find a positive correlation between relative knowledge and trading activity, and state that relative knowledge could be treated as an overconfidence measure as well.

Overconfidence is only one potential explanation for active trading. For example, background risk can affect investors' trading activity. Investors face different levels of uncertainty which may stem from income, occupation, age or amount of total wealth. This creates differing needs to hedge the portfolio as shown in the form of active trading (Haliassos & Bertaut 1995, Heaton & Lucas 2000a or 2000b, Campbell & Viceira 2002). Investor sophistication might influence trading volume too. Calvet *et al.* (2009a) use investors' education, income and wealth level as measures of financial sophistication. When studying Swedish households' entry and exit decisions during the 1999–2002 period, they find financially sophisticated investors to be more likely to enter and less likely to exit from the stock market. Dorn & Huberman (2005) also measure investors' financial sophistication by using their subjective characteristics (self-perceived investment experience, knowledge on financial instruments and risk attitude) and link those attributes to portfolio turnover. The authors find that more risk-tolerant investors as well as those who perceive their investment knowledge to be higher than peers tend to trade more actively. Investors perceiving themselves as experienced ones trade less.

Overconfidence has also been linked to under-diversification of stock portfolio. Investors should be mindful of risk-return ratio and select a portfolio consisting of a variety of stocks to reduce unsystematic risk. Relying too much on their abilities and own information, overconfident investors might choose to hold portfolios marked by stock-picking and under-diversification. These investors might focus on certain industries they are familiar with or might invest only in domestic stocks. Guiso & Jappelli (2006) use gender and self-perceived knowledge of stocks as measures of overconfidence and test rational and overconfidence models to examine differences in diversification, information acquisition, portfolio performance and delegation of investment decisions. They find that investors who acquire more information have less diversification. The negative correlation is larger with overconfident investors.

Goetzmann & Kumar (2008) use high turnover and low performance as measures of overconfidence and find the factors to explain below average diversification. In contrast with the results of Goetzmann & Kumar, Dorn & Huberman (2005) do not find self-attribution bias or illusion of control measures of overconfidence to explain diversification decision. Rather, they find self-perceived experience in investing, higher risk aversion and investor's own evaluation as well as his actual knowledge of investing to explain wider diversification.

It is essential to take into account also other aspects than overconfidence when analyzing diversification decision. Goetzmann & Kumar (2008) use U.S. data and find that under-diversification is largest among young, low-income, less-educated and less-sophisticated investors. By sophistication they mean option trading, short-selling, occupation, income, wealth and investment experience. Investors who diversify widely by investing in mutual funds and foreign stocks diversify their domestic stock portfolios better than other investors. Other variables which explain wider diversification are longer experience and the disposition effect, that is, investors' reluctance to realize losses. Goetzmann & Kumar also test the influence of trend chasing on diversification decision. To do this they create a trend score: a large negative trend score indicates a belief in market reversal (contrarian strategy) and a large positive trend score indicates a belief in continuation of market trend (trend chasing strategy). They hypothesize that those investors who are more sensitive to past price trends hold less-diversified portfolios and find support for this hypothesis. Diversification also shows through the investors' Sharpe ratios and Jensen's alphas; under-diversified investors earn lower returns measured by these figures. The highest losses are associated with older investors. As a curiosity, they find high-turnover and under-diversified portfolios to perform better than high-turnover but better-diversified portfolios. They judge this result to implicate a small group of very skilled investors.

Guiso & Jappelli (2006) relate diversification to investment in information, risk aversion, wealth, demographic variables and to investors' trust in financial advisors. Those investors who spend 2–4 hours/week on investment information diversify less than those who spend no time. Trust in financial advisors and high risk aversion is associated with larger diversification. In Guiso & Jappelli's later research (2009) they link under-diversification to investors' financial literacy. They measure financial literacy with questions that objectively measure investors' understanding of the riskiness of asset categories, interest rates and inflation as well as the meaning of diversification. They find higher financial literacy to be positively correlated with diversification. Guiso & Jappelli also clarify investors' self-perceived financial sophistication by asking them to evaluate how well they know the characteristics of various financial instruments. They find self-perceived financial sophistication to correlate only weakly with actual sophistication. They state that investment advisors should not rely on clients' own perceptions about their financial knowledge but should measure their knowledge by the standard test.

Many empirical findings indicate that familiarity is a factor in under-diversification. People tend to bet on domestic stocks, their employers' stocks, companies which have headquarters close to their living area, or simply the stocks they are familiar with. They may think they have more superior information than the market has and that they can utilize this information to achieve return. This belief leads investor to put money in familiar stocks and to ignore the need for diversification as a tool for risk control[11]. De Bondt (1998) asks U.S. investors' opinions on risk and return. He finds investors to express the belief that proper understanding of several firms is a more effective way to manage risk than wider diversification. Huberman (2001) assesses the tendency towards familiarity as "a nonpecuniary dimension to the traditional risk-return trade-off". Heath & Tversky

[11] See for example Merton (1987), Heath & Tversky (1991), Huberman (2001), Grinblatt & Keloharju (2001) or Graham & Harvey (2009)

(1991) use the term "competence hypothesis" when they refer to investors' self-perceived confidence of their knowledge in a given context. They state that the competence hypothesis "might help explain why investors are sometimes willing to forego the advantage of diversification and concentrate on a small number of companies with which they are presumably familiar".

1.5 Purpose of the thesis and research problems

The purpose of this thesis is to test the power of investors' *subjective attributes* – self-perceived attitudes, evaluations and judgments – to explain investment behavior and its cross-sectional variation. As examples of subjective attributes we specify ability to withstand risk, investment experience, activeness in collecting economic information and confidence level in own investment abilities. We link variation in investment behavior to investors' demographic and socio-economic characteristics as well, which we refer to *objective attributes*. Whereas prior research on objective attributes is comprehensive, subjective attributes are much less investigated. The importance of also identifying psychological-based subjective attributes stems from their predictive power as regards investors' portfolio choices and actions in their portfolios. Better understanding of the attributes that generate differences in investing hold potential for understanding deviations from standard financial theories and for taking into account the comprehensive mix of attributes when developing behavioral models. Also, better understanding of the causes which drive investment behavior has implications for the financial sector, its regulators and its researchers as well as for authors who attend to personal financial literacy education (discussed further in Chapter 6).

We approach the influence of subjective and objective attributes on investment behavior from three dimensions and construct empirical research around each dimension (see Chapters 3–5). In the following paragraphs, we introduce these dimensions by setting a research problem for each dimension and clarifying its background. We specify hypotheses for the research problems in the empirical research chapters and discuss the implications of results in Chapter 6.

The influence of subjective attributes on portfolio choice (Chapter 3)

Question 1a: *Does risk profile, asked by simple questions on investor-specific risk-standing ability and return target, allow measurement of an investor's actual risk-standing ability, as shown through his actual portfolio choice?*

Question 1b:
Which investor-specific subjective and objective attributes best explain risk profile?

We start the empirical research on subjective and objective attributes by testing the ability of simple questions on risk-standing ability and return target to capture actual, investor-specific risk-standing ability[12]. In answering these questions, the investor classifies himself as a certain risk profile. To verify whether this risk profile describes the investor's actual risk-standing ability, we test the risk profile against his actual risky share i.e. his portfolio choice. Then we test the ability of other subjective attributes to explain the risk profile choice. Those attributes are self-perceived investment experience, activeness in following economic events and willingness to make one's own investment decisions or, alternatively, to request a ready proposal from an investment advisor. We also test the power of objective attributes like gender, age, education, income level and wealth to explain risk profile choice.

The real-world need to measure risk profile and other investor-specific attributes comes from EU legislation, which requires investment advisors to measure their clients' risk-standing ability, their investment objectives, experience, knowledge and existing wealth on the asset-class level. In addition to fulfilling the requirements of legislation, measurement of these subjective and objective attributes represents excellent data in which the attributes are connected with investors' actual investment decisions, i.e. their portfolio choices and breakdown of wealth into a single asset-class level. This data is useful for the purposes of our thesis in two ways. Firstly, it gives us a possibility to test the influence of subjective as well as objective attributes on actual investment behavior. Secondly, we can verify if the EU legislation ordering collection of risk profiles and other attributes is meaningful as regards understanding investor-specific needs and their influence on investment behavior. If these attributes have the capacity to predict investment

[12] These simple questions are the following ones: How would you describe yourself as a saver and as an investor? How do you react to value fluctuations in your savings and investments? For both questions the investor has five alternatives from which to choose. His answers define which of the five risk profiles he belongs to.

behavior, the legislation is meaningful, i.e. that collecting attributes and taking them into account in investment consultation betters investor protection.

Rebalancing behavior during the stock market crises 2008–2009 and 2011 (Chapter 4)

Question 2: *Does financial sophistication, measured by subjective and objective attributes, explain differences in rebalancing behavior during the stock market crises?*

Our second empirical research is useful for the purpose of our thesis by linking subjective and objective attributes to investors' actions with their fund portfolios. We test the power of those attributes to show investors' rebalancing behavior during the two severe market crises at the turn of the last decade. By rebalancing behavior we mean investors' own transactions within their stock and combination fund portfolios, i.e. we separate this active rebalancing behavior from the passive changes to which portfolios are exposed because of market value fluctuations. In that way we classify investors into three rebalancing groups: sellers, no rebalancing and buyers. As a theory base for differences in rebalancing behavior we use the effect of investors' financial sophistication, which we measure by using the same investor-specific subjective and objective attributes than in the first research problem. Based on previous findings (see, for example, Calvet *et al.* 2009a, 2009b or Bucher-Koenen & Ziegelmeyer 2011) on the positive correlation between financial sophistication and investment capability, we expect the more financially sophisticated investors to understand the long-term character and non-predictability of the stock market. This would assumedly preclude them from selling their fund portfolios partly or totally at decreased market values and perhaps even encourage them to be bold enough to resist the decline of their portfolio's market value and buy more fund shares at low prices. Similarly, low financial sophistication would show as opposite behavior. In addition to fitting the purpose of our thesis, this research provides useful information for authors who attend to personal financial literacy education and for financial institutions.

Investor-specific trading and diversification decisions: due to overconfidence or something else? (Chapter 5)

Question 3a: *Do the following subjective and objective attributes explain trading activity and diversification decisions?*

3a1) *Self-perceived confidence in one's own investment abilities*
3a2) *Other subjective and objective attributes*

Question 3b: *Do investors see total withdrawal from the stock market as an alternative to proper diversification or as a means to hedge the portfolio?*

In our third empirical research we further examine investors' actions with their portfolios by investigating trading activity and diversification decisions of common stock portfolios. As the main subjective explanatory attribute, we use investors' self-perceived confidence in their investment abilities, which can also show as overconfidence. Prior research links overconfidence to active trading and to under-diversification of portfolio (Odean 1999, Glaser & Weber 2007). In the present research, we test also the power of other investor-specific subjective and objective attributes to explain trading and diversification decisions. We gather our data via a questionnaire targeting members of the Finnish Shareholders' Association. In order to avoid relying on a single measure, we construct a comprehensive mix of measures of overconfidence and take into account various manifestations of overconfidence: illusion of knowledge, illusion of control, self-attribution bias and miscalibration (presented in Chapter 5.2.1). We use calibration-based techniques (respondents give their best prediction and a 90% confidence interval) as well as claims in which the respondent chooses his answer from five alternatives. Construction of several overconfidence measures gives us a possibility to compare the measures and their correlations as well as their influence on actual investment behavior. As other investor-specific attributes we use the same variables cited in earlier research problems (Questions 1 - 2) and also create new attributes in order to supplement the results of the thesis.

Research question 3b indicates that we ask investors' opinion about total withdrawal from the stock market (referred to as the *On/off variable*) in the situation of stock market decline and use it as potential variable to explain under-diversification. This variable arises from rebalancing behavior research (Chapter 4); investors classified as sellers had a propensity to sell their fund portfolios totally, not only partly. We test whether this phenomenon is discernible in another dataset. We state that investors can view total withdrawal as an alternative to proper diversification or as a means to hedge their portfolios.

Overconfidence research completes our investigation of the influence of subjective attributes on investment behavior and cross-sectional variation within it. Overconfidence results can be utilized by financial institutions, researchers and authors who attend to personal financial literacy education when they cooperate with individuals.

1.6 Significance of our research: why is it important to investigate investment behavior?

Does it matter what causes give rise to cross-sectional differences in investment behavior? Should we take into account these differences when giving investment advice? Should we put more effort into teaching individuals to better understand financial tasks and to limit investment mistakes? We argue the answer to these questions is *Yes.* There are many points to support this argument. Understanding investment behavior is important because of the growing popularity of stock ownership. Investments in the stock market are not a privilege of the wealthy but millions of middle-income individuals invest their savings in direct or indirect stock holdings. Much of this is due to increased standards of living around the world as well as the growth of individual control over retirement plans. The growth of investments in risky assets fulfills the basis of financial theory which states that every individual should hold some amount of equities. As compensation for the risks they take, investors get a risk premium over the risk-free rate. Invested in stock the market, wealth grows larger and enables bigger consumption in the future.

Investment decisions are not easy – they are complex and require many kinds of information. Investors may not be educated about financial tasks, they must plan over long but finite horizons, they may have important non-tradable assets (human capital), they hold illiquid assets (home or their own firm), they face constraints on their ability to borrow, and they are subject to taxation. Differences in individuals' abilities to make right investment decisions can widen wealth differences and living standards. Haliassos & Bertaut (1995) use the term "stockholding puzzle" when they analyze potential reasons for non-participation in the stock market. They divide the reasons into fundamental and inertial factors. Fundamental factors are, for example, differences in income or total wealth level, income risk, and life-cycle stage. Inertial reasons may arise from cultural reasons, like race, gender or marital status, and from costly information. We should be able to lower the barriers of non-participation by identifying those barriers and trying to cross them. Campbell (2006) argues that education may reduce the costs of stock market participation. Those costs are, for example, fixed entry costs or costs due to information acquisition. Using Swedish data, Campbell finds that educated households diversify their portfolios more efficiently than less-educated ones. This leads the more educated investors to achieve higher return expectations per unit of risk. Using the same Swedish data, Calvet *et al.* (2009a, 2009b) find that the mistakes investors make result in a cross-subsidy from less-educated households to more educated ones.

Investment behavior is also worth understanding because of its influence on asset prices. Prices do not consist only of fundamentals as the theory of rational expectations says. Prices consist of fundamentals but also a behavioral aspect, market sentiment. Shefrin (2005) argues that the sentiment component arises because of “greed and fear”, the changing mind of investors. When individuals invest in the stock market, they are confronted by fundamentals and sentiment alike and they take both into account when making decisions. Sentiment can cause, for example, herding behavior; investors can be prone to go with the crowd by buying securities with high prices and selling those with low prices.

Growing interest in stockholding also has influences on the investment product sector. Understanding investment behavior helps financial institutions to take into account the cross-sectional differences of investors and to develop products that take those differences into consideration. The need to pay attention to various needs also stems from financial market regulation authorities, which have made much effort to better investor protection. The development work of financial institutions should concentrate not only on construction of investment products but also on building up modern technology-based systems, combining knowledge of finance and information technology. These financial planning systems could have an important role in providing investment advice to help households make their decisions. Examples of such computer programs are, for example, the Financial Engines website (financialengines.com) and Australian-based risk profiling system (riskprofiling.com). In our home country, Finland, investors can find investment advisory tools, for example, from financial institutions’ websites (e.g. op.fi/op/henkilöasiakkaat/saastot-ja sijoitukset/sijoittajakuva).

1.7 Contribution of the thesis

In the following chapter we outline the main contributions of our thesis. We examine these in three parts analogously to the progression of the thesis, i.e. by clarifying the contribution of each of the three empirical research chapters. In the end of our thesis (Chapter 6), we shortly re-address the contributions and discuss the implications of our research.

As a joint conclusion of our research, we state that our results confirm the importance of considering self-perceived attitudes, evaluations and judgments – subjective attributes – when investigating investment behavior and its cross-sectional variation. These attributes have even more predictive power regarding investors' portfolio choices and actions with their portfolios than the more commonly used socio-economic and demographic variables (=objective attributes). Better understanding of the attributes that generate differences in investment behavior is important and holds potential for understanding deviations from standard financial theories and for taking into account the comprehensive mix of attributes when developing behavioral models. Although objective attributes need to be taken into account as well, researchers should turn their focus to subjective attributes, developing methods how to measure them and how to link them to behavioral models. We assert that our results are based on data which allows us to link subjective and objective investor attributes with investors' actual investment behavior. This opportunity is afforded only rarely in research on subjective attitudes.

We contribute to the existing research by confirming the meaning and importance of European Union regulation. Investor's risk-standing ability and return target, i.e. the investor-specific risk profile, can be described by using non-complex risk-standing measurement tools. This risk profile is tightly connected with the investor's actual risk-taking level, which is visible through his former and future portfolio choice decisions i.e. his actual risky share. Knowledge of a client's risk profile helps the investment advisor to find suitable products for his client's personal needs. This in turn betters investor protection. Additionally, the other self-perceived, subjective investor attributes represent a contribution to investment behavior and portfolio choice research. Their explanatory power regarding risk profile and risky share choice emphasizes the importance of taking these attributes into account in portfolio choice models.

The results of rebalancing behavior research were quite a surprise to us. According to our ex ante assumption, higher financial sophistication measured by subjective and objective investor attributes should show as more professional investment behavior; as an ability to understand the long-term character and non-predictability of stock instruments precluding sophisticated investors from selling their fund portfolios and even encouraging them to resist the decline of the portfolio's value and to buy more at low prices. Low financial sophistication would accordingly show as the opposite behavior. We show this to hold true only in part. Three attributes of sophistication – higher monthly net income, male gender and belonging to higher risk profiles – showed as boldness to belong to the buyer category. In contrast with investors of lower sophistication, financially more sophisticated investors, measured by their subjective characteristics, i.e. investors considering themselves experienced investors, following economic events most actively, or having a willingness to make their own investment decisions, were active in selling their portfolios. Most typically they sold their portfolios totally, not only partly. We contribute to the prior research by showing that financial sophistication as measured by subjective attributes does not necessarily always result in more professional investment behavior. We put forward the notion that financial sophistication – in addition to its very positive influences on wealth care – can lead an investor to make mistakes like total withdrawal from the stock market, realization of short-term losses or exposure to timing problems of stock portfolio rebuilding. Low investor sophistication can protect an investor from reacting to market fluctuations with the same intensity. Of course, the argument on investment mistake of sophisticated investors holds only if the reader is a proponent of efficient market theorem stating that prices cannot be foreseen.

We find several measures of overconfidence, asked as claims, to explain the trading activity of stock portfolio. The more confidently the investor relies on his investment ability and knowledge or superior past performance in comparison to others (Self-attribution bias claim, Illusion of knowledge claims), or the more he relies on his ability to foresee future price level (Illusion of control claim), the more actively he trades with his stock portfolio. Diversification decisions are much less linked with measures of overconfidence. Still, belief in one's own ability to time the selling point right (Illusion of control claim) is reflected in narrower diversification. This observation is supported by investors' On/off movements, i.e. willingness to sell their portfolios wholly instead of partly before a self-evaluated stock market decline. Such total realization of portfolio accords with our empirical findings on rebalancing behavior. We contribute to prior research by arguing that investors may rely on their market-timing skills as a tool to control or hedge portfolio risk to the detriment of diversification. In behaving that way, they ignore the random walk of stock prices which states that market prices cannot be reliably foreseen. Also, we contribute by showing that simple questions asked as claims seem to work better as measures of overconfidence than more commonly used calibration-based techniques. Additionally, the other self-perceived subjective characteristics also have explanatory power regarding both trading and diversification.

1.8 Structure of the thesis

In this chapter we introduce the progression of the forthcoming chapters of our doctoral thesis. In Chapter 2 we present the theoretical background to our research on investment behavior. Because our empirical research is composed of three sections which each investigate investment behavior from unique angles, we consider theory from these three perspectives. The perspectives are as follows: 1) Theoretical background on portfolio choice problem, 2) Theories explaining trading and rebalancing behavior, and 3) Theory basis for overconfidence. Chapters 3 – 5 detail the three empirical research works. They contain a conjunctive aspect to fulfill the overall objective of our research: to draw attention to the role of self-perceived attitudes and evaluations (subjective investor attributes) in investment behavior. The importance of shifting the focus onto these characteristics is based on their predictive power regarding investment behavior.

Chapter 3 contains the first empirical research *The influence of investor's subjective attributes on portfolio choice*. We test the ability of simple questions about risk and return to capture investor-specific risk-standing ability (measured as risk profile) as shown through portfolio choice, i.e. investor's risky share. We run regressions in which we use investors' subjective and objective attributes as explanatory variables and test their power to explain variation in risk profiles. The measurement of investor-specific risk profile and factors which explain its variation between investors is very important also from a legal aspect. EU regulation requires financial advisors to measure these profiles and other investor characteristics. We test whether such regulation is meaningful; do these investor characteristics accord with the investor's actual risk-standing ability and portfolio choice.

Chapter 4 focuses on our second research problem, investors' rebalancing behavior during the serious stock market crises at the turn of the last decade. We title the research *Rebalancing behavior during the stock market crises 2008–2009 and 2011*. By rebalancing behavior we mean investors' own actions with their stock and combination fund portfolios, i.e. we separate the passive changes to which the portfolios are exposed due to market value fluctuations from active changes. Our aim is to draw attention to the financial sophistication characteristics that explain rebalancing behavior and related differences. As characteristics of financial sophistication we use the same subjective and objective attributes which we use in the first empirical research. We test if higher financial sophistication is visible as more professional rebalancing behavior. This should show as understanding of the long-term character and non-predictability of the stock market precluding investors from selling their fund portfolio, or even emboldening them to resist the value decline and buy more fund shares at the low prices.

In chapter 5 we focus on investors' confidence level in their own investor abilities – which sometimes shows as overconfidence – as a potential explanation for differences in trading and diversification decisions in common stock portfolios. We entitle the research *Investor-specific trading and diversification decisions: due to overconfidence or something else?* As explanatory variables we also test a number of new subjective and objective attributes in addition to those used in Chapters 3 and 4. We test the investors' confidence level (measures of overconfidence) by creating several measures in order to avoid relying on only a single or a few measures of overconfidence. By employing a large variety of overconfidence measures and by examining various manifestations of this phenomenon, we aim to increase the knowledge of how to measure potential overconfidence. Also, this research chapter gives us a good opportunity to test the influence of self-perceived, subjective attributes on investment behavior once again, and with a different database than the first and second empirical chapters.

Chapter 6 concludes the thesis. The chapter contains a discussion of our empirical findings and their contributions, implications for financial sector and for various agents, as well as motivation for further research. The references and appendices complete the thesis.

2 Theoretical background

Despite researchers' laudable efforts, we cannot say we wholly understand the mechanisms that drive individuals' investment behavior. There is an ongoing debate as to whether we should base the research on standard financial theory, which rests on utility maximization and uncompensated risk avoidance, or whether we should use behavioral models with non-rationality and heuristics. The investment mistakes individuals commit – the differences between positive and normative economics – cast a shadow over the models of normative economics. Can they ever completely explain the behavior of individuals? Or perhaps it is better put another way around: can individuals be trained to behave rationally and maximize their utility to avoid mistakes? Or do we simply need to accept that rationality-based economic theories can recognize the non-rationalities and cross-sectional differences in investment behavior but cannot capture, or can only partly capture, the causes of these differences?

Our doctoral thesis includes reflections on both rational and behavioral theories of finance. Being old, having small total wealth, low education or salary are natural explanations for smaller risky share. These people's behavior with low risky shares or small number of asset classes can well be explained as following rational behavior. On the other hand, their total nonparticipation in the stock market can be regarded as an investment mistake and considered through behavioral modeling. And of course, overreaction to stock market fluctuations or overly strong confidence in one's own investor abilities are manifestations of behavioral finance. Rather than speaking of a rational or behavioral theory basis, we consider our research *household finance research* with rational and non-rational reflections. Household finance examines how households use financial instruments to attain their objectives and how they invest their existing wealth (Campbell 2006). In the overview below, we present the theoretical background which our three empirical researches lean on.

2.1 Theoretical background of portfolio choice problem

Investor's portfolio choice problem is classically modeled by a concave utility function on final consumption. The investor will select a portfolio consisting of risk-free assets and number of risky assets which maximizes his expected utility of lifetime consumption. The model assumes that there are no transaction costs and the risky portfolio includes all existing stocks with weights offering the best risk-return combination. Thus, zero risky asset ownership should not be seen – only different shares invested in a risky asset portfolio resulted from different risk attitudes. The degree of concavity of the utility function describes the investor's degree of absolute risk aversion. The larger the investor's absolute risk aversion, the smaller is the portion of wealth he invests in risky assets. Thereby, all portfolio choice heterogeneity should be explained by different risk attitudes (Markowitz 1952, Samuelson 1969, Merton 1969).

Researchers have tried to capture risk attitudes by using various measurement techniques. The most formal way is to use standard lottery questions. This means that the investor is asked to make a choice between certain and uncertain outcome. His answer reveals his certainty equivalent, which enables the calculation of his risk aversion (Barsky *et al.* 1997). Another way to measure risk-standing ability is to use a questionnaire or experiment. The most well-known risk attitude question belongs to the question pattern of the Survey of Consumer Finances (SCF), which is a survey of U.S. families with a long history. The question has the following form:

Which of the following statements comes closest to the amount of financial risk that you are willing to take when you make your financial investment?

- Take substantial financial risks expecting to earn substantial returns
- Take above average financial risks expecting to earn above average returns
- Take average financial risks expecting to earn average returns
- Not willing to take any financial risks

Grable & Lytton (2001) criticize that the SCF question does not capture the multidimensional nature of risk-standing ability and does not offer a possibility to contrast its results with another risk attitude question. For their part, Grable & Lytton (1999) create a 13-item risk tolerance tool which measures various dimensions of risk tolerance. Grable & Lytton's tool is widely acknowledged by other researchers and it is used in real-life investment consultation. Kapteyn & Teppa (2011) test various risk attitude measurement techniques. They use the certainty equivalent technique of Barsky *et al.* (1997) as well as ad hoc questions which clarify the investors' investment strategies and saving motives in an informal way. They find the simple ad hoc questions to explain portfolio choices better than the more sophisticated measures with a firmer basis in economic theory. They argue this is due to the simplicity; the simple questions are easier to understand and they demand less financial capability. In Chapter 1.2.1 we present the prior empirical research on risk-aversion measurement.

2.2 Theories explaining trading and rebalancing behavior

According to traditional financial models with rational expectations, there is no or only little space for trading with a risky portfolio (Milgrom & Stokey 1982, Tirole 1982). Because stock market-linked mutual funds and saving insurances are well-diversified, there should be even less need to trade with them than to trade with common stock portfolios. The reasons behind trading with a risky portfolio can be a willingness to take into account the market value fluctuations to which the portfolio is exposed because of stock market up- or downturn and to modify the portfolio against these movements, i.e. to rebalance the portfolio. In the theory summary below, we do not separate trading and rebalancing but rather expect both terms to fit the theories.

There is no commonly accepted, single theory determining the reasons for trading and rebalancing. They may be enhanced by the disposition– a propensity to hold losing stocks and sell winning stocks too quickly (Shefrin & Statman 1985, Odean 1998). Trend chasing is motivated partly by the same reasons; investors may prefer funds operated by successful wealth managers with good performance and sell funds with bad returns (Brown & Goetzmann 1995, Bailey *et al.* 2011). Overconfidence in own investment skills can cause investors to rely on their abilities too much, which in turn enhances their buying and selling decisions (Klayman & Soll 1999, Barber & Odean 2001, Glaser & Weber 2007). Background risk can affect investors' activity in their portfolios; investors face different amounts of uncertainty related to their income, age or amount of total wealth, which creates differences in levels of uncertainty and need for liquidity and shows as trading and rebalancing (Haliassos *et al.* 1995, Heaton & Lucas 2000a or 2000b, Campbell *et al.* 2002).

When we link trading and rebalancing tighter to stock market up- or downturn periods, the theory basis can be enlarged. Actions in risky portfolios can be explained according to the theory of herding (Banerjee 1992, Santacruz 2009). Banerjee describes the information on future returns as signals. Each investor notices the decisions of other investors. The investor then chooses to use his own signal or the other investors' signals. Herding investors are prone to choose the same signal as the other investors rather than use their own signals i.e. herding investors share a common view that a market uptrend or downtrend will continue. This view causes investors to invest more in order to take advantage of a positive market situation or, conversely, to sell their portfolios to diminish the losses during a negative market. By behaving that way, investors have a propensity to buy when the stock prices are high and to sell when the prices are low. Trading and rebalancing behavior can be seen also as a manifestation of mental accounting (see, for example, Thaler 1985, Statman 1999 or Shefrin & Thaler 1988). Instead of seeing their wealth as a one unity with different correlations between wealth classes, investors segregate their wealth into separate "layers"; they see cash, bonds, mutual funds and directly owned stocks in different layers. They overlook the correlations between the layers and focus on the risk of each layer. Statman (1999) calls these behavioral portfolios. Separate layers induce investors to trade to minimize the value decline of single layer even though the decline has no large effect on total wealth.

Trading and rebalancing behavior can be explained according to empirical findings on varying risk aversion. During a decline of stock prices, investors tend to become more risk averse, which can prohibit them from buying risky instruments despite lower prices. Barberis *et al.* (2001) find that after a boom in stock prices investors are less risk averse because the gains they have achieved during the boom give them patience to withstand the declining prices of a stock market downturn. When the fall of stock prices continues, investors start worrying over further losses and become more risk averse. These fluctuations in risk aversions lead to higher volatility of stock prices than predicted by traditional asset pricing models with rational expectations.

Lastly, we review trading and rebalancing behavior through investors' financial sophistication. Campbell (2006) states that people do not seem to invest according to standard financial theories based on rationality and utility maximization. Their behavior seems to follow more or less behavioral models with non-rationalities and heuristics. Financially sophisticated investors have more ability to avoid investment mistakes – "the discrepancies between observed and ideal behavior" – than less sophisticated ones. Calvet *et al.* (2009a) use investors' education, income level and wealth as measures of financial sophistication. Dorn & Huberman (2005) measure financial sophistication by using investors' subjective characteristics: self-perceived investment experience and knowledge about financial instruments. As explanatory variables, financial sophistication characteristics have been linked to investment behavior also regarding other aspects than trading or rebalancing. As an example we cite financially sophisticated investors' more professional diversification decisions (see Guiso & Jappelli 2006 or Goetzmann & Kumar 2009).

2.3 Theory base for overconfidence

According to traditional financial theories like the capital asset pricing model and efficient market hypothesis (Markowitz 1952, Fama 1970), people make rational choices and maximize their expected utility. In practice, however, these theories have been criticized due to people's irrational behavior in the real world. For example, it is commonly accepted that people have a tendency to be overconfident about the precision of their own knowledge (Griffin & Tversky 1992, Daniel *et al.* 1998, Odean 1998, 1999). This happens especially with difficult tasks and when the feedback is slow and noisy. Selecting stocks which will outperform peers (stocks from the same industry) or the market is a difficult task and the feedback is both slow and noisy. People tend to overweigh salient information and to put overly large probabilities on extreme circumstances. Also, they focus attention on information which is consistent with their prior information and overlook information which does not support their own beliefs. People calibrate their private information too tightly by setting too tight confidence intervals around their own signals. In behaving that way, they underestimate their own forecast errors and trade according to their spurious forecasts, which leads to overreaction of stock prices. When new public information signals arrive, the stock prices move closer to their full-information value. Kahneman & Tversky (1973) state: "In making predictions and judgments under uncertainty, people do not appear to follow the calculus of chance or the statistical theory of prediction. Instead, they rely on a limited number of heuristics which sometimes yield reasonable judgments and sometimes lead to severe and systematic errors." Overconfidence shows also as positive self-evaluations; people see themselves as better than average or they see themselves more positively than others see them. They attribute the honor of their success to themselves and blame their failures or miss-success on others. People also have a tendency to overestimate their control over outcomes (Kahneman & Tversky 1973, Langer 1975, Odean 1998).

There are two phenomena which are typically assumed to be consequences of overconfidence; overly active trading and lack of proper diversification. Investors rely too much on their own present and posterior information. The more overconfident the investors are, the more their beliefs deviate. They give too little attention to public information or other investors' information. This results in differences in opinion, which causes active trading. By trading too frequently, the investors lower their expected utility. This contrasts with rationality, which says that investors trade only when doing so increases their expected utility (Daniel *et al.*

1998, Odean 1998). Odean (1998) divides investors into price takers (information is well disseminated in market), market insiders (information is concentrated) and market makers (investors select to buy or not to buy costly information). All of these types have their special ways to suffer from overconfidence, which shows through their trading activity. In addition to overconfident traders, there are also rational traders. Their information can be overlooked because of overconfident traders' false belief in their own information.

In addition to trading activity, overconfidence can be seen through diversification decisions. Again, relying too much on their own investor abilities or information, overconfident investors might choose to hold portfolios marked by stock-picking. They do not properly take into account that the volatility of a portfolio is less than the volatilities of single stocks. They falsely believe they have an ability to choose those few stocks with the highest returns. Even though they hold several stocks, they may prefer certain types of stocks and ignore the correlations between them. Insufficient diversification then shows as excessively high unsystematic risk in the portfolio. This is in contrast with rationality-based models, which say that unsystematic risk can be reduced or eliminated through proper diversification. (Goetzmann & Kumar 2008, Guiso & Jappelli 2009).

2.4 Guidance to empirical research and data

After introducing the purpose of our thesis, setting the research problems, reviewing the prior research and linking the theory basis to this entity, we turn to the empirical research chapters. We consider one research question at a time, construct hypotheses around it and conduct empirical research by testing those hypotheses and discussing the results. Taken together, the research aims to fulfill the purpose of our doctoral thesis, i.e. to test the power of investors' subjective attributes – self-perceived attitudes, evaluations and judgments – to explain investment behavior and related cross-sectional variation.

Our three empirical research chapters are based on two different databases. In the first and second chapter, we use a dataset which describes the clients of a Finnish financial institution. The second dataset is collected from a survey which we made among the members of the Finnish Shareholders' Association. We describe each database in the empirical research chapter in which it is used. As we use the same database in the first and the second empirical chapter, we do not repeat the same information. Rather, we describe the information in the second research chapter, which is essential to that research. Because of the advantages of each data – they include the possibility to link subjective attributes with actual investment behavior, a requirement seldom fulfilled – we dedicate significant space to descriptive statistics so as to highlight the cross-sectional differences of investors and their portfolio choices. Each empirical research chapter follows the same structure. The chapter starts with the development of the hypotheses. Then we describe our data and the methodology used. Then we provide the descriptive statistics. After that, we proceed to the results and discuss our findings. Lastly, we recap the research with a concluding section.

3 The influence of investor's subjective attributes on portfolio choice

The target of this chapter is to increase the empirical knowledge on the influence of investors' self-perceived, subjective attributes on their portfolio choices. We test the ability of simple questions on risk-standing ability and return target to capture investors' actual risk tolerance. By answering the risk and return questions, the investor classifies himself in a certain risk profile. We test if the investor-specific risk profile has a connection with actual portfolio choice, as shown through the risky share of the investor's total wealth. Also, we test which other investor-specific subjective attributes best explain his risk profile and portfolio choice. These other subjective attributes are as follows: self-perceived investment experience, activeness in following economic events, and willingness to make own investment decisions or to receive a ready proposal from an investment advisor or wealth manager. In addition to subjective attributes, we link risk profile to investors' demographic and socioeconomic variables, which we refer to as objective attributes.

3.1 Development of hypotheses

According to European Union regulations on investor protection (The Markets in Financial Instruments Directive, MiFID), financial institutions must make sure the products and services they offer are appropriate for the clients' personal needs. For the products or services to be considered appropriate, the institutions must base the evaluation on information which they collect from their clients. Among other things, the institutions must clarify the clients' preferences on risk taking by measuring their risk profiles. This requirement provides the need for our first hypothesis:

Hypothesis 1: *Risk profile describes the investor's actual portfolio choice.*

We use a database from a Finnish financial institution which includes risk profiles in compliance with EU requirements. The risk profiles are measured through two questions on client-specific risk-standing ability and return target. By answering these questions, the clients reveal their personal risk profiles, classified on a five-point scale from 1 = most risk averse to 5 = least risk averse. We test if the risk profiles are connected with clients' actual portfolio choices, i.e. their risky shares. We calculate the risky shares (=stock instruments / total wealth excluding the value of home) by using the information the clients provide about their wealth and its breakdown. The reason the database contains the clients' wealth and its breakdown also stems from EU requirements; the institutions have to clarify their clients' financial situation including their assets, investments and real property.

Also, the institutions have to clarify the clients' subjective, self-perceived experience and knowledge of investments in order to ensure the clients understand the risks the products or services entail. We connect this information with risk profiles and actual risky shares to test the predictive power of these investor characteristics on risk-taking level. In this way, our data fills an important requirement for good quality data on subjective characteristics investigation; it contains investors' self-perceived attitudes and judgments as well as their actual portfolios, a requirement only seldom fulfilled. Based on prior findings (see Chapter 1.2.1) on the link between subjective attributes and risk-standing ability, we form the following hypothesis:

Hypothesis 2: *Investor-specific subjective attributes influence the investor's risk profile choice. The following investors are represented in more risk tolerant profiles:*

2a) *More experienced*
2b) *Investors who follow economic events more actively*
2c) *Investors who want to make their own investment decisions*

In addition to subjective attributes, we test the power of socioeconomic and demographic variables, i.e. objective attributes, to explain the clients' risk profiles and portfolio choices. We form the third hypothesis analogously with Hypothesis 2:

Hypothesis 3: *Investor-specific objective attributes influence the investor's risk profile choice. The following investors are represented in more risk tolerant profiles*:

3a) *Men*
3b) Investors with higher education
3c) Investors with higher income
3d) Investors with higher wealth

3.2 Data and methodology

In Chapters 3.2.1 and 3.2.2 we introduce our data and methodology. We dedicate significant space to data description because it serves the needs of the second empirical research chapter (see Chapter 4) as well. In both chapters (3 and 4), we use the same database but in Chapter 4 we use a subsample of this research data.

3.2.1 Data

We are privileged to use an excellent and rare dataset describing subjective and objective investor attributes among Finnish investors to test the influence of these characteristics on investors' risk profiles and portfolio choices. We point out that our data includes investors' *actual* wealth allocation in various investment instruments. This enables us to calculate the actual risky share, compare it to the investor's self-perceived risk profile and to test the power of subjective and objective investor characteristics on risk profile choice. Grable & Lytton (2001) emphasize that the risk measurement tool should be related to actual portfolio choice to confirm its validity and reliability.

The data is gathered from investor questionnaires which the clients of a Finnish financial institution have filled in prior to the beginning of investment negotiations (see Appendix 1.2 and 1.3). The questionnaire fulfills the European Union legislation requirements (MiFID) regarding investor guidance. These requirements require the investment advisory company to ensure that they understand the client's investment objectives, the client is able to bear the investment risks consistent with his objectives and that he has enough experience and knowledge to understand the risk involved. Also, the advisor has to be aware of the client's financial situation, income, expenses, financial commitments, investment time and the purpose of investing. We then link this information with the client's demographic and socioeconomic variables, which are available within the financial institution. The clients answer both objective and subjective characteristics questions. The objective questions concern the client's monthly income level and source, living expenses and the amount of total wealth divided between various investment instruments. The subjective questions clarify the client's self-perceived preferences regarding risk and return, investment experience, activeness in following economic events and willingness to personally make investment decisions or to get a ready solution from an investment advisor. The questionnaires are handled with Investment Advisory Tool software, which configures an investor-specific risk profile according to the investor's risk and return attitudes, current and suggested distribution between asset classes suitable to investor's risk profile, investment plan and product recommendations. The software also gives a demonstration of the correlation between risk and return. Lastly, we link the questionnaire with additional information on the client's socioeconomic and demographic attributes, which we take from the institution's database. The questionnaires are filled between Jan.1, 2008 – June 30, 2008. The dataset includes information on 697 Finnish investors. Private banking customers are ignored. The dataset is treated in a way such that no single individual can be identified. For the purpose of our second empirical research chapter (see Chapter 4), we employ a repetition of the same data with different investors. This repetition data is collected during a time period of Jan.1 – May 31, 2011 and contains 3,408 investors. To confirm our results in this chapter we re-run the regressions with that latter data and put the results in Appendix 1.5.

The investor questionnaire begins with questions concerning the client's investment target, attitudes towards risk and return, education and investment experience (see Appendix 1.2). Using answers to the following questions on risk taking and return target, the software classifies the client in a certain risk profile:

How would you describe yourself as a saver and as an investor?

- I aim at the best possible return in the long run and I am ready to take large risks.
- I aim at good long term return and I am ready to take risks.
- I aim at good value growth and I am ready to take some risk.
- I aim at steady value growth and I am ready to take some risk.
- I aim at small value growth and I want my invested capital to be safe.

How do you react to value fluctuations in your savings and investments?

- I understand value fluctuations belong to investments and I accept even large fluctuations with my investments.
- I understand value fluctuations belong to investments and I accept that the value of my investments can fluctuate quite a lot.
- I understand value fluctuations belong to investments and I accept that the value of my investments can temporarily decrease to some extent.
- I don't like value fluctuations but I accept that the value of my investments can temporarily decrease a little.
- I do not accept value fluctuations with my investments under any circumstances.

The client's risk profile is determined by the level of risk specified in the answers to the two questions. The answers cannot differ by more than a one point. For example, if the client selects an alternative 3 (in the middle) to either question, the software accepts only alternative 2 or 4 for another question. The risk profile alternatives are as follows: *1 = Very cautious, 2 = Cautious, 3 = Moderate, 4 = Return seeking and 5 = Very return seeking.*

Next the client proceeds to questions which are meant to help formulate an investment or saving plans. There are plans for saving for a particular target, pension plan, saving during loan amortization or a plan to invest already acquired wealth. Our data consists of clients with plans to invest already acquired wealth (= Investment plan). This is because the Investment plan consists of the client's whole wealth divided into asset categories. The amount of wealth and distribution of asset categories is not completely precise because the client has to estimate the value of real property, i.e. the value of home, investment apartment, land, forest and private entrepreneurial property. The value of financial wealth that is invested through this bank is exact. The financial wealth in other institutions – if there is any – is included according to the client's best memory, which can cause some inaccuracy. We assume the error is not significant and does not affect the results. If the client owns some property together with his spouse, he is advised to indicate the value of his own portion. In addition to wealth distribution, the investment plan contains questions on client's monthly net earnings and expenses as well as the subjective attributes questions essential to our research: willingness to make personal decisions or to get a ready solution proposal, activeness in following economic events, and investment experience. We put the variable descriptions in Table 1. We use the division of subjective and objective attributes when we formulate the table. In Figure 1 we present a picture of a moderate client's risk profile and Investment plan.

Table 1. Variable descriptions.

This table describes the variables we use in our research. We divide the variables into subjective and objective analogous to the progression of our research.

Variable	Description
Subjective attributes	
Risk profile	1 = Very cautious 2 = Cautious 3 = Moderate 4 = Return seeking 5 = Very return seeking
Activeness in following economic events	1 = Infrequently 2 = Weekly 3 = Daily
Investment experience	1 = Novice 2 = Some experience 3 = Experienced
Investment decisions	0 = The investor wants to get a ready solution which is taken care of investment advisor or wealth manager 1 = The investor wants to use time to take care of investments and wants to make his own decisions
Objective attributes	
Gender	0 = Woman 1 = Man
Age	Investor’s age in years
Net income, € / month	1 = < 1 000 € 2 = 1 000 – 2 999 € 3 = 3 000 – 4 999 € 4 = 5 000 – 7 999 € 5 = 8 000 € -
Education	1 = Elementary school 2 = Vocational school 3 = Gymnasium 4 = Polytechnic 5 = University
Stock instruments, €	Total value of stock investments the investor owns: stocks in brokerage account, stock funds, saving insurance, derivatives
Interest instruments, €	Total value of interest investments the investor owns: deposits in accounts, interest funds, bonds, saving insurance
Other property, €	Total value of other property the investor owns: other real property, leisure apartment, private business etc.
Land property, €	Total value of land and forest property the investor owns
Apartment in own use, €	Value of apartment which is used as a home
Investment apartment, €	Total value of investment apartment/s
Total wealth, €	Investor’s total wealth: stock instruments + interest instruments + other property + land property + apartment in own use + investment apartment
Risky share, %	Stock instruments (€) / total wealth (€) excluding the value of home

Distribution of existing financial wealth

Asset class	Share, %	Return expectation, %	Volatility, %
Short term interest instruments	49	3.25	0.2
Long term interest instruments	1	4.0	2.5
Stock instruments	50	8.0	15.0

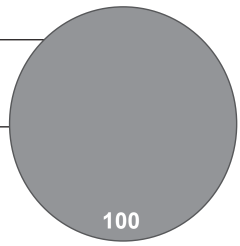
Risk profile	Moderate
Attitude on risk and return	Moderate investor understands the amount of his invested capital can depreciate in some circumstances. Still he aims for moderate return as a compensation of risk.

Risk profile and investor characteristics

Risk profile	Moderate
Experience	I am an experienced investor with experience of many years
Activity	I follow economic events only infrequently
Investment time	Over 7 years or thus far
Recommendation	Model of moderate investor
Main source of income	Salary or pension
Net income per month	3 000 - 5 000 €
Regular expenses per month	2 000 - 5 000 €

Investment proposal to moderate investor

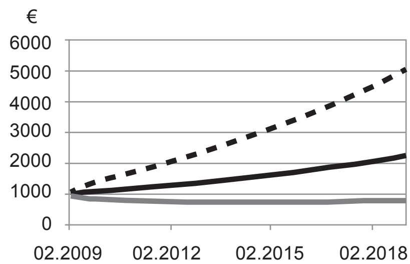
Asset class	Share, %	Return expectation, %	Volatility, %
Short term interest instruments	0	3.25	0.2
Long term interest instruments	0	4.0	2.5
Stock instruments	100	8.0	15.0



Portfolio's return expectation is 8% and risk (volatility) 15%.
Return expectation is always an estimation on future return.
Depending on market situation, actual return will be larger or smaller than return expectation.

Return expectation of investment proposal

Uppermost line	Interval between the uppermost and the lowest line describes
Lowest line	The range within the return prediction of investment proposal is estimated to be with a probability of 95 %.
Centermost line	Return expectation of investment proposal



Recommendation	Alternative 1:	Mutual fund which invest in global stock market
	Alternative 2:	Well diversified stock portfolio to Finnish stock market
	Alternative 3:	Index-linked bond which return follows the return of certain large companies' asset return

Figure 1. Risk profile and Investment plan.

This figure describes Risk profile and Investment plan of moderate investor. Because the original figure is written in Finnish, we have translated it into English.

Halko *et al.* (2011) partly use the same data as ours when they research the gender effect on risk taking. Their data is very large, containing 85,063 clients. The focus of their research is different than ours, and for that reason, of possible self-perceived attributes, they use only Risk profile and Investment experience, i.e. their data does not include Activeness in following economic events or Investment decisions attributes, which are important ones for the purpose of our research. Also, their data does not include a breakdown of total wealth to the instrument level other than the risky share. The total breakdown is critical for our purposes because we attempt to show the wealth structure differences between wealth classes and risk profiles. Halko *et al.* use the data in two ways: to research the effect of gender on risk-taking attitude (i.e. risk profile) and the effect of gender on participating or not participating in the stock market. They find men to belong to higher risk profiles, although gender loses some of its significance when they add the control variables (investment experience, education, income and total wealth). Investment experience turns out to be the most important variable in affecting the choice of risk profile. The influence of investment experience on risk profile is then analogous with our results (see Chapter 3.4) and confirms our results regarding experience using a larger dataset.

3.2.2 Methodology

We explain the process of our empirical research along with its progression in Chapter 3.4. In this methodology chapter we mainly concentrate on describing dependent variable choice and its formulation as well as its influence on regression methodology.

When testing the influence of subjective and objective attributes on risk-standing ability, we have two alternatives regarding dependent variable. Firstly, we could use the Risky share, a continuous variable, as a dependent variable and run a linear regression model. Secondly, we could use the Risk profile, an ordinal variable, and run an ordered logistic regression model. The reason for using either arises from the observation in Hypothesis 1 that Risky share and Risk profile positively correlate with each other with high statistical significance (we show this result in the empirical results in Chapter 3.4). We choose to use Risk profile as a dependent variable to be able to highlight the link between Risk profile and investors' other subjective characteristics. Risk profile as a dependent variable drives us to use the following ordered logistic regression model:

$$logit[Pr(Y \leq i \mid x)] = \alpha_i + \beta x,$$

where Y = Risk profile classified into three categories (1= Very cautious or Cautious, 2 = Moderate and 3 = Return seeking or Very return seeking), α_i = intercept parameters, β = a vector of regression coefficients and x = a vector of explanatory variables i.e. subjective and objective attributes. The methodology to use Risk profile/Risky share as a dependent variable and subjective and objective attributes as explanatory variables follows for example Dorn & Huberman's (2005), Halko *et al.*'s (2011) and Kapteyn & Teppa's (2002, 2011) research.

We present the descriptive statistics of risk profiles as a five-categorical form, but when we proceed to logistic regressions, we connect the profiles to larger entities. We combine profiles *Very cautious* and *Cautious* (category 1), keep the profile *Moderate* unchanged (category 2), and combine profiles *Return seeking* and *Very return seeking* (category 3) as a third category. The reason for combining the profiles is to simplify and summarize the regressions. Both of the most risk-averse profiles include investors with risky shares below 10% on average. The combination of the two most risk-tolerant profiles enlarges the amount of investors belonging to this category.

Of the three subjective attributes used as explanatory variables two are ordinal and one is dichotomous. Objective attributes consist of continuous, ordinal and dichotomous variables. When we run the regressions with ordinal variables, we use the lowest category as a reference category and contrast the other categories against it. As Risky share is a kind of substitute for Risk profile, we do not insert it as an explanatory variable in our regressions.

3.3 Descriptive statistics

We divide the descriptive statistics chapter into two parts. Firstly, we introduce investors' average wealth and its breakdown. Also, we compare their wealth and its breakdown to that of the average Finn. Secondly, we describe the distribution of risk profiles as well as risky shares and breakdown of wealth by risk profiles. We also include information on wealth level and its breakdown by classifying investors according to other subjective attributes as well as objective attributes. Lastly we show the correlation coefficients between the variables.

3.3.1 Descriptive statistics: asset allocation

We classify the sample statistics describing the aggregate wealth of investors and its breakdown into asset categories. Table 2 includes frequency, mean, median, standard deviation (Panel A – C) as well as skewness, minimum and maximum (Panel A - B). We include the median to give a sense of "typical holding". This is because of the skewed nature of wealth distribution; wealthy households have a strong influence on aggregate statistics. Our findings on the skewness of wealth distribution follow earlier research (see for example Campbell 2006). To further emphasize the differences in portfolio choices, we calculate the wealth distribution conditional of participating in the stock market and divide the dataset into subgroups according to total wealth.

Table 2. Descriptive statistics, asset allocation.

Descriptive statistics by asset categories and participating status (Panel A-B) and by total wealth classes (Panel C). Sample size is 697 investors. The number of investors participating in the stock market is 504.

Panel A: Descriptive statistics by asset categories; whole data (N = 697)

	Mean	Median	Std dev	Skewness	Min	Max
Absolute values, €						
Total wealth, €	171 000	131 000	209 000	4.08	0	1 982 000
Relative weights by instruments, %						
Interest instruments	44.83	31.98	36.27	0.40	0	100
Stock instruments	8.53	2.29	15.51	3.01	0	99.35
Other investments	5.05	0	12.23	3.38	0	96.98
Apartment in own use	34.59	31.10	34.98	0.37	0	100
Investment apartment	2.35	0	8.70	4.64	0	81.88
Land and forest property	4.07	0	13.32	4.06	0	85.67

Panel B: Descriptive statistics by participating status;conditional of participating in stock market (N = 504)

	Mean	Median	Std dev	Skewness	Min	Max
Absolute values, €						
Total wealth, €	194 000	150 000	226 000	4.08	100	1 982 000
Relative weights by instruments, %						
Interest instruments	39.19	29.12	32.10	0.59	0	99.85
Stock instruments	11.79	4.87	17.16	2.55	0.01	99.35
Other investments	5.64	0	12.71	3.04	0	87.77
Apartment in own use	36.39	35.78	34.14	0.27	0	99.83
Investment apartment	2.58	0	8.93	4.59	0	81.88
Land and forest property	4.42	0	14.11	3.97	0	85.67

Panel C: Descriptive statistics by asset categories; investors are divided to classes according to their total wealth (N = 697)

	Mean	Median	Std dev	Mean	Median	Std dev
Relative weights by instruments, %	Total wealth 0 – 10 000 €, N = 86			Total wealth 10 001 – 50 000 €, N = 118		
Interest instruments	84.21	99.68	29.81	79.54	88.30	26.44
Stock instruments	11.14	0	23.34	13.23	7.32	17.75
Other investments	0	0	0	2.61	0	13.85
Apartment in own use	0	0	0	3.21	0	15.92
Investment apartment	0	0	0	0	0	0
Land and forest property	0	0	0	1.41	0	8.27

Relative weights by instruments, %	Total wealth 50 001 – 100 000 €, N = 92			Total wealth 100 001 – 300 000 €, N = 296		
Interest instruments	55.23	58.92	35.15	24.65	19.48	22.03
Stock instruments	9.73	3.53	15.86	6.02	2.13	11.97
Other instruments	2.43	0	10.16	5.38	0	11.55
Apartment in own use	29.26	0	37.25	56.48	61.77	30.53
Investment apartment	0	0	0	2.61	0	9.82
Land and forest property	3.35	0	12.47	4.87	0	14.79
Relative weights by instruments, %	**Total wealth 300 001 – 500 000 €, N = 77**			**Total wealth 500 001 € -, N = 28**		
Interest instruments	22.09	15.66	20.22	20.28	13.53	18.56
Stock instruments	5.54	2.61	10.21	11.34	7.68	14.14
Other investments	13.04	9.43	14.21	14.14	9.09	16.12
Apartment in own use	44.63	44.43	20.44	32.32	27.99	26.17
Investment apartment	7.48	0	13.31	8.64	0.87	11.67
Land and forest property	7.21	0	15.54	13.27	0	21.96

According to a Statistic Finland survey (2011, information gathered in 2009), household average gross total wealth in Finland is 192,000 euros and the amount of mortgage is 26,980 euros. This information cannot be compared directly to our data because our data describes personal wealth. The Statistic Finland survey reports the average household size in Finland to be 2.08 persons. The average gross total wealth in our data is 171,000 euros (median 131,000 euros). Thus, we can make the conclusion that our data consists of Finnish people who are some wealthier than average. The natural explanation for that is the fact that many of persons included in the data have come to the financial institution in order to get investment advice. The average mortgage in our data (9,468 euros, median 0 euros, we do not cite mortgage data in Table 2) supports the observation of higher wealth than in Finland on average. The Statistic Finland survey (2011) shows apartment in own use to represent a share of 56% of Finnish people's total wealth. In our data the share is 35%. The remaining wealth is composed of investment instruments. Interest-bearing instruments are the most common ones, representing on average 45% of total wealth. The average share of stock instruments is 8.5% and it rises to 11.8% when we take into account only those who participate in the stock market. When we examine the portfolio composition by total wealth classes, we notice the investors in the two lowest wealth classes hold mainly interest instruments. Still, stock market participation begins in the lowest wealth level. Researchers of the SCF data find participation in the equity market to increase together with the value of financial wealth[13]. Calvet *et al.* (2007) find the same results with Swedish data; the share of risky assets increases quickly between the 20th and 30th percentile of investors. We think the reason why our investors' stock ownership begins in the lowest wealth level is again the nature of our data; the clients have come to the financial institution in order to get investment advice, which reflects their interest in other instruments than deposits as well. Participating in home ownership begins to grow from the wealth level of 50,000 euros. Beyond the wealth level of 100,000 euros a large mix of asset classes is used[14].

3.3.2 Descriptive statistics: risk profiles and other attributes

Investors' attitudes to questions concerning their ability to withstand investment risks and the return they desire are used to categorize the investors into five risk profiles. The most common risk profile is *Moderate*: 39% of clients define themselves as moderate investors. The profile *Cautious* is almost as common as Moderate. Only 2.7% of investors define themselves as *Very return seeking*.

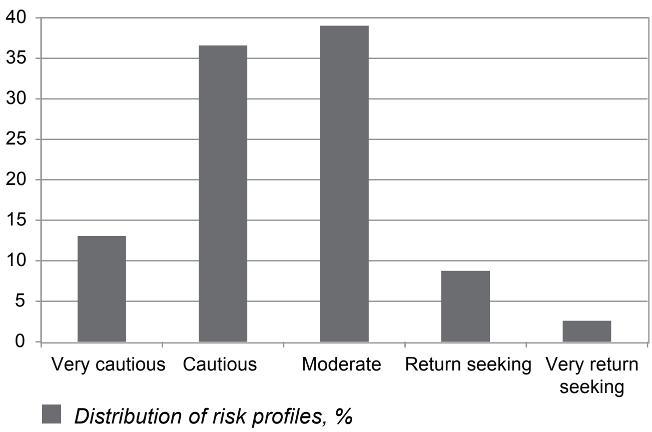


Figure 2. Distribution of risk profiles.

This figure presents the distribution of risk profiles. N = 697 investors. We describe the risk profile formulation in Chapter 3.2.1.

---

[13] Haliassos et al. (1995), Heaton & Lucas (2000a), Campbell (2006), Wachter & Yogo (2010) and Bucks et al. (2009)

[14] This finding is in line with prior research. See, for example, Haliassos et al. (1995), Campbell (2006), Calvet et al. (2007) or Bucks et al. (2009).

Next we show the link between risk profile and actual risky share. From this point on, we calculate the risky share excluding the value of apartment which is used as a home because the home cannot be considered as an investment instrument. The term Total wealth, however, includes the value of home if not mentioned differently. When we compare the actual portfolio decisions and self-perceived risk profiles, we notice a clear positive relationship: investors who belong to more risk-standing profiles have actually invested more in stock instruments. On average, *Very cautious* investors have invested only 5% of their accumulated wealth in stock instruments whereas the *Very return seeking* investors have a share of 35.5% in the stock market.

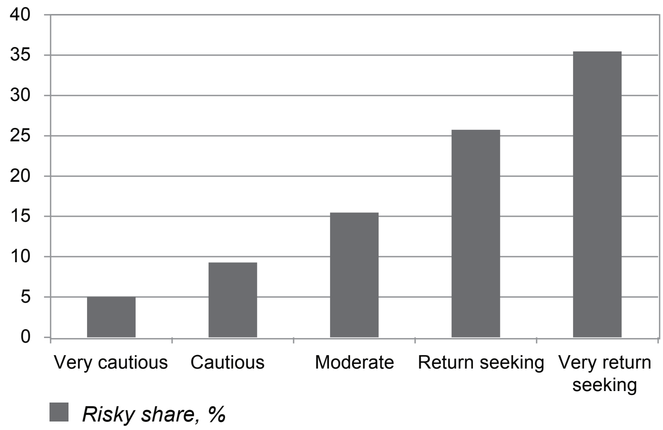


Figure 3. Risky shares by risk profiles.

This figure presents the relative weights of stock instruments (=risky share) by risk profiles. N = 697 investors. Risky share is calculated without the value of apartment in own use. All other wealth categories are included in total wealth when calculating the risky share: interest instruments, stock instruments, other investments (other real property, most typically leisure apartment), investment apartment(s) and land and forest property.

In Table 3 we show the absolute and relative wealth levels of investors. We observe the *Very cautious* investors to have the smallest total wealth. After the *Very cautious* profile, the total wealth increases markedly but the differences among the following three profiles are small. The *Very return seeking* investors are wealthier as investors in the other risk profiles (the result must be considered carefully because the small frequency of *Very return seeking* profile). As described in Figure 3, the relative share of stock instruments increases with the risk profile. The share of interest instruments declines almost by half when we compare the most and the least risk-averse investors. The share of interest instruments shifts mainly to stocks and investment apartments. Land and forest property are typically understood as low risk instruments and their ownership begins in the most risk-averse profile. The ownership of other investments (mainly leisure apartment) is typical of all profiles.

Table 3. Wealth by risk profiles.

This table presents descriptive statistics by risk profiles and by wealth levels. We show the absolute value (€) of total wealth (own apartment included) and the breakdown (%) of total wealth into asset categories (own apart¬ment not included because it is not an investment instrument). N = 697 investors.

	Profile 1: Very cautious (N = 91)			Profile 2: Cautious (N = 255)		
	Mean	Median	Std dev	Mean	Median	Std dev
Absolute values, €						
Total wealth	133 000	111 000	119 000	171 000	133 000	201 000
Relative weights by instruments, %						
Interest instruments	78.91	97.93	31.23	70.51	81.29	30.09
Stock instruments	5.03	0	9.34	9.27	3.79	12.47
Other investments	8.79	0	24.07	10.62	0	22.18
Investment apartment	0.56	0	5.39	3.41	0	12.42
Land and forest property	6.70	0	18.51	5.40	0	15.34

	Profile 3: Moderate (N = 272)			Profile 4: Return seeking (N = 61)		
	Mean	Median	Std dev	Mean	Median	Std dev
Absolute values, €						
Total wealth	172 000	136 000	208 000	187 000	133 000	230 000
Relative weights by instruments, %						
Interest instruments	64.77	73.18	32.33	52.40	44.43	35.93
Stock instruments	15.46	7.91	20.24	25.75	17.40	28.04
Other investments	8.73	0	20.70	9.84	0	21.22
Investment apartment	4.80	0	15.62	6.21	0	17.77
Land and forest property	5.50	0	17.43	5.80	0	15.48

	Profile 5: Very return seeking (N = 18)		
	Mean	Median	Std dev
Absolute values, €			
Total wealth	285 000	161 000	459 000
Relative weights by instruments, %			
Interest instruments	42.06	36.52	35.12
Stock instruments	35.48	29.48	31.42
Other investments	13.14	0	26.17
Investment apartment	7.37	0	20.38
Land and forest property	1.94	0	4.58

In addition to risk profile questions, our data contains the following other subjective attributes: *Investment experience, Activeness in following economic events*, and *Investment decisions* (willingness to make own investment decisions or to get a ready solution from an investment advisor or wealth manager). These subjective attributes are our main explanatory variables when we show the results of ordered logistic regressions in Chapter 3.4. Table 4 describes these attributes by showing their link with total wealth and risky share.

Table 4. Descriptive statistics by subjective attributes and by participating status.

This table presents descriptive statistics by subjective attributes and by participating status. We show the absolute value (€) of total wealth (own apartment included) and the risky share of each category of subjective attributes. Risky shares are calculated without the value of apartment in own use. Sample size is 697 investors. The amount of investors participating in the stock market is 504 investors.

	Whole data (N = 697)			Conditional of participating in stock market (N = 504)		
Subjective attribute	N	Risky share, %	Total wealth, €	N	Risky share, %	Total wealth, €
Activeness in following economic events						
Infrequently	393	10.13	140 000	258	15.43	158 000
Weekly	206	15,96	188 000	166	19.80	204 000
Daily	98	20.07	258 000	80	24.58	287 000
Investment decisions						
Ready solution	593	11.98	160 000	422	16.83	182 000
Wealth manager	7	8.19	267 000	6	9.56	310 000
Own decision	97	21.41	226 000	76	27.32	248 000
Investment experience						
Novice	226	7.36	111 000	118	15.00	130 000
Some experience	393	14.71	183 000	311	18.59	195 000
Experienced	78	22.97	280 000	75	23.89	289 000

The positive link between risky share and each subjective attribute is obvious. The same phenomenon holds also with total wealth. Activeness in following economic events is associated with higher risky share and larger wealth level. Investors with at least some investment experience have a larger risky share and bigger total wealth than novice investors. The more willing the investor is to make his own decisions rather than utilizing ready solutions, the more he invests in stock instruments and the more wealth he has accumulated. We present those investors who want to use a wealth manager separately in the table above; when we fit the regression model, we combine them with the investors who want to get a ready solution from an investment advisor. Lastly we provide descriptive statistics of objective attributes.

Table 5. Descriptive statistics by objective attributes and by participating status.

This table presents descriptive statistics by objective attributes and by participating status. We show the absolute value (€) of total wealth (own apartment included) and the risky share of each category of objective attributes. Risky shares are calculated without the value of apartment in own use. Sample size is 697 investors. The amount of investors participating in the stock market is 504 investors.

	Whole data (N = 697)			Conditional of participating in stock market (N = 504)		
Objective attribute	N	Risky share, %	Total wealth, €	N	Risky share, %	Total wealth, €
Gender						
Woman	335	11.44	145 000	227	16.89	162 000
Man	362	14.93	195 000	277	19.50	220 000
Education						
Elementary school	134	8.77	199 000	88	13.35	231 000
Vocational school	277	12.30	154 000	198	17.21	174 000
Gymnasium	36	12.07	93 000	21	20.69	113 000
Polytechnic	124	15.92	173 000	98	20.14	198 000
University	126	17.83	197 000	99	22.70	213 000
Net income, € / month						
< 1 000 €	108	6.33	124 000	57	11.99	161 000
1 000 – 2 999 €	506	13.47	163 000	375	18.17	179 000
3 000 – 4 999 €	61	19.29	226 000	53	22.20	231 000
5 000 – 7 999 €	11	23.60	515 000	9	28.85	568 000
> 8 000 €	5	14.07	654 000	4	17.58	816 000
Age, years						
< 18	7	17.60	35 000	3	41.07	21 000
19 – 30	85	11.92	34 000	47	21.55	49 000
31 – 45	133	18.54	131 000	100	24.54	146 000
46 – 60	243	13.84	203 000	189	17.79	222 000
61 -	229	9.93	216 000	165	13.78	235 000

We notice risky share and total wealth to be larger among men than women, holding true even when we take into account only those investors who participate in the stock market. The risky share slightly increases with education, but the differences in risky share lessen among the stock market participants. Ownership of stock instruments is more typical when the investor's monthly net income level is 1,000 euros or higher. Total wealth increases with income level and age. Participation and age follow the typical pattern shown in other empirical studies (see for example Riley & Chow 1992, Heaton & Lucas 2000a or Agnew *et al.* 2003); the risky share starts to diminish as the investor gets older. In Table 6 we show the correlation coefficients between our variables.

Table 6. Spearman correlation coefficients between subjective and objective attributes.

This table presents Spearman correlation coefficients between subjective and objective attributes. The formulation of attributes is described in Table 1. Risky share is calculated without the value of apartment in own use.

Attribute	Risk profile	Risky share	Activeness in following econ. events	Investment decisions	Investment experience	Log total wealth	Gender	Education	Net income	Age
Risk profile	1									
Risky share	0.29	1								
	(<0.00)									
Activeness in following econ. events	0.27	0.21	1							
	(<0.00)	(<0.00)								
Investment decisions	0.21	0.13	0.31	1						
	(<0.00)	(0.00)	(<0.00)							
Investment experience	0.31	0.36	0.38	0.17	1					
	(<0.00)	(<0.00)	(<0.00)	(<0.00)						
Log total wealth	0.04	0.12	0.16	0.04	0.32	1				
	(0.35)	(0.00)	(<0.00)	(0.26)	(<0.00)					
Gender	0.15	0.10	0.17	0.20	0.15	0.15	1			
	(0.00)	(0.01)	(<0.00)	(<0.00)	(<0.00)	(<0.00)				
Education	0.22	0.14	0.12	0.12	0.09	-0.08	-0.03	1		
	(<0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.05)	(0.44)			
Net income	0.25	0.22	0.17	0.10	0.21	0.16	0.19	0.30	1	
	(<0.00)	(<0.00)	(<0.00)	(0.01)	(<0.00)	(<0.00)	(<0.00)	(<0.00)		
Age	-0.31	-0.04	-0.00	-0.08	0.16	0.43	-0.01	-0.30	-0.16	1
	(<0.00)	(0.34)	(0.92)	(0.04)	(<0.00)	(<0.00)	(0.71)	(<0.00)	(<0.00)	

The link between Risk profile and Risky share shows through their correlation coefficient. Subjective attributes correlate quite strongly with each other as well as with some objective attributes. Still, when we run multicollinearity test by using Risk profile as a dependent variable and our subjective and objective attributes as explanatory variables, we find no problems with multicorrelation.

3.4 Empirical results

We begin the empirical results by describing the results to Hypothesis 1: *Risk profile describes the investor's actual portfolio choice*. Our results confirm this hypothesis. Using the Risk profile as a dependent variable and the Risky share as an explanatory variable, we observe the Risky share to be significant at 0.001% significance level in explaining the choice of Risk profile (we provide the coefficient, standard error and p-value in Table 7): for each percentage point increase in the risky share, the odds of belonging to higher risk profiles increase by a multiple of 1.03. Our finding gives support to prior research[15] indicating that investor's personal attitude to risk and return, asked with simple questions, has a tight correlation with his actual portfolio choice. Our results support the importance of EU regulations which require financial institutions to clarify the investor's risk profile; the profile is very closely connected to the investor's actual portfolio choice.

Next we continue to the results of Hypothesis 2: *Investor-specific subjective attributes influence the investor's risk profile choice. The following investors are represented in more risk-tolerant profiles: 2a) More experienced, 2b) Investors who follow economic events more frequently, 2c) Investors who want to make their own investment decisions*. We use Risk profile as a dependent variable and three other subjective attributes as explanatory variables. We combine Willingness to get a ready solution from an investment advisor and To use a wealth manager responses into a single class (0) and keep Willingness to make own decisions as another class (1) (*Investment decisions* variable). We keep *Investment experience* as well as *Activeness in following economic events* attributes in a three-level form. Table 7 shows the individual effects of subjective attributes and analyses their importance as single variables affecting risk profile and portfolio choice. Table 8 contains the results of ordered logistic regressions where we fit the model by adding the explanatory variables one by one to same model.

[15] See, for example, Barsky et al. (1997), Grable & Lytton (1999), Hallahan et al. (2004), Dorn & Huberman (2005) or Kapteyn & Teppa (2002)

Table 7. The results of ordered logistic regressions, subjective attributes.

This table describes the results of ordered logistic regressions. In both panels the dependent variable is Risk profile classified into three categories: 1= Very cautious or Cautious, 2 = Moderate and 3 = Return seeking or Very return seeking. The model has the form $logit[Pr(Y \le i \mid x)] = \alpha + \beta x$, where Y is Risk profile, α is intercept parameter, β is a regression coefficient and x is explanatory variable. In panel A we show the results of Hypothesis 1., i.e. we test the link between Risk profile as a dependent variable Y and relative weight of stock instruments (= Risky share) as an explanatory variable x. Risky share is calculated without the value of apartment in own use but all other wealth categories are included in total wealth: interest instruments, stock instruments, other investments (other real property, most typically leisure apartment), investment apartment(s) and land and forest property. In panel B we show the results when analyzing the importance of subjective attributes as single explanatory variables on Risk profile choice. Explanatory variables (x) are Investment experience (1 = Novice, 2 = Some experience, 3 = Experienced), Activeness in following economic events (1 = Infrequently, 2 = Weekly, 3 = Daily) and Investment decisions (dummy variable, 0 = The investor wants to get a ready solution which is taken care of by an investment advisor or wealth manager, 1 = The investor wants to use time to take care of investments and wants to make his own decisions). Table contains maximum likelihood estimates, standard errors and p-values.

Panel A

Dependent variable = Risk profile Explanatory variable	Coefficient	Standard error	P-value
Risky share	0.0329	0.0040	<0.0001

Panel B

Dependent variable = Risk profile Explanatory variable	Coefficient	Standard error	P-value
Investment experience (reference category Novice)			
Some experience	0.6257	0.1676	0.0002
Experienced	2.1837	0.2657	<0.0001
Activeness in following economic events (reference category Infrequently)			
Weekly	1.0549	0.1687	<0.0001
Daily	1.3000	0.2194	<0.0001
Investment decisions (0 = Ready solution, 1 = Own decisions)	1.3143	0.2124	<0.0001

Table 8. The influence of subjective attributes on Risk profile choice.

This table describes the influence of subjective attributes on Risk profile choice. The model is ordered logistic regression and has the form $logit[Pr(Y \leq i | x)] = \alpha_i + \beta x$. *Y* is Risk profile classified into three categories (1= Very cautious or Cautious, 2 = Moderate and 3 = Return seeking or Very return seeking), α_i are intercept parameters, β is a vector of regression coefficients and *x* is a vector of explanatory variables. The table contains maximum likelihood estimates and p-values (parentheses below). AIC refers to the Akaike information criterion value. Pseudo R-square refers to Nagelkerke Pseudo R-square.

Dependent variable = Risk profile		Model	
Explanatory variable	(1)	(2)	(3)
Investment experience (reference category Novice)			
Some experience	0.6257	0.4023	0.4122
	(0.0002)	(0.0216)	(0.0191)
Experienced	2.1837	1.7606	1.7145
	(<0.0001)	(<0.0001)	(<0.0001)
Activeness in following economic events (reference category Infrequently)			
Weekly		0.8556	0.7274
		(<0.0001)	(<0.0001)
Daily		0.8120	0.5853
		(0.0005)	(0.0152)
Investment decisions (0=Ready solution, 1=Own decisions)			0.8661
			(0.0001)
Intercept 3	-2.8170	-3.0684	-3.1600
	(<0.0001)	(<0.0001)	(<0.0001)
Intercept 2	-0.5538	-0.7414	-0.7822
	(<0.0001)	(<0.0001)	(<0.0001)
Number of observations	697	697	697
AIC	1278	1254	1241
Pseudo R-square	0.1120	0.1535	0.1747

When we fit the ordered logistic regression model in Table 8, all subjective attributes remain significant in explaining the choice of risk profile, which in turn is connected with risky share. This confirms our Hypotheses 2a to 2c: *Investor-specific subjective attributes influence the investor's risk profile choice.* The more experienced the investor is, the more obviously he defines himself to belong to higher risk profiles (Hypothesis 2a). The more actively the investor follows economic events, the higher risk profile he belongs to (Hypothesis 2b). And thirdly, investors who want to make their own decisions belong to more risky profiles than those who are willing to get a ready solution (Hypothesis 2c).

Whereas our main interest is investor-specific subjective attributes, the most commonly used variables in portfolio choice research are demographic and socioeconomic variables. We refer to them as objective attributes: gender, age, total wealth, income level and education and thereby form the third hypothesis: *Investor-specific objective attributes influence the investor's risk profile choice. The following investors are represented in more risk-tolerant profiles: 3a) Men, 3b) Investors with higher education, 3c) Investors with higher income, 3d) Investors with higher wealth.*

The descriptive statistics section offered the first hint that objective attributes are related to portfolio choice. We show their power in explaining risk profile choice as separate variables in Table 9. In Table 10 we add them (excluding Total wealth) to our ordered logistic regression models in addition to the subjective attributes.

Table 9. The results of ordered logistic regressions, objective attributes.

This table describes the results of ordered logistic regressions in which we analyze the importance of objective attributes as single explanatory variables. The model has the form $logit[Pr(Y \leq i \mid x)] = \alpha + \beta x$. Y is Risk profile classified into three categories (1= Very cautious or Cautious, 2 = Moderate, and 3 = Return seeking or Very return seeking), α is intercept parameter, β is a regression coefficient and x is explanatory variable. Explanatory variables (x) are Log total wealth (= Total wealth (€) in logs calculated without the value of apartment in own use), Income (= Monthly net earnings classified in four categories), Education (= Education classified into three categories), Gender (dummy variable, 0 = Woman, 1 = Man) and Age in years. The table contains maximum likelihood estimates, standard errors and p-values.

Dependent variable = Risk profile Explanatory variable	Coefficient	Standard error	P-value
Log total wealth	-0.0407	0.0369	0.2709
Gender (0 = Woman,1 = Man)	0.6090	0.1474	<0.0001
Age	-0.0325	0.0047	<0.0001
Net income, € / month (reference category < 1 000 € / month)			
1 000 – 3 000 € / month	1.1164	0.2328	<0.0001
3 000 – 5 000 € / month	1.7576	0.3260	<0.0001
5 000 € / month –	1.3811	0.5203	0.0079
Education (reference category lower than Polytechnic)			
Polytechnic	0.5477	0.1938	0.0047
University	0.7443	0.1926	0.0001

Our results strengthen prior findings on objective variables[16]. The investor's income level has a positive and significant effect on risk profile. Higher income level means a more positive attitude to risk taking. Education has the same effect as income. Gender has an influence on risk taking; men are more often represented in higher risk profiles. Being older (variable Age) indicates the investor belongs less often to higher risk profiles. We use investor's Age as a control variable in Table 10 (Model 7) in order to standardize its effect on risk profile. The reason for this arises from prior findings pointing to a pattern of risky share increasing with age but falling after retirement (see, for example, Riley & Chow 1992, Heaton & Lucas 2000a, or Agnew *et al.* 2003). The amount of total wealth (calculated without the value of apartment in own use) is the only variable which is not significant. This is why we do not include wealth as an explanatory variable in Table 10, where we connect the subjective and objective explanatory variables to the same models by adding one variable at a time.

[16] See, for example, Carroll (2002), Guiso *et al*. (2002), Calvet *et al.* (2007) or Campbell (2006)

Table 10. The influence of subjective and objective attributes on Risk profile choice.

This table describes the influence of subjective and objective attributes on Risk profile choice. The model has the form $logit[Pr(Y \leq i \mid x)] = \alpha_i + \beta x$, where Y is Risk profile classified into three categories (1= Very cautious or Cautious, 2 = Moderate and 3 = Return seeking or Very return seeking), α_i are intercept parameters, β is a vector of regression coefficients and x is a vector of explanatory variables. Table contains maximum likelihood estimates and p-values (parentheses below). AIC refers to the Akaike information criterion value. Pseudo R-square refers to Nagelkerke Pseudo R-square.

Dependent variable = Risk profile				Model			
Explanatory variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Investment experience (reference category Novice)							
Some experience	0.6257	0.4023	0.4122	0.3213	0.3119	0.3051	0.6227
	(0.0002)	(0.0216)	(0.0191)	(0.0740)	(0.0832)	(0.0906)	(0.0012)
Experienced	2.1837	1.7606	1.7145	1.5280	1.5113	1.4805	1.9473
	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)
Activeness in following economic events (reference category Infrequently)							
Weekly		0.8556	0.7274	0.7102	0.6996	0.6760	0.6465
		(<0.0001)	(<0.0001)	(<0.0001)	(0.0001)	(0.0002)	(0.0005)
Daily		0.8120	0.5853	0.5874	0.5800	0.5642	0.6531
		(0.0005)	(0.0152)	(0.0164)	(0.0180)	(0.0218)	(0.0097)
Investment decisions							
(0 = Ready solution, 1 = Own decisions)			0.8661	0.8324	0.8001	0.7395	0.6424
			(0.0001)	(0.0003)	(0.0005)	(0.0014)	(0.0066)
Net income € / month, (reference category < 1000 € / month)							
1 000 – 3 000 € / month				0.8496	0.7917	0.7549	0.7660
				(0.0004)	(0.0011)	(0.0019)	(0.0025)
3 000 – 5 000 € / month				1.2324	1.0810	0.9925	0.8414
				(0.0003)	(0.0022)	(0.0054)	(0.0211)
5 000 € / month –				0.8457	0.7170	0.5790	0.3349
				(0.1188)	(0.1919)	(0.2960)	(0.5492)

Dependent variable = Risk profile				Model			
Explanatory variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Education (reference category lower than Polytechnic)							
Polytechnic					0.2537	0.2725	0.0684
					(0.2147)	(0.1837)	(0.7439)
University					0.2799	0.3312	0.2051
					(0.1882)	(0.1230)	(0.3483)
Gender (0 = Woman, 1 = Man)						0.2779	0.2828
						(0.0842)	(0.0873)
Age							-0.0400
							(<0.0001)
Intercept 3	-2.8170	-3.0684	-3.1600	-3.8905	-3.9178	-4.0198	-2.2531
	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)
Intercept 2	-0.5538	-0.7414	-0.7822	-1.4651	-1.4856	-1.5787	0.3347
	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(0.3395)
Number of observations	697	697	697	691	691	691	691
AIC	1278	1254	1241	1217	1218	1217	1163
Pseudo R-square	0.1120	0.1567	0.1747	0.1986	0.2022	0.2064	0.2818

The results in Table 10 confirm Hypothesis 3 only from the viewpoint of 3c: *Investors with higher income are represented in more risk-tolerant profiles* (excluding net income class 5 000 euros or more). Even though objective variables are statistically significant as single variables, they lose their significance when we connect them to the same model with subjective explanatory variables. Our main explanatory variables – self-perceived subjective attributes – retain their coefficients and statistical significances very well. The most experienced investors are 7.01 times[17] more likely to belong to higher risk-standing profiles than the novice investors (some experience: odds ratio is 1.86), holding all other variables constant. Investors who follow economic events daily are 1.91 times more likely to belong to higher risk-standing profiles than those who follow economic events only infrequently (weekly: odds ratio is 1.90). Investors who want to make their own investment decisions are 1.90 times more likely to belong to higher profiles than investors who request a ready proposal from an investment advisor.

Age as a control variable does not counter the significances of other variables and has its own explanatory power too: for each year of age, the odds of belonging to higher risk profiles decrease by a multiple of 0.96.

Our unique data, with the possibility to test several subjective attributes affecting the choice of risk profile and actual portfolio choice, represents a contribution to household finance research. Firstly, it strengthens the findings that investors' risk attitudes can be described by using non-complex risk-standing measurement tools. This would validate EU regulation that requires the advisor to clarify his client's risk profile as well as other investor-specific subjective and objective attributes. The profile is closely connected to the client's actual portfolio choice and is thereby helpful when seeking the right risk- and return-level products for a given investor. Secondly, our findings on the explanatory power of other subjective attributes on risk profile strengthen the idea that subjective characteristics need to be taken into account when investigating variation in portfolio choices and developing behavioral models as well. Our results also give support to, for example, Dorn & Huberman's (2005) term financial knowledge, Guiso & Japelli's (2005) financial awareness term, and the notion of financial sophistication index offered by Lusardi *et al.* (2009), Rooij *et al.* (2011) and Calvet *et al.* (2009b). All of these are based on the observation that investor-specific subjective and objective attributes (they use investment experience and actual knowledge on investment issues as subjective explanatory variables) have a connection with stock market participation and risk tolerance.

[17] Odds ratios are obtained by exponentiating the parameter estimates in Table 10, Column 7

Robustness check

We conclude the empirical results with several robustness checks. Firstly we run linear regression models with the same explanatory variables as above but replace Risk profile as a dependent variable with Risky share (a continuous variable which relates the relative share of stock instruments in the investor's total portfolio). The change of dependent variable does not influence the results; the link between risk-standing ability and subjective and objective attributes remains.

We repeat the measurement of risk profiles with another dataset taken from the same database but from a different time period. The other dataset is gathered for a time period of Jan. 1 – May 31, 2011, i.e. three years later than our original data (2008), which our results in this chapter are based on. We use data from 2011 together with year 2008 data in Chapter 4, in which we investigate rebalancing behavior during the stock market crises of 2008 – 2009 and 2011. Also, we repeat the measurement of risk profiles once again by using data which is taken from a different database – i.e. the data which we use in our overconfidence research in Chapter 5. By using these two other datasets and identical method to measure risk profiles as in our original data, we show the connection between risk profile and risky share in descriptive statistics level in Appendix 1.4. We find that there is a clear positive link between risky share and risk profile according to these other data as well. We make a conclusion that the link between risk profile and actual risky share is robust regardless of a change of data.

As a last robustness check, we run the same regressions on the year 2011 data taken from the same database as our original 2008 data and test the influence of subjective and objective attributes on risk profile choice. The estimation method and variables used are identical with those in the original empirical research. We find the same variables to explain the choice of risk profile as in original research. We detail these results in Appendix 1.5.

3.5 Conclusions

Our research evidences that investors' self-assessments of their risk-standing ability as well as other investor-specific subjective characteristics are helpful when analyzing differences in portfolio choices. Investors' actual risk tolerance can be measured with simple questions concerning the return they desire and their willingness to withstand stock market volatility. By answering questions on risk and return, investors classify themselves as a certain risk profile. These risk profiles are closely related to investors' actual portfolio allocation decisions; risk profile choices go hand in hand with their actual risky shares. Also, the other investor-specific subjective attributes work well in explaining risk profiles and risky share choices: investment experience, activeness in following economic events and willingness to make own investment decisions instead of using the help of an investment advisor or wealth manager. We make a conclusion that investors' subjective attributes offer a very important window into understanding investor-specific risk profile and risky share choice. We argue that researchers should focus especially on self-perceived investor attributes in order to understand variation in investment behavior.

Our results have implications for financial institutions and EU legislation authors. The results give support to the EU legislation requirements that require investment advisors to measure their clients' risk profiles and other investor-specific subjective and objective attributes. Knowing investor-specific risk profiles and other investor attributes may help investment advisors to find suitable products for their clients' personal needs. This improves investor protection and in that way fulfills the aims of EU legislation.

One may ponder the causality between subjective attributes and investing behavior. Does the individual have an interest in following economic issues actively which shows as higher risk-standing profile and higher actual risky share? Or does he start his investor career which then increases his interest in economic issues? And also, what is the role of investment experience in risk tolerance? Does risk-standing ability increase with experience and show as larger risky share? And thirdly, we highlighted that investors with a willingness to make their own investment decisions belong to higher risk profiles and have higher risky shares. Have investors with a willingness to make their own decisions always wanted to make their own investment decisions or have their started their investor careers with ready solutions from advisors? Should we encourage individuals to take responsibility for their own investment decisions if it fosters risk tolerance, which in turn results in higher risky shares and hopefully larger wealth in the long run? But do these individuals have the ability to take care of investments on their own or should they be assisted by advisors to avoid investment mistakes?

The above-questions invite discussion. We assert that there is still much work to be done before the mechanisms driving portfolio choice are deeply understood. Our opinion is that research on subjective, psychology-based attributes is worth continuing. This encourages us to continue on to our next empirical research, Chapter 4.

4 Rebalancing behavior during the stock market crises 2008 – 2009 and 2011

In this empirical research we continue to test the explanatory power of subjective and objective attributes on investment behavior by approaching the issue from a different perspective than in Chapter 3. We link the attributes used in the previous chapter to investors' rebalancing behavior during the severe stock market crises in 2008 – 2009 and again in 2011. By rebalancing behavior we mean investors' personal transactions in their stock and combination fund portfolios, i.e. we separate active rebalancing behavior from the passive changes which portfolios are exposed because of market value fluctuations. In that way we can classify investors into three rebalancing groups: sellers, no rebalancing and buyers. We use a sub-sample of the Chapter 3 data by selecting information on investors who own stock and / or combination fund portfolios during the 2008 – 2009 crisis. We repeat the research for the 2011 crisis, but with different investors. We use the investors' subjective and objective characteristics as measures of financial sophistication and attempt to answer the following questions: How do stock and combination fund owners behave with their portfolios in a severe stock market crisis: do they sell their portfolios partially/entirely, enlarge them, or make no rebalancing at all? Do differences in financial sophistication explain the differences in behavior?

4.1 Development of hypothesis

The importance of this research stems from the findings of behavioral finance research indicating that there exist differences in individuals' abilities to make investment decisions. Differing abilities to make quite complicated investment decisions has an effect on individuals' wealth accumulation, which in turn influences their own and forthcoming generations' well-being. We refer to these investment abilities as *financial sophistication* and measure it with the same subjective and objective attributes as in Chapter 3. The deep stock market crises in 2008 – 2009 and 2011 give an excellent opportunity to study how differences in financial sophistication show in rebalancing behavior in a situation of stock market shocks.

Based on previous findings (see, for example, Calvet *et al*. 2007, 2009a, 2009b, Bilias *et al.* 2010 or Bucher-Koenen & Ziegelmeyer 2011), we hypothesize that the more financially sophisticated investors have superior skills to manage their fund portfolios and to understand the long-term character and non-predictability of the stock market. This should discourage them from selling their portfolios at reduced market values and even encourage them to be bold enough to resist the market value decline and buy more fund shares at decreased prices. We refer to this kind of rebalancing behavior as more professional behavior. Low financial sophistication would accordingly show as the opposite behavior. By subjective financial sophistication characteristics we mean investors' self-perceived attitudes to risk and return (risk profile), investment experience, activeness in following economic events and willingness to make their own investment decisions rather than utilizing a ready investment solution. We state that the higher the category the investor belongs to, as measured by these variables, the higher is his financial sophistication and vice versa. By objective financial sophistication characteristics we mean investors' demographic and socio-economic variables: their total wealth level, education, monthly net income, age and male gender. We state that the higher the investor's wealth level or education or net income class, the higher is his financial sophistication and vice versa. Excepting when higher age can show as a need to hedge a risky portfolio from a stock market decline, age also brings investment experience, which inspires us to classify higher age as a measure of higher financial sophistication. Based on prior research indicating that men's more active participation in the stock market provides them more experience of financial market and investment issues, we hypothesize that male gender equates to higher financial sophistication[18.] We admit this choice is debatable because of, for example, men's more active trading or overconfidence in one's own abilities[19.] Still, we make this rough choice to be able to use gender as a measure of financial sophistication.

To test the influence of financial sophistication measured by subjective and objective attributes on rebalancing behavior, we put the following hypothesis for empirical testing:

Hypothesis*: During a stock market crisis higher financial sophistication shows as more professional rebalancing behavior in fund portfolio.*

We aim to classify investors into the following groups: sellers, no rebalancing and buyers. To do that we need to separate each investor's own actions in his fund portfolio from the market value fluctuations. We introduce our technique in the methodology section (see Chapter 4.3). After classifying investors into these groups, we test the power of financial sophistication characteristics as variables explaining differences in rebalancing behavior.

[18] In addition to prior research on men's more active participation in the stock market giving them more experience in investing, Lusardi & Mitchell (2005) and Rooij *et al*. (2011) measure financial literacy levels of men and women and find men to be financially more knowledgeable than women.
[19] See, for example, Barber & Odean (2001) or Graham *et al*. (2009)

4.2 Data

Because we use the same database as in the first empirical research, we do not re-introduce the source of data and the variables it contains. Instead, we concentrate only on that information which is essential to the research at hand. Our original data, i.e. which we use in our first empirical research, contains information on Finnish investors who answered an investor questionnaire between Jan.1, 2008 – June 30, 2008. We pick a subsample which contains those investors who own a stock and/or combination fund portfolio (invested through the financial institution at hand) and then follow their rebalancing behavior in the fund portfolios during the first stock market crisis in 2008 – 2009. We then investigate the investors' rebalancing behavior during the second market decline in 2011. The data concerning the latter crisis contains the same information as the former data but the investors we follow are not the same as in the first crisis. The latter data is gathered among investors who answered the investor questionnaire during the time period of Jan.1, 2011 – May 31, 2011. We follow their rebalancing behavior until the end of the second market crisis in autumn 2011.

Firstly, the global and very sharp stock market decline happened between summer 2008 and spring 2009 (see Figure 1 in Appendix 2). This happened as a consequence of a financial crisis in the U.S. mortgage market which transferred rapidly into other financial markets. After June 2008 the global crisis culminated in a panic in financial markets and the values of stocks and stock-related instruments decreased rapidly in all markets. The lowest stock market values were seen in March 2009. For this reason we analyze the rebalancing behavior in fund portfolios during this time period, i.e. between June 30, 2008 and March 31, 2009. The situation calmed because of strong support from central banks and the U.S. government, which normalized economic growth and allowed stock prices to recover. The upturn of stock prices lasted two years but stock prices were hit again during the year 2011. Now the reason was in the EU. Those countries that use the euro as their currency were found to have violated the Maastricht Treaty, which regulates the deficit of GDP and government's leverage ratio. The financial markets lost their trust in the ability of Euro countries to honor their commitments. The risk premiums of bonds increased rapidly and pushed stock prices into a sharp decline. The decline lasted from May 2011 to Sept. 2011(see Figure 1 in Appendix 2). This is the latter research period we focus on: a time period between May 31, 2011 and Sept. 30, 2011.

The first data, from 2008 – 2009, contains 697 investors, of which 258 own a stock and/or combination fund portfolio. The number of stock fund owners is 162 investors and when we take into account the combination fund owners we arrive at 258 investors. The data concerning the latter crisis of 2011 contains 3,429 investors, of which 1,303 own a stock and/or combination fund portfolio. The number of stock fund owners is 843 and when we include the combination fund owners we get 1,303 investors. We admit the data from the first crisis is small. Still, it describes the investors' actual fund portfolios and their actual rebalancing behavior in their portfolios. Oftentimes this kind of information is lacking when researchers do empirical research. The data also contains many investors' subjective and objective attributes which enable us to investigate the influence of those characteristics on rebalancing behavior. The latter data is much bigger and gives more reliability to our results.

In addition to stock and combination fund portfolios, our data includes information on risky interest fund and brokerage account owners. By risky interest funds we mean those interest funds whose values are quite closely connected with stock market fluctuations, for example funds invested in corporate or emerging market bonds. We elucidate the rebalancing behavior in the risky interest fund portfolios as a descriptive statistics level[20]. The brokerage accounts consist mainly of stocks listed in the Nasdaq OMXHelsinki Stock Exchange. For brokerage accounts we cannot separate the investors' personal transactions from market value fluctuations. Still, we offer some observations on those accounts too[20].

4.3 Methodology

In this chapter we firstly describe the technique which we use to separate investor's personal decisions in his fund portfolio, i.e. his rebalancing behavior, from the market value fluctuations to which his portfolio is passively exposed. Understanding the methodology allows an understanding of our rationale for classifying investors into three categories: sellers, no rebalancing and buyers.

To be able to distinguish active rebalancing decisions from market value fluctuations, we use the same technique as Calvet *et al*. (2009a). We decompose the change in mutual fund portfolio value (=total change) between *t* (June 30, 2008 / May 31, 2011) and *t+1* (March 31, 2009 / Sept. 30, 2011) into a passive and active change. Passive change is driven by the market value fluctuation of those funds the investor's portfolio consists of; it represents the return the investor would have

[20] We offer the results in Chapter 4.6.

earned if he had not made any rebalancing actions. Active change results from rebalancing behavior; selling the fund portfolio or part of, keeping the portfolio untouched, or buying more shares. In this way we differentiate the investors as three groups - sellers, no rebalancing, and buyers.

We start by calculating the passive change $1+r_{(P,i,t+1)}$ of each fund the investors in our data own, i.e. the market value fluctuations between t and $t+1$ in 2008 – 2009 as well as 2011. We take the market values from mutual fund websites (www.op.fi). The first stock market crisis was very deep: between June 2008 and March 2009 the average market value decline of stock funds was -42.52%, ranging from -73.22% to +1.37%. With combination funds the average decline was -18.12%, ranging from -34.57% to -9.62%. In the same time frame, the S&P500 index[21] fell -37.67% and the global index[22] -43.56%. The latter crisis from May 2011 to September 2011 made stock funds decline on average -22.08% (range -30.33% – +1.31%) and combination funds -10.26% (range -18.30% – -6.57%). The S&P500 index fell -13.93% and the global index -17.14%. In both crises the decline of the OMX Helsinki index was larger than the drop of worldwide indexes. The Finnish stock market being small, lacking wide conspicuousness and having concentrated branch of industries are explanations for this phenomenon.

Secondly, we proceed to the single investor level. We calculate the total change (=passive change + active change) $1+r_{(T,i,t+1)}$ between t and $t + 1$ for each fund i the given investor owns. This is possible because we have the breakdown of the client's fund portfolio at the beginning and at the end of research period, in 2008 and in 2011 respectively. For example, if the client owns a portfolio of funds, every fund has a separate row in our data, i.e. we make the calculation for each fund.

Next we turn to active changes, i.e. rebalancing decisions. We calculate the active change $1+r_{(A,i,t+1)}$ as the difference between total and passive change for each fund i the given investor owns:

$$1+r_{(A,i,t+1)} = 1+r_{(T,i,t+1)} - 1+r_{(P,i,t+1)}.$$

[21] The index includes 500 leading companies in leading industries of the U.S. economy, capturing 75% coverage of the market value of U.S. equities

[22] The S&P Global Broad Market Index, comprised of the S&P Developed BMI and S&P Emerging BMI)

When we calculate the rebalancing decisions, we limit the active change to +/-100%. That means, for example:

- ownership of stock funds 0 € (June 30, 2008) and 10,000 € (March 31, 2009), active change 100 %
- ownership of stock funds 10,000 € (June 30, 2008) and 0 € (March 31, 2009), active change -100 %.

Finally, after we have calculated the returns of the separate funds, identified the contents of the investors' portfolios and differentiated the passive change from the active change, we calculate the weighted active change per investor, i.e. his rebalancing behavior in his fund portfolio. If the investor owns only a single fund in the research period, there is no need for weighting. If he owns more than a one fund, then we calculate the weighting according to the composition of the fund portfolio. We clarify the idea of weighting in Table 11.

Table 11. Rebalancing.

Calculation of rebalancing behavior of stock and combination fund portfolios. The fund code identifies the fund the investor owns. This is an example from the crisis in 2008 – 2009. We make the calculation in the same way also during the crisis in 2011.

Investor (1 – 4) Fund code Total, €	Fund's return June 30, 08– March 31, 09 (=passive change), %	Market value of fund portfolio per June 30, 08, €	Market value of fund portfolio per March 31, 09, €	Change of fund portfolio June 30, 08 – March 31, 09 (=total change), %	Rebalancing (=active change), %
Investor 1					
3	-18.92	5 124	4 154	-18.92	0
214	-20.40	3 249	3 413	+5.05	25.45
Total, €		8 373	7 567		weighted +9.88
Investor 2					
3	-18.92	6 409	6 817	´6.37	+25.29
12	-44.57	2 236	1 239	-44.57	0
203	+1.37	995	2 813	+182.71	100
212	-58.72	1 090	1 791	+64.31	100
Total, €		10 730	12 660		weighted +34.54
Investor 3					
1	-43.01	8 870	2 938	-66.87	-23.86
3	-18,92	30 681	19 271	-37.19	-18.26
Total, €		39 551	22 209		weighted -19.51
Investor 4					
36	-9.62	14 644	0	-100	-100
Total, €		14 644	0	(no weighting needed)	-100

We specify the number of investors in each rebalancing group in the Descriptive statistics section, (Chapter 4.4). In the Empirical results section (Chapter 4.5) we use the three-category formulation and test if higher financial sophistication is evidenced as more professional rebalancing behavior, that is, as non-participation as sellers and even as participation as buyers. To do this we analyze each rebalancing group at a time by separating it from the two other groups. To make the separation, we treat the dependent variable (=rebalancing behavior) as a dummy variable. For example, when we want to separate sellers from the buyers and no rebalancing group, we give a value 1 to sellers and 0 to the other groups. As a result of the dichotomous form of dependent variable, we use probit regressions of the following form:

$$Probit(Y) = \alpha + \beta x,$$

where Y = a binary variable taking a value of 1 when the investor is a seller / no rebalancing / buyer and taking a value of 0 when the investor belongs to other groups, α = intercept parameter, β = vector of regression coefficients and x = vector of explanatory variables.

Instead of probit regression, we could use multinomial logistic regression. The interpretation of results would be more complex because of two models in the same regression. Also, we would need to choose one rebalancing group as a reference group (no rebalancing being the most obvious reference group) which would prohibit us to classify investors to all our three rebalancing groups.

We also consider the financial sophistication variables in the opposite direction to underline the differences in rebalancing behavior caused by varying financial sophistication levels. We clarify this with an example: Activeness in following economic events is a three-category variable. When we use it as a marker of high financial sophistication, we use the lowest category (*Infrequently*) as a reference category, contrast categories *Weekly* and *Daily* against it, and test which rebalancing groups investors with higher activeness level belong to. When we use this variable as a marker of low financial sophistication (potentially showing as less professional rebalancing behavior) we use the highest category (*Daily*) as a reference category and contrast categories *Weekly* and *Infrequently* against it.

In addition to financial sophistication characteristics, we analyze the influence of risky share on rebalancing behavior (= we summarize investor's total risky instruments and divide it by his total wealth excluding the value of apartment used as a home). According to Calvet et al's research (2009a), the larger the initial share of risky assets is, the less likely the investor is to have a positive active change. Inserting subjective variables and the risky share into the same regression is problematic because they correlate very strongly with each other. That is why we see the risky share and subjective characteristics as substitutes for each other and do not use risky share as a measure of financial sophistication. In the robustness check section we re-run the rebalancing regressions by controlling the risky shares.

4.4 Descriptive statistics

There is ownership of 34 different mutual funds in the first crisis and in 30 funds in the latter crisis. Most are stock funds in which stocks are the only possible investment instrument, if we ignore cash for liquidity reasons. The combination funds include both stock and interest instruments: the relative share invested in the stock market differs from 20 – 80%. Every fund is an open-end fund. This means that each business day the mutual fund company buys shares back from investors and sells shares to new investors. The price of the fund's share is calculated as net asset value: the total value of the assets owned by the fund minus expenses divided by the number of shares outstanding. The price is the same both for sellers and buyers. We categorize the funds according to their investment targets below.

Table 12. Mutual funds under research, crisis 2008 – 2009 and 2011.

	Crisis in 2008 – 2009	Crisis in 2011
Fund category	N	N
Stock funds		
Finland	4	4
Europe	6	5
USA	1	1
Japan	2	1
Pacific area	2	1
Emerging markets	4	7
Global fund	3	1
Sector fund	5	3
Stock funds, N	27	23
Combination funds, N	7	7
Stock and combination funds, N	34	30

We provide the descriptive statistics for both datasets in Table 13. We separate the stock fund owners from the overall data to highlight the differences between stock fund owners and the overall data, which includes both stock and combination fund owners. When we turn to probit regression estimation, we use data which contains both stock and combination fund owners.

Table 13. Descriptive statistics.

Characteristics of the stock fund owners and the overall data (stock and combination fund owners). Panel A describes the data concerning the first stock market crisis June 30, 2008 – March 31, 2009 and panel B the second crisis May 31, – Sept. 30, 2011, respectively. The variable definitions occur in Chapter 3, Table 1.

Panel A, data 2008 – 2009

Investor characteristics	Stock fund owners, N = 162			Stock and combination fund owners, N = 258		
	Mean	Median	Std dev	Mean	Median	Std dev
Subjective and objective attributes						
Risk profile	3.01	3.00	0.85	2.77	3.00	0.88
Investment experience	1.94	2.00	0.64	1.91	2.00	0.64
Activeness in following economic events	1.80	2.00	0.74	1.68	2.00	0.74
Investment decisions	0.25	0	0.44	0.20	0	0.40
Risky share, %*	31.44	24.45	25.19	22.56	15.71	21.44
Gender	0.65	1.00	0.48	0.59	1.00	0.49
Age in years	47	49	15	49	51	15
Net income / month	2.17	2.00	0.62	2.09	2.00	0.58
Education	3.09	3.00	1.42	2.99	2.00	1.43
Wealth, €						
Value of total wealth	183 000	126 000	362 000	178 000	119 000	315 000
Total wealth (value of home excluded)	110 000	47 000	314 000	105 000	47 300	264 000
Value of interest instruments	44 900	20 400	99 100	45 500	23 100	84 000
Value of stock instruments	25 300	6 100	75 000	19 400	4 900	60 600
Value of fund portfolio in June 30, 2008*	7 700	4 400	9 400	9 200	4 800	11 000
Value of fund portfolio in March 31, 2009*	4 400	2 800	4 900	6 200	3 300	8 000
Rebalancing behavior, %						
Average rebalancing behavior (=active change)*	5.94	0.60	38.23	1.48	0	42.00

* Values of fund portfolios and average rebalancing behavior (indicated by asterisks) are calculated for those investors who own a fund portfolio of 1,000 € at minimum. The other attributes are calculated without this restriction. Risky share is calculated without the value of apartment in own use.

Panel B, data 2011

Investor characteristics	Stock fund owners, N = 843			Stock and combination fund owners, N = 1303		
	Mean	Median	Std dev	Mean	Median	Std dev
Subjective and objective attributes						
Risk profile	3.12	3.00	0.85	2.86	3.00	0.88
Investment experience	1.75	2.00	0.57	1.68	2.00	0.56
Activeness in following economic events	1.70	2.00	0.76	1.58	1.00	0.73
Investment decisions	0.23	0	0.42	0.19	0	0.39
Risky share, %*	35.04	27.80	28.52	29.53	22.56	25.83
Gender	0.52	1.0	0.50	0.48	0	0.50
Age in years	44	43	18	45	44	19
Net income / month	2.20	2.00	0.71	2.13	2.00	0.66
Education	3.35	4.00	1.43	3.04	3.00	1.43
Wealth, €						
Value of total wealth	211 000	153 000	294 000	192 000	140 000	270 000
Total wealth (value of home excluded)	76 000	21 000	184 000	66 000	18 000	160 000
Value of interest instruments	24 000	8 700	49 000	23 000	8 600	45 000
Value of stock instruments	14 500	3 200	49 000	10 900	2 500	40 400
Value of fund portfolio in May 31, 2011*	7 500	4 300	10 200	9 100	5 000	11 400
Value of fund portfolio in Sept. 30, 2011*	5 400	3 100	7 100	7 100	4 100	8 800
Rebalancing behavior, %						
Average rebalancing behavior (=active change*)	1.62	0	33.98	0.29	0	32.20

* Values of fund portfolios and average rebalancing behavior (indicated by asterisks) are calculated for those investors who own a fund portfolio of 1,000 € at minimum. The other attributes are calculated without this restriction. Risky share is calculated without the value of apartment in own use.

The trends in the descriptive statistics mirror our findings about *The influence of subjective attributes on portfolio choice*: investors with riskier investments (stock funds) are wealthier, better educated, see themselves to belong to more riskier profiles, have more investment experience, follow economic events more actively, are willing to make their own investment decisions, and they have invested a larger portion of their wealth in stock instruments.

Next, we examine those investors who own a stock and/or combination fund portfolio whose value is 1,000 euros at minimum either in the beginning or in the end of the research period. The reason to use that euro limitation is the monthly saving plans which some investors may have (we cannot identify which investors have such plans). A monthly saving plan means that the client has licensed the bank to make a automatic monthly withdrawal from his account to be invested in a mutual fund, typically 30 – 100 euros. For this reason, there are some investors with small fund portfolios, of which we drop the smallest ones. The monthly savings plans can increase the amount of buyers to some extent because the portfolios increase automatically with these investments. Nevertheless, it is not false to say that automatic monthly saving is an investment decision which should be accounted as a buying decision. In the table below, we report the investors' distribution as sellers, no rebalancing group and buyers. Due to small statistical reconciliations, we use a weighted active change of -1 – +1% instead 0% as the definition of no rebalancing group. When running the regressions, we further enlarge the range of the no rebalancing group to -10 – +10% to minimize the effect of potential saving plans. The wider range reduces the number of buyers and drops them to the no rebalancing group. Using this wider range has only minor influence on the number of sellers because of the high proportion of sellers with rebalancing over -10%. In Appendix 2 (Table 1) we indicate the relative shares of sellers, no rebalancing and buyers, using both ranges.

Table 14. Rebalancing behavior, stock and combination fund portfolios.

Rebalancing behavior of stock and combination fund portfolios during the stock market crises of June 30, 2008 – March 31, 2009 and May 31 – Sept. 30, 2011. The table includes investors with the value of fund portfolio 1,000 euros at minimum either in the beginning or in the end of research period. We classify investors into no rebalancing group if his rebalancing behavior (=active change) ranges from -1% to +1%. Rebalancing from -1% to -100% classifies him as a seller and rebalancing from +1% to +100% as a buyer.

Panel A: Crisis 2008 – 2009				
Stock fund owners	Sellers	No rebalancing	Buyers	Total
N	13	34	45	92
%	14	37	49	100
Stock and combination fund owners				
N	33	65	85	183
%	18	36	46	100
Panel B: Crisis 2011				
Stock fund owners	Sellers	No rebalancing	Buyers	Total
N	52	244	191	487
%	11	50	39	100
Stock and combination fund owners				
N	87	395	304	786
%	11	50	39	100

During the first stock market crisis in 2008 – 2009 14% of stock fund owners are classified as sellers. In unreported statistics we find them almost without exception to sell their fund portfolios totally, not only partly. Among the overall data, i.e. including both stock and combination fund owners, the share of sellers is 18%. And just as with stock fund owners, almost without exception they sell their whole portfolios – not only a part of it (mean -63%, median -74%, mode -100%[23]). During the slightly smaller stock market decline in 2011 the share of sellers drops to 11%. And again, the most typical selling decision is total withdrawal from the stock market by selling the whole fund portfolio (mean -65%, median -71%, mode -100%1)). The withdrawal observation is remarkable also because the crisis in 2011 was much shorter (4 months) than the crisis in 2008 – 2009 (9 months). On the other hand, there is also rebalancing behavior to increase the portfolio despite the stock market crises. During the decline of 2008 – 2009 the share of buyers is almost

[23] When we widen the no rebalancing group to -10 – +10% (we use this definition in regressions), the weighted active changes of sellers are even larger. During the crisis in 2008 – 2009: mean -82%, median -100%, mode -100% and during crisis in 2011: mean -69%, median -75%, mode -100%.

50%. The relative size of buying decisions is smaller than that of selling decisions: among the stock and combination fund owners the average active change is +28%. The amount of buyers drops to about 40% during the crisis in 2011 and the decrease in buyers shifts to the no rebalancing group. The average active change is 21% (stock and combination fund owners).

When we compare our investors' rebalancing behavior to Bilias *et al.'s* (2010) findings on U.S. households' trading behavior in upswing and downswing periods, we notice some similarity. According to Bilias *et al.'s* results, during the downswing of stock market values in 1999 – 2003 more than half of U.S. households did not trade at all. The remaining 44% of households were much more likely to buy (18%) than to sell stocks (5.5%) and 20.5% were both buying and selling. When Bucher-Koenen & Ziegelmeyer (2011) investigate the rebalancing behavior of German investors during the financial crisis in 2008, i.e. the same time period we use, they find 13% of the German investors to sell their entire risky portfolios and 11.6% to sell their portfolios partly. Calvet et al. (2009a) use Swedish data and find that households with a large initial risky share reduce their risky portfolios more aggressively than other investors in the bear market of 2000 – 2002. We analyze the possibility of the same phenomenon in our probit regressions.

4.5 Empirical results

We start by testing the predictive power of subjective and objective attributes as measures of financial sophistication on rebalancing behavior as separate variables. We use the dependent variable, i.e. the mutual fund rebalancing behavior, in a dichotomous form (seller/no rebalancing/buyer vs. other groups) to be able to categorize each explanatory variable as predictor of a certain rebalancing group. We run the probit regressions in two ways. The first method follows our hypothesis of the predictive power of higher financial sophistication to reflect more professional rebalancing behavior, which could be visible as non-participation as sellers and potentially even as participation as buyers. Then we invert the explanatory variable categories to test the effect of low sophistication on rebalancing behavior. After that, we continue according to the formulation of our hypothesis, i.e. we fit the regression model by linking the explanatory variables of higher financial sophistication to the same regressions and run the regressions of sellers, buyers and no rebalancing group.

The results in the table below show the financial sophistication variables which have predictive power as separate variables in classifying investor with this character to a certain rebalancing group. Because the data from the crisis in 2008 – 2009 is small, we take into account significances up to 10%. We also show the influence of risky share (see the argumentation in the methodology section, Chapter 4.3). To take into account minor portfolio changes caused by small liquidity needs or additions stemming from saving plans, we widen the no rebalancing group in the Descriptive statistics section from -1 – +1% to -10 – +10%. We run the regressions with investors who own fund portfolios of 1,000 euros at minimum in the beginning or in the end of the research period.

Table 15. The results of ordered logistic regressions, the lowest financial sophistication category as a reference category.

This table shows coefficients, standard errors and p-values of financial sophistication characteristics (measured by subjective and objective attributes) when using the lowest sophistication category as a reference category and contrasting other categories against it. In that way we can show to which rebalancing group investors with higher financial sophistication belong. The model is probit regression and has the form $Probit(Y) = \alpha + \beta x$. Y is a binary variable taking a value of 1 when the investor is a seller (Panel A), no rebalancing (Panel B) or buyer (Panel C) and taking a value of 0 when the investor belongs to other groups. α is intercept parameter (not reported in table below), β is regression coefficient and x is explanatory variable. We test each explanatory variable x in a separate regression and show the results of those variables which have statistical significance (Some variables are significant during either one of the crisis. If there is not significance, we do not show its statistics). We combine Risk profile categories of Very cautious and Cautious as a single category, keep profile Moderate as an separate category and combine Return seeking and Very return seeking categories as a single category. With crisis 2008 – 2009 data, we separate the Net income class 3 000 – 5 000 € / month from other income categories (dummy variable 1 = 3 000 – 5 000 € / month, 0 = less than 3 000 € / month or more than 5 000 € / month). With 2011 data we treat Net income as a four-category variable. We take into account those investors who own fund portfolio of 1,000 euros at minimum in the beginning or in the end of the research period.

Panel A: Dependent variable: Seller (1) vs. No rebalancing or Buyer (0)

	Crisis 2008 – 2009			Crisis 2011		
	Coefficient	Standard error	P-value	Coefficient	Standard error	P-value
Subjective attribute as an explanatory variable						
Investment decisions						
(0 = Ready solution, 1 = Own decisions)	0.6806	0.2631	0.0097	0.3302	0.1338	0.0136
Activeness in following economic events (reference category Infrequently)						
Weekly	0.3530	0.2721	0.1945	0.0285	0.1456	0.8451
Daily	0.6845	0.3093	0.0269	0.5366	0.1519	0.0004
Investment experience (reference category Novice)						
Some experience				0.0765	0.1470	0.6030
Experienced				0.7112	0.2215	0.0013
Risky share				0.0050	0.0022	0.0238
Objective attribute as an explanatory variable						
Log total wealth (value of home excluded)	0.2398	0.1029	0.0198	See Panel B		
Observations	Sellers N = 25, others N = 158, total 183			Sellers N = 81, others N = 705, total = 786		

Panel B: Dependent variable: No rebalancing (1) vs. Seller or Buyer (0)

	Crisis 2008 – 2009			Crisis 2011		
	Coefficient	Standard error	P-value	Coefficient	Standard error	P-value
Subjective attribute as an explanatory variable						

Objective attribute as an explanatory variable						
Log total wealth (value of home excluded)		See Panel A		0.1423	0.0342	<0.0001
Age, years (reference category -41 years)						
41 – 64				0.0794	0.1114	0.4760
65 -				0.3658	0.1326	0.0058
Observations	No rebalancing N = 97, others N = 86, total 183			No rebalancing N= 589, others N = 197, total = 786		

Panel C: Dependent variable: Buyer (1) vs. No rebalancing or Seller (0)

	Crisis 2008 – 2009			Crisis 2011		
	Coefficient	Standard error	P-value	Coefficient	Standard error	P-value
Subjective attribute as an explanatory variable						
Risk profile (reference category Very cautious or Cautious)						
Moderate	0.3932	0.2139	0.0660	0.2632	0.1288	0.0410
Return seeking or Very return seeking	0.5683	0.2919	0.0515	0.2534	0.1529	0.0973
Objective attribute as an explanatory variable						
Gender (0 = Woman, 1 = Man)				0.2547	0.1105	0.0212
Net income, € / month, data 2008-2009 (0 = Less than 3 000 € or More than 5 000 €, 1 = 3 000 – 5 000 €)	0.4453	0.2716	0.1011			
Net income, € / month, data 2011 (reference category < 1 000 € / month)						
1 000 – 2 999 €				0.6666	0.2402	0.0055
3 000 – 4 999 €				0.8464	0.2584	0.0011
5 000 € -				1.0003	0.3208	0.0018
Observations	Buyers N = 61, others N = 122, total = 183			Buyers N = 116, others N = 670, total = 786		

According to the results of Table 15, the influences of subjective and objective financial sophistication characteristics are divided into three rebalancing groups. Mainly, the same variables in each rebalancing group are significant during both crises, which increase the robustness of the results. Still, we are far from our ex ante assumption that more financially sophisticated investors should behave more professionally, precluding them from belonging to sellers and perhaps encouraging them to be bold enough to resist the market decline and buy more fund shares at low prices. Investors classified as the most financially sophisticated ones according to their subjective attributes – the most experienced investors (crisis in 2011), those who follow economic events the most actively, and those who want to make their own investment decisions – actually belong to sellers. The only subjective attribute associated with the buyer group is risk profile; belonging to higher risk profiles predicts a boldness to buy regardless of the market decline. In addition to being a marker of financial sophistication, this notion supports the findings of Chapter 3 that self-perceived risk profile reveals actual risk-standing ability.

The influence of the objective financial sophistication attributes is two-fold. Belonging to higher income categories correlates with the buyer group. During the first crisis the buyer propensity culminates in the net income class 3 000 – 5 000 € / month. During the latter crisis, the net-income effect is seen across all income categories contrasted to lowest income category. Male gender as a measure of financial sophistication shows as significant buyer variable in the latter crisis. Being middle-aged or older or having higher total wealth is not associated with courage to belong to buyers: in the 2011 crisis older investors and those having higher total wealth are typically representatives of the no rebalancing group. Wealthier investors even belong to sellers in the 2008 – 2009 crisis. During the crisis of 2008 – 2009 there are no significant attributes which would classify investors in the no rebalancing group. Higher education has no statistical significance in either crises, and we do not include it in Table 15.

According to Calvet et *al's* rebalancing behavior research (2009a), the larger the initial share of risky assets is, the less likely the investor is to have a positive active change. The statistical significance of risky share in the 2011 crisis follows Calvet *et al.'s* findings, whereas during the 2008 – 2009 crisis the risky share is not significant. We suppose the reason to be the lower average risky share of the first crisis data; the amount of investors with a risky share of at least 30% is 26% in the first crisis. In the latter crisis the share is 40%.

Next we invert the reference categories of the financial sophistication variables in order to supplement the findings in Table 15. In that way we can also classify investors with lower financial sophistication in the rebalancing groups they belong to.

Table 16. The results of ordered logistic regressions, the highest financial sophistication category as a reference category.

This table shows coefficients, standard errors and p-values of financial sophistication characteristics (measured by subjective and objective attributes) when using the highest sophistication category as a reference category and contrasting other categories against it. In that way we can show to which rebalancing group investors with lower financial sophistication belong. The model is probit regression and has the form *Probit(Y)* = $\alpha + \beta x$. *Y* is a binary variable taking a value of 1 when the investor is a seller (Panel A), no rebalancing (Panel B) or buyer (Panel C) and taking a value of 0 when the investor belongs to other groups. α is intercept parameter (not reported in table below), β is regression coefficient and x is explanatory variable. We test each explanatory variable x in a separate regression and show the results of those variables which have statistical significance. We combine the Risk profile categories of Very cautious and Cautious as a single category, keep profile Moderate as a separate category and combine Return seeking and Very return seeking categories as a single category. We take into account those investors who own fund portfolios of 1,000 euros at minimum in the beginning or in the end of the research period.

Panel A: Dependent variable: Seller (1) vs. No rebalancing or Buyer (0)

	Crisis 2008 – 2009			Crisis 2011		
	Coefficient	Standard error	P-value	Coefficient	Standard error	P-value
Subjective attribute as an explanatory variable						

Objective attribute as an explanatory variable						

Observations	Sellers N = 25, others N = 158, total 183			Sellers N = 81, others N = 705, total = 786		

Panel B: Dependent variable: No rebalancing (1) vs. Seller or Buyer (0)

	Crisis 2008 – 2009					Crisis 2011
	Coefficient	Standard error	P-value	Coefficient	Standard error	P-value
Subjective attribute as an explanatory variable						
Activeness in following economic events (reference category Daily)						
Infrequently				0.5939	0.1286	<0.0001
Weekly				0.5207	0.1395	0.0002
Investment experience (reference category Experienced)						
Novice				0.4068	0.1960	0.0379
Some experience				0.3757	0.1808	0.0377
Risk profile (reference category Very return seeking or Return seeking)						
Very cautious or Cautious				0.3144	0.1331	0.0182
Moderate				0.1125	0.1246	0.3667
Objective attribute as an explanatory variable						
Gender (0 = Man, 1 = Woman)				0.2408	0.0975	0.0136
Net income, € / month, data 2011 (reference category 5 000 € -)						
<1 000				0.6287	0.2736	0.0216
1 000 – 2 999				0.0826	0.2234	0.7117
3 000 – 4 999				0.0138	0.2408	0.9543
Observations				No rebalancing N= 589, others N = 197, total = 786		

Panel C: Dependent variable: Buyer (1) vs. No rebalancing or Seller (0)

	Coefficient	Standard error	P-value	Coefficient	Standard error	P-value
Subjective attribute as an explanatory variable						

Objective attribute as an explanatory variable						
Age, years (reference category 65 - years)						
-40	0.5714	0.3204	0.0743	0.4788	0.1584	0.0025
41 – 64	0.5748	0.2658	0.0306	0.4403	0.1528	0.0040
Observations	Buyers N = 61, others N = 122, total = 183			Buyers N = 116, others N = 670, total = 786		

Compared to the results indicating that higher financial sophistication as measured by subjective attributes is evident as selling propensity (Table 15), lower financial sophistication cannot be shown to hold the same predictive power (Table 16). Instead, investors with lower sophistication belong to the no rebalancing group. Those who follow economic events less actively than the daily followers do not engage in any rebalancing. The same is true of experience: novices and investors with some experience belong to the no rebalancing group contrasted to experienced investors. Willingness to utilize ready investment solutions (i.e. as opposed to those who want to make their own decisions and were sellers) is not significant in either the no rebalancing or buyer group. The above results hold true for the 2011 crisis data; the no rebalancing group does not separate in the 2008 – 2009 data.

In Table 15 we showed that belonging to higher risk profiles is a marker of the buyer group. In Table 16 we show that investors with lower risk profiles belong to the no rebalancing group. The same is also true of gender: men as representatives of sophisticated investors were buyers but women do not engage in rebalancing. Investors belonging to higher net income categories were buyers but those with net income less than 1,000 euros do not engage in rebalancing. Investors older than 65 contrasted with those less than 41 belonged to the no rebalancing group; in Table 16 younger investors (less than 65) appear as buyers.

Next we come back to our hypothesis and investigate the rebalancing behavior of investors with higher financial sophistication. We fit the regression model by combining in the same regression those variables which have predictive power as single variables explaining either the selling, no rebalancing or buying propensity of sophisticated investors. Thus, the regression concerning the crisis in 2008 – 2009 consists of the following variables: Activeness in following economic events, Investment decisions (0=ready solution, 1=own decisions), Log total wealth, Risk profile and Net income. The regression model of the crisis in 2011 consists of the following variables: Activeness in following economic events, Investment decisions (0=ready solution, 1=own decisions), Investment experience, Log total wealth, Age, Risk Profile, Gender and Net income. In each panel (A–F) of Table 17 we show statistics only for those variables which characterize the given rebalancing group. Similar to regressions with single variables, the dependent variable is dichotomous in order to separate sellers, buyers and no rebalancing group.

Table 17. The influence of financial sophistication on rebalancing behavior.

This table shows the results of probit regressions when using the investors' rebalancing behavior with their stock and combination fund portfolios as a dependent variable (we divide investors into sellers, no rebalancing group and buyers according to their actual transactions in their fund portfolios during the stock market crises in 2008 – 2009 and 2011) and as explanatory variables financial sophistication characteristics, which we separate into subjective and objective attributes. The model has the form *Probit(Y) = α + βx. Y* is a binary variable taking a value of 1 when the investor is a seller (Panel A and B), no rebalancing (Panel C and D) or buyer (Panel E and F) and taking a value of 0 when the investor belongs to other groups. *α* is intercept parameter (not reported in table below), *β* is a vector of regression coefficients and *x* is a vector of explanatory variables. The regression model of the crisis in 2008 – 2009 consists of the following explanatory variables: Activity to follow economic events, Willingness to make own investment decisions, Log total wealth, Risk profile (we combine the risk profile categories of Very cautious and Cautious as a single category, keep profile Moderate as a single category and combine Return seeking and Very return seeking categories as a single category) and Net income € / month (0 = Less than 3 000 € / month or More than 5 000 € / month, 1 = 3 000 – 5 000 € / month). The regression model of the crisis in 2011 consists of the following variables: Activity to follow economic events, Willingness to make own investment decisions, Investment experience, Gender, Log total wealth, Age, Risk profile and Net income € / month (categorical variable). In each panel we report coefficients, standard errors and p-values of those variables which were significant as single variables (see Table 15) in classifying investors as sellers, buyers or no rebalancing group. We take into account those investors who own fund portfolios of 1,000 euros at minimum in the beginning or in the end of the research period. Pseudo R-square refers to Nagelkerke Pseudo R-square.

Panel A: Dependent variable: Seller (1) vs. No rebalancing or Buyer Crisis 2008 – 2009			
Explanatory variable	Coefficient	Standard error	P-value
Investment decisions			
(0 = Ready solution, 1 = Own decisions)	0.6854	0.3048	0.0246
Activeness in following economic events (reference category Infrequently)			
Weekly	0.3780	0.2996	0.2071
Daily	0.6891	0.3603	0.0558
Log total wealth (value of home excluded)	0.2410	0.1122	0.0317
Observations	Sellers N = 25, others N = 158, total = 183		
Pseudo R-square	0.1925		
Panel B: Dependent variable: Seller (1) vs. No rebalancing or Buyer (0) Crisis 2011			
Investment decisions			
(0 = Ready solution, 1 = Own decisions)	0.1498	0.1587	0.3451
Activeness in following economic events (reference category Infrequently)			
Weekly	-0.0338	0.1640	0.8364
Daily	0.4250	0.1860	0.0223
Investment experience (reference category Novice)			
Some experience	0.0090	0.1624	0.9556
Experienced	0.5127	0.2730	0.0604
Observations	Sellers N = 81, others N = 705, total = 786		
Pseudo R-square	0.0710		

Panel C: Dependent variable: No rebalancing (1) vs. Seller or Buyer (0) Crisis 2008 – 2009			
Explanatory variable	Coefficient	Standard error	P-value

Panel D: Dependent variable: No rebalancing (1) vs. Seller or Buyer (0) Crisis 2011			
Log total wealth (value of home excluded)	0.1948	0.0395	<0.0001
Age, years (reference category -41 years)			
41 – 64	0.0242	0.1244	0.8459
65 -	0.3780	0.1560	0.0154
Observations	No rebalancing N = 589, others N = 197, total = 786		
Pseudo R-square	0.1414		
Panel E: Dependent variable: Buyer (1) vs. No rebalancing or Seller (0) Crisis 2008 - 2009			
Risk profile (reference category Very cautious or Cautious)			
Moderate	0.3694	0.2304	0.1088
Return seeking or Very return seeking	0.7782	0.3266	0.0258
Net income, € / month (0 = Less than 3 000 € or More than 5000 €, 1 = 3 000 – 5 000 €)	0.6519	0.2863	0.0228
Observations	Buyers N = 61, others N = 122, total = 183		
Pseudo R-square	0.2010		
Panel F: Dependent variable: Buyer (1) vs. No rebalancing or Seller (0) Crisis 2011			
Risk profile (reference category Very cautious or Cautious)			
Moderate	0.0994	0.1434	0.4883
Return seeking or Very return seeking	-0.1931	0.1897	0.3087
Gender (0 = Woman,1 = Man)	0.2099	0.1308	0.1085
Net income, € / month (reference category < 1000 €)			
1 000 – 2 999 €	1.0826	0.2772	<0.0001
3 000 – 4 999 €	1.2104	0.2952	<0.0001
5 000 € -	1.5210	0.3707	<0.0001
Observations	Buyers N = 116, others N = 670, total = 786		
Pseudo R-square	0.1807		

The results of Table 17 accord with the findings from regressions where we use these variables as single explanatory variables (Table 15). Self-perceived, subjective attributes mainly keep their significances as characteristics of selling behavior; high investment experience contrasted with least experience, activity to follow economic events most actively contrasted with investors who follow the economy only infrequently and willingness to make own investment decision instead of ready solutions from investment advisor or wealth manager (crisis in 2008 – 2009). The selling propensity is further strengthened by the notion that those who belong to sellers most typically sell their entire fund portfolios, not only a part of them (see descriptive statistics in Chapter 4.4). According to the results of Calvet *et al.* (2009a), wealthier households tend to resist the value decline of risky assets in a stock market downturn by buying more risky assets. Our investors behave differently. During the first crisis the wealthier investors are even sellers. Larger wealth does not stimulate resistance to market decline in the latter crisis either; wealth occurs as a significant variable in no rebalancing group. In addition to wealth, age 65 years or more retains its significance as characteristic of no rebalancing.

Monthly net income keeps its significance among buyers. During the first crisis the income class of 3 000 – 5 000 euros separates from other income classes. The positive active change among income class 3 000 – 5 000 euros is 16% on average, but among higher income investors the active change is negative, which is the case among investors with net income less than 3 000 euros as well. During the latter crisis the net income class 5 000 euros or more has the largest active change (+12% on average). Belonging to the highest risk-standing profiles, contrasted to the lowest risk-standing profiles, keeps its significance as a buyer feature during the first crisis. During the latter crisis risk profile does not keep its significance when we connect it with other significant variables.

In the Development of hypothesis section, Chapter 4.1, we predict a positive link between higher financial sophistication and expertise: *During the stock market crisis higher financial sophistication shows as more professional rebalancing behavior in fund portfolio*. We show this to hold only partly true. Investors with high net income and men – two objective attributes of sophistication – are bold enough to belong to buyers. Yet, there are also financial sophistication characteristics which classify investors into the no rebalancing group, which investors with mainly lower sophistication also belong to. In that way, financially sophisticated investors do not stand out from investors with lower sophistication. And in contrast to lower sophistication investors, financially sophisticated investors, as measured by their subjective attributes, belong to sellers. We conclude that the above-referenced results do not support our hypothesis of the more professional behavior of sophisticated investors. Thus, null hypothesis cannot be rejected.

We contribute to financial research by showing that the rebalancing behavior of more sophisticated investors does not always appear as more professional behavior. Financially more sophisticated investors – measured by their subjective attributes – are active in selling their portfolios. Selling propensity can lead them to rely too much on their own investment abilities and lead to the illusion that they can foresee market trends. This issue is further enlarged by their propensity to sell their entire fund portfolios, not only a part of them. We offer that financial sophistication – in addition to its very positive influences on investor's wealth care – may lead him to make investment mistakes like total withdrawal from the stock market, realization of short-term losses and exposure to timing problems of stock portfolio rebuilding. Lower investor sophistication can protect the investor from reacting to market volatility with the same intensity. However, belonging to higher risk profiles shows as boldness to buy despite the stock market decline. This observation further strengthens the finding from Chapter 3 that risk profile has an important link with actual investment behavior; investors belonging to higher risk profiles not only have higher risky shares but their risk-standing ability is also evident in their rebalancing behavior.

The argument that the selling propensity of sophisticated investors, as measured by subjective attributes, is an investment mistake is based on the random walk hypothesis, which states that stock prices cannot be predicted. In other words, the efficient-market hypothesis (Fama 1970) holds; prices reflect all public and no-public information, and no one can time his transactions in such a way as to achieve superior returns. If the reader is a proponent of the efficient market theorem, selling behavior is a mistake. Still, a reader can question whether the random walk of the stock market really exists. Shiller (2003) states that "There is a clear sense that the level of volatility of the overall stock market cannot be well explained with any variant of the efficient markets model in which stock prices are formed by looking at the present discounted value of future returns". If stock prices can at least partly be foreseen, were those financially sophisticated investors right when they sold their portfolios? Did they only react to huge volatility caused by non-rational behavior and market overreaction which they understood would lead to collapse of prices? By selling did they only want to save their portfolios from the collapse? But when the prices continued to fall, why did they not return to the market? We leave these questions open to the reader.

Robustness check

As a robustness check we run the regressions shown in Table 17 by using OLS regression models. We use the dependent variable – the active change – as a continuous variable, i.e. we do not classify investors into three separate rebalancing groups. As explanatory variables we use the same subjective and objective attributes of financial sophistication which were shown to be significant in the probit regressions. The results of the OLS regressions confirm the signs of the explanatory variables' coefficients.

We control the risky share by re-running the probit regressions from Table 17. This test is motivated by Calvet *et al's* research (2009a), who find the initial risky share to have effect on rebalancing behavior (investors with larger risky share are less likely to buy stocks during the market decline). In the 2008 – 2009 crisis data the variables significant for sellers keep their significances. The same is true for the Net income and Risk profile variables among buyers. The Risk profile Moderate rises in significant too. In the 2011 crisis data the selling propensity of investors who follow economic events most actively keeps its statistical significance. The significance of Investment experience weakens from 6% to 13%. Among sellers, the Risky share itself is significant too. Among no rebalancing group Age and Total wealth keep their significances. Net income keeps it significance among buyers.

4.6 Other remarks on rebalancing behavior: directly owned stocks and risky interest funds

In this chapter we offer remarks on rebalancing behavior with risky interest funds and brokerage accounts which contain directly owned stocks. We base our remarks on the descriptive statistics, i.e. we do not run regressions. With the risky interest funds regression would be possible as we can separate the active change from passive change in the same way as with stock and combination funds. Although the values of risky interest funds partly follow stock market fluctuations, they do not consist of stock instruments, which are the main focus of our research. With directly owned stocks we are not able to separate the active change from passive change.

Our data includes 134 (2008 – 2009) / 899 (year 2011) brokerage account owners. Their stock portfolios consist of stocks listed mainly on the Helsinki Stock Exchange. During the crisis in 2008 – 2009 the OMX Helsinki index fell -47%. The index fall in the 2011 crisis was -26%. In contrast to fund portfolios, with directly owned stocks we would need the transaction data in order to separate the market value fluctuations from rebalancing behavior. Although we do not have the transaction data, we do have the balances of brokerage accounts in the beginning and in the end of the research periods. That makes it possible to compare the changes of brokerage account values with index values. The results, however, should be read carefully as the contents of brokerage accounts differ from OMX Helsinki index weights. Bearing this shortcoming in mind, we shortly describe the value changes of stock portfolios.

During the crisis in 2008 – 2009 the share of brokerage account owners whose accounts lose value was 72%. Among the diminished accounts the average drop was -42%, i.e. slightly less than the index drop. In contrast to mutual fund owners, there were only six out of 134 account owners (4.5%) who sold their stock portfolios totally. Also, there were more investors who established stock portfolios under the crashing market conditions than with fund portfolios. During the crisis in 2011, 59% of brokerage account owners were hit by the value decline of stock portfolio. The average decline among them was almost the same as the market decline, being -25%. Again, only 18 investors (2.00%) of 899 sold their stock portfolios totally.

The reason for brokerage account owners' bolder behavior during the crises may arise from several issues. The disposition effect can show as unwillingness to sell stocks below purchasing prices or at decreased values. With fund portfolios, investors may suffer from trend chasing: they may have a propensity to withdraw from such portfolios whose values they believe will continue to fall. Also, as a result of selecting to invest directly in stocks instead of funds taken care of by wealth managers, brokerage account owners may have a higher risk tolerance than fund owners have, providing them ability to withstand the bad market conditions.

In Table 18 we show the distribution of risky interest fund owners as sellers, buyers and no rebalancing group. Investors who own risky interest fund portfolios are partly the same ones who own stock and/or combination funds. The rest are investors whose fund portfolios consist of only interest funds. By risky interest funds we mean mutual funds which correlate with stock market values but do not consist of stock instruments. The investment target of those funds is corporate bonds, emerging market bonds, convertible bonds or some combination of risky interest instruments. Because of the small number of risky interest fund owners, we do not run regression models. Nor do we include the risky interest fund portfolios in our regressions with stock and combination funds to target our research on stock market instruments.

The average decline of risky interest funds during the first crisis was -12% on average, ranging from -23% to -5%. During the latter crisis market values of risky interest funds declined on average -7% and the range was large, from -38% to +2%.

Table 18. Rebalancing behavior, risky interest fund portfolios.

Rebalancing behavior, risky interest fund portfolios. The rebalancing behavior of risky interest fund portfolios during June 30, 2008 – March 31, 2009 and May 31, 2011 – Sept. 30, 2011, fund ownership min. 1,000 euros. We classify investors into no rebalancing group if his rebalancing behavior (=active change) ranges from -10% to +10%. Rebalancing from -10% to -100% classifies him as a seller and rebalancing from +10% to +100% as a buyer.

	Sellers	No rebalancing	Buyers	Total
Crisis 2008 – 2009				
N	46	25	17	88
%	52	29	19	100
Crisis 2011				
N	11	27	9	47
%	23	58	19	100

We notice the clear prudence of risky interest fund owners especially during the first crisis. The share of sellers is much larger with risky interest fund portfolios than with stock and combination funds. During the first crisis more than half of interest fund owners belonged to sellers whereas the share of sellers among stock and combination fund owners was 14%[24]. During the latter crisis, 23% of risky interest fund owners were sellers compared to the 10 percent[24] among the stock and combination fund owners. And as with stock and combination fund owners, the risky interest fund owners most typically sold their entire fund portfolios – not only a part of them.

4.7 Conclusions

In this research we investigate the individual investors' rebalancing behavior in their stock and combination fund portfolios during the two sequential stock market crises between summer 2008 and spring 2009 as well as from spring 2011 to autumn 2011. By rebalancing behavior we mean investors' own decisions in their fund portfolios. We separate investors' active rebalancing behavior from passive changes caused by market value fluctuations and divide investors into three groups: sellers, buyers and no rebalancing.

[24] The range of no rebalancing group -10% - +10%.

We contribute to the earlier research by showing that the positive link between financial sophistication and ability to better portfolio management need not always be the case. In contrast to our ex ante assumptions, investors with financial sophistication, measured by their subjective attributes – investors considering themselves as experienced investors, following economic events most actively or willing to make their own investment decisions – belong to sellers. Neither financial sophistication through higher education, wealth level, or age as a means of longer history with investments encourages investors to take advantage of the decreased prices and buy more funds and/or to resist the depreciation of portfolio value due to general stock market decline. In that way they do not separate from investors with lower sophistication, who most typically leave their portfolios untouched during crises. Only membership in higher income classes and belonging to higher risk-standing profiles was associated with boldness to invest further. Our observation on risk profile also strengthens the finding of Chapter 3 that self-perceived risk profile predicts actual risk-standing ability, which in this context is evidenced as bolder rebalancing behavior.

We put forth the question of whether – in addition to positive influences of financial sophistication on investor's wealth care – higher financial sophistication can lead the investor to make mistakes like total withdrawal from the stock market, realization of short-term losses or exposure to timing problems of stock portfolio rebuilding. Financially less-sophisticated investors can be slower to engage in rebalancing due to less investment information or hesitancy to make personal investment decisions.

Our existing research supports the results of our previous empirical research *The influence of subjective attributes on portfolio choice* (Chapter 3) that investors' subjective attributes are a prominent way to understand investment behavior, portfolio choices and actions in portfolios. This gives us a stimulus to further investigate the effect of investor-specific subjective variables on investment behavior. We offer these results in Chapter 5: *Investor-specific diversification and trading decisions: due to overconfidence or something else?*

5 Investor-specific trading and diversification decisions: due to overconfidence or something else?

We continue our research on self-perceived attitudes, evaluations and judgments from a third perspective. Confidence in one's own investor abilities – which can show as overconfidence – is indeed a very subjective perception. We test the power of investors' confidence level as a potential explanation for differences in trading and diversification, two important aspects of investment behavior. Also, in line with the purpose of our thesis, we test the influence of other investor characteristics on diversification and trading. Analogously with the empirical researches in Chapters 3 and 4, we divide the characteristics into self-perceived, subjective attributes and objective attributes, which describe investors' demographic and socio-economic characteristics. The attributes are in part the same as used in Chapter 3 and 4, but a number of new ones are also introduced. For example, the questions which indicate investor-specific risk profile are identical with the earlier chapters. We use a database which we gather among experienced investors who are members of Finnish Shareholders' Association.

5.1 Development of hypotheses

According to prior research, confidence in one's own investor abilities can lead to too active trading in common stock portfolios. That happens because of too strong belief in the superiority of one's own information and capability. This causes differences in investors' opinions and generates active trading. Overconfident investors overestimate the expected profits and engage in trades where the profits are insufficient to cover the costs of trading. This is in contrast to the rationality theory, which predicts investors to maximize their expected utility (Daniel *et al.* 1998, Odean 1998). We test this phenomenon by forming the following hypothesis:

Hypothesis 1: *The more overconfident the investor is, the more actively he trades in his stock portfolio*.

Previous research has also indicated another possible consequence of overconfidence, namely poor diversification (Guiso & Jappelli 2006, Goetzmann & Kumar 2008). When investors rely too strongly on their abilities or on their own information, they may choose to hold portfolios marked by stock picking. This is in contrast with rational utility's view on uncompensated risk avoidance. Therefore, we form the following hypothesis:

Hypothesis 2: *The more the investor is overconfident, the less he diversifies his stock portfolio*.

We create a comprehensive mix of measures of overconfidence to test Hypotheses 1 and 2. We pick the manifestations of overconfidence studied in prior research (we present them in Chapter 1.4.1) and construct two questions to measure each manifestation. We use the same questions used in earlier research but we also formulate our own questions. We describe our measures of overconfidence in detail in the Data section (Chapter 5.2.1).

We also test a large variety of other subjective and objective attributes to explain trading/diversification decisions. This is in line with the overall purpose of our research, i.e. to give new information especially on self-perceived issues as generators of differences in investment behavior. We do not list these attributes in Hypothesis 3. In the data section we discuss ex ante assumptions of the signs of those variables. As an example of the attributes we test in Hypothesis 3, we highlight investors' *actual knowledge* of economy and investment issues. We measure the actual knowledge of investors using questions we formulate and by using the questions of Lusardi & Mitchell (2005, 2009). Lusardi & Mitchell encourage researchers to use their questions with different investors and with different research problems to get comparison results. We form the third hypothesis:

Hypothesis 3: *In addition to measures of overconfidence, investor-specific*
3a: subjective attributes
3b: objective attributes
explain trading activity/diversification decisions.

Hypothesis 4 has a connection to our research on rebalancing behavior during the stock market crises (see Chapter 4). According to the results of the rebalancing behavior research, investors who belong to the rebalancing group of sellers (other groups are buyers and no rebalancing group) have a propensity to sell their fund portfolios entirely, not only partly. We test whether this phenomenon is valid also with another dataset. We construct an On/off variable by asking the investors' opinion about total withdrawal from the stock market: "When stock prices start going downwards, it is best to sell the whole stock portfolio, not only a part of it" (scale from 1 = Strongly disagree to 5 = Strongly agree). The theoretical basis for this variable arises from the rule of random walk, which says that market prices cannot be foreseen. Still, investors may think they can forecast future stock prices. This motivates them to withdraw totally from the stock market when they estimate the stock prices to start decreasing. They may view total withdrawal as an alternative to proper diversification or as a means of hedging their portfolio (this can show as more active trading too and we test the matter in trading regressions). We thus formulate our fourth hypothesis:

Hypothesis 4: *On/off movement, i.e. willingness to totally withdraw from the stock market rather than partially withdraw, shows less diversification of stock portfolio.*

5.2 Data and methodology

5.2.1 Data

We gather our data by constructing a questionnaire which targets investors who belong to the Finnish Shareholders' Association (Osakesäästäjien Keskusliitto). Membership in this organization reveals interest in direct stockholding and focuses our results on experienced investors with common stock portfolios. There are over 10,000 members of the Finnish Shareholders' Association and they cover all geographical areas of the country. The questionnaire was sent to all those members who had given their e-mail addresses to the Association, i.e. about half of the members. The respondents answered the questionnaire mainly through e-mail (976 pieces). The rest of the questionnaires were filled by hand during stockholders' meetings (50 pieces) using printed questionnaires. As a whole the data covers about 1,024 individuals. The survey was conducted through e-mail link between May 13, – June 13, 2012 and the printed questionnaires were gathered between April 20, – May 26, 2012.

We ask the respondents to indicate their *trading activity* by choosing the alternative that best describes their trading activity: How actively do you trade with your stock portfolio? (1 = More seldom than once a year, 2 = Once a year, 3 = Biannually, 4 = Quarterly, 5 = Monthly, 6 = Weekly, 7 = Daily). To investigate the *diversification decision*, we ask about the number of stocks in the respondent's stock portfolio: How many companies' stocks do you own? (1 = 0 stocks, 2 = 1-2 stocks, 3 = 3-6 stocks, 4 = 7-10 stocks, 5 = 11 or more stocks). According to an often-cited article of Evans & Archer (1968), much unsystematic risk is eliminated by adding the 8th stock series to the portfolio. We use an even higher boundary to describe the best diversified stock portfolio, namely 11 or more stocks.

We construct our measures of overconfidence in order to test a comprehensive mix of manifestations of overconfidence: *illusion of knowledge, illusion of control, self-attribution bias* and *miscalibration*. To avoid relying on a single measure, we examine each manifestation with two separate measures. We clarify potential miscalibration by using confidence interval questions. We ask the respondents to give their best return prediction as well as upper and lower bound of 90% confidence intervals. The other measures we ask as claims. The response scale of claims follows a five-category Likert type scale (Likert 1932, Boone et al. 2012) which is aimed at measurement of attitudes. In Likert type scale the response categories have an order, but the intervals between the categories cannot be measured. We numerate the categories in the following way: 1 = Strongly disagree, 2 = Somewhat disagree, 3 = Do not know, 4 = Somewhat agree, 5 = Strongly agree. We also give the respondents the alternative to choose the Do not know answer. This enables us to recognize whether any uncertainty exists about a certain question. When we run the factor analyses and regressions, we drop the Do not know answers and numerate the answers in a new way: 1 = Strongly disagree, 2 = Somewhat disagree, 3 = Somewhat agree, 4 = Strongly agree.

Next we present the questions which we use to measure the manifestations of overconfidence. In the empirical research we use 1) - and 2) – symbols to differentiate separate measures of each manifestation (for example, Illusion of knowledge 1) as well as Illusion of knowledge 2)).

Manifestation 1: Illusion of knowledge

Dorn & Huberman (2005) state that the interpretation "I am better informed than the average investor" is not defined clearly enough. For that reason we define the peer group to refer to the other members of the Shareholders' Association.

Measure 1): I have more useful investment knowledge than the average member of the Shareholders' Association.

Measure 2): I believe that I have had better investment performance than the average member of the Shareholders' Association.

(For example Dorn & Huberman (2005) use the same technique to ask self-perceived investment knowledge relative to others but their questions differ slightly from ours.)

Manifestation 2: Illusion of control

We construct claims in the following way to measure the potential illusion of control:

Measure 1): Typically, I have been right when I have had to predict the future price level of investment instruments.

Measure 2): It is very probable that in a situation of economic fluctuation I know how to time my selling point right, i.e. I can sell before the decline of stock market starts.

(See for example Dorn & Huberman (2005), who use four questions on perceived control in risky situations. Alternatively, see De Bond (1998). Still, Measures 1) and 2) are our own formulations.)

Manifestation 3: Self-attribution bias

We solicit responses about the two dimensions of the self-attribution bias: the propensity to take the honor of successful investments, and a denial to take the responsibility of miss-success and instead blame external factors.

Measure 1): Success in investing has happened mainly because of my personal ability and knowledge.

Measure 2): Miss-success in investing has happened mainly because of some external circumstances which have not been dependent on my personal ability or knowledge.

(The wording of Measure 1) follows quite closely the question used by Dorn & Huberman 2005.)

Manifestation 4: Miscalibration

We ask the respondents to provide their best return prediction as well as upper and lower bound of 90% confidence intervals concerning the 12-month return of the Finnish stock market (OMX Helsinki 25 index) and their own stock portfolio. We use the following question:

What is your prediction about the return of the OMX Helsinki 25 index during the following 12 months? Indicate your best return prediction (+/-) and the upper and lower bound in such a way that you are 90% sure the return lies between these bounds.

The best return prediction _____%
Lower bound _____%
Upper bound _____%

(We solicit the return prediction and bounds concerning respondent's own stock portfolio by using a similar question.)

These two questions enable us to compare if the respondents estimate their own portfolios to outperform the market return, which could point to overconfidence in their own abilities. The upper and lower bounds also enable us to calculate the respondents' volatility estimates[25] and compare those estimates to historical and implied volatility. Thirdly, we calculate the difference between the upper (lower) bound and the best return prediction to see if the respondents see the bounds symmetrically or as skewed. We use the same technique as Graham & Harvey (2003) to check potential skewness. We calculate the differences between the best return prediction and lower and upper bounds and subtract those differences from each other. We standardize the skewness by cubing the difference and dividing by the cube of the respondent's standard deviation.

As Measure 1) on miscalibration we use the difference between the 12-month return prediction of the investor's own portfolio compared to that of the market. As Measure 2) on miscalibration we use a dummy variable which gets a value 1 (0) if the respondent evaluates the 12-month volatility of the OMX Helsinki 25 index to be even smaller (larger) than the 12-month volatility of the OMX Helsinki 25 index calculated as an average among all respondents.

(See De Bondt (1998), Odean (1998), Barber & Odean (2002), Graham & Harvey (2003), Glaser & Weber (2007), Graham et al. (2009) and Deaves et al. (2010) who use the miscalibration techniques)

[25] We calculate the volatility in the following way (Keefer & Bodily (1983): variance = $([x(0.95) - x(0.05)]/3.25)^2$, volatility = square root(variance).)

In addition to measures of overconfidence, our questionnaire includes a large variety of subjective and objective attributes that describe the respondents. We use those attributes as explanatory variables in order to fulfill the purpose of our research, i.e. to test the influence of subjective and objective attributes on portfolio choices and actions. In the following paragraphs we mainly introduce the subjective variables. A complete list of variables as well as how they were constructed is offered in Appendix 3.1.

We measure the respondent's risk-standing ability, his *Risk profile*, through two questions. The first question reveals his return target and the second his attitude towards stock market fluctuations. The questions are the same that we use in the research *The influence of investor's subjective attributes on portfolio choice* (see Chapter 3) in order to get comparative information. Our results in Chapter 3 give support to earlier findings (see, for example, Dorn & Huberman 2005) that non-complex risk-standing measurement tools help to clarify investor-specific risk tolerance. Based on earlier findings (Dorn & Huberman 2005) about the positive link between higher risk tolerance and more active trading, we expect the respondents who belong to higher risk profiles to trade more actively. In line with Guiso & Jappelli's (2006) findings, we expect higher risk aversion, i.e. belonging to lower risk profiles, to correspond to larger diversification.

We test whether the amount of *Self-perceived* and/or *Actual investment knowledge* shows as more professional investment behavior when diversifying the portfolio. We expect the respondents with higher actual investment knowledge to diversify their portfolios more widely in order to take advantage of the lower volatility of a diversified portfolio. Also, we expect respondents with higher knowledge to avoid overly frequent trading. We measure the actual knowledge by using six questions constructed by Lusardi & Mitchell (2005, 2009, see also Rooij et al. 2011, 2012) and construct three additional questions. We solicit the self-perceived knowledge through two questions: how do the respondents estimate the level of their financial information and how do they evaluate their ability to describe various investment instruments to their friends. If the respondent has a realistic perception of his investment knowledge, self-perceived knowledge is visible in the same way as actual knowledge, i.e. through less active trading and wider diversification. If he overestimates his knowledge, he should be prone to overactive trading and under-diversification.

We solicit the respondents' *Investment experience* by using a three-alternative scale: Experience of less than 5 years, 5-10 years, or over 10 years. In prior research there are different findings on the influence of experience on investment behavior.

Experienced investors can be prone to active trading, (see for example Barber & Odean 2001), but Dorn & Huberman (2005) find the opposite. Goetzmann & Kumar (2008) find investors with longer experience to hold more diversified portfolios. On the other hand, experience can also show as a strong confidence in one's own abilities, which may translate into narrower diversification (Deaves *et al.* 2010).

We have two separate variables to describe the respondents' *Activeness in following economic events*. The respondents choose their activity in market-following on the following scale: Infrequently, Weekly or Daily. In the second question the respondents indicate the amount of time (hours/week) which they spend gathering investment information. Spending a large amount of time on gathering investment information can drive investors to rely too strongly on their own knowledge, which can be seen as as active trading or under-diversification (Dorn & Huberman 2005, Guiso & Jappelli 2006).

We ask the respondents to indicate their most important information channel when making investment decisions: relatives, friends or other acquaintances, newspapers, internet or personal counseling of banks or financial institutions. Because 77% of respondents cite the internet to be their most important channel, we construct a dummy variable, *Internet* (1=Internet / 0=Other channel), and test its effect on trading activity. The variable *Tradespeed* is meant to determine how important it is to our respondents to have a fast access to stock market to be able to make transactions quickly. We expect both of these variables to show as more frequent trading.

We increase the evidence of subjective attributes' influence on investment behavior by testing the effect of the familiarity bias on diversification decisions. Investors are prone to pick those stocks they are familiar with, which can be discerned as a lack of proper diversification (see, for example, Graham *et al*. 2009 or Huberman 2001). For that purpose we construct a *Familiarity bias* variable: I would rather own only a few stocks which I am familiar with than own a diversified portfolio including stocks unfamiliar to me. We use the same scale as with measures of overconfidence, which we solicit as claims (scale from Strongly disagree to Strongly agree). De Bondt (1998) uses quite similar wording when investigating a small group of brokerage account owners in the USA. We admit it is quite unsurprising that the familiarity bias exists especially in Finland, and assume it causes Finnish individuals to prefer familiar stocks listed in the Helsinki index. The investment culture of Finland people is quite young; Finland is situated a long away from the world's largest stock exchanges and has its own, small language area. Still, because our respondents are very experienced, i.e. they are well-educated investors with a great deal of information on Finnish stocks, it is interesting to test whether the Familiarity bias shows among them also.

We broaden the investigation of familiarity by asking how well the respondent perceives himself to be *Familiar with each of the 25 companies on the OMX Helsinki 25 index* (scale from 1 = Very poorly to 5 = Very well, we sum the scores the respondent gives to the stocks). We test if higher familiarity with the stocks shows as wider diversification. This is opposite to the way that the concept of familiarity is normally tested and supplements the results of the familiarity bias variable. We expect a familiarity with the stocks to be evidenced as wider diversification.

We test if the respondents' background risk, as measured by career choice, is indicative of trading activity or diversification decisions. There are findings that show that entrepreneurs can be more risk tolerant than domestic sector workers, see Cooper *et al*. (1998), Bernando & Welch (2001) or Selcuk *et al*. (2011). We solicit the respondent's career choice: public sector worker, private sector worker, entrepreneur, student, retired, or other life situation. We construct dummy variables, *Entepreneur* (1=Entepreneur / 0=Else than entrepreneur) as well as *Domestic sector worker* (1=Domestic sector worker / 0=Else than domestic sector worker). We expect the background risk to be visible as differences in behavior: entrepreneurs should be inclined toward more active trading and toward lower degree of diversification.

The *On/off* variable, ”When stock prices start going downwards, it is best to sell the whole stock portfolio, not only a part of it” (scale from Strongly disagree to Strongly agree) has its roots in our research *Rebalancing behavior during the stock market crisis 2008 – 2009 and 2011* (see Chapter 4). We find that those investors who belong to sellers most typically sell their entire fund portfolios, not only a part of them. We argue the investors falsely assume they can "know the ups and downs of the stock market", which motivates them to withdraw from the market completely by realizing their portfolios. By doing so they ignore the rule of the random walk of the stock market, which says that market prices cannot be foreseen. We test whether the propensity to On/off movements is visible also in another dataset, i.e. as an alternative to proper diversification or as a means to hedge the portfolio against the market value decline.

5.2.2 Methodology

In the data section, Chapter 5.2.1, we presented the methodology used to construct the measures of overconfidence as well as formulate the other attributes. In the descriptive statistics section, Chapter 5.3, we run a principal factor analysis to test if those measures of overconfidence which we ask as claims load on certain factors. We end up forming three factors (one of them is not a real factor because only one variable loads on it). When we run ordered logistic regressions with trading activity or diversification as a dependent variable, we can use these factors as measures of overconfidence instead of separate variables of overconfidence. We do this but put the results in Appendix 3.4 and 3.5. In our main tables describing the trading activity and diversification results, we use separate measures of overconfidence to bring out the potential explanatory power of each individual measure. However, we organize the regression results according to our factors. For example, we designate Factor 1 as the Success caused by own skills factor, which both Illusion of knowledge measures and one of the Self-attribution bias measures load on. In regression tables (Table 24 and 25) we show the results of the regressions, each separately, where we have used these three measures of overconfidence (one measure at a time) as explanatory variables and numerate the regressions as numbers 1, 2 and 3.

Both dependent variables, trading activity and diversification, are ordinal variables. For that reason we run ordered logistic regressions. Similarly, most of our explanatory variables are ordinal. We use them by defining as a reference category the lowest category of each variable and contrasting other categories against it. At the end of the empirical results section, we perform several robustness checks to test the validity and reliability of the results. The ordered logistic regression model has the following form:

$$\text{Trading activity: } logit[Pr(Y \leq i \mid x)] = \alpha_i + \beta x,$$

where Y = the respondent's trading activity measured as a categorical form: 1) Once a year or Biannually, 2) Quarterly, 3) Monthly and 4) Weekly or Daily, α_i = intercept parameters, β = a vector of regression coefficients and x = a vector of explanatory variables.

$$\text{Diversification decision: } logit[Pr(Y \leq i \mid x)] = \alpha_i + \beta x,$$

where Y = diversification decision of respondent's stock portfolio measured as a categorical form: 1) 1-2 or 3-6 stocks, 2) 7-10 stocks and 3) 11 – stocks, α_i = intercept parameters, β = a vector of regression coefficients and x = a vector of explanatory variables.

Methodology to model trading activity / diversification decision and its explanatory variables in the above described form follows for example Glaser & Weber's (2007), Guiso & Jappelli's (2009) and Graham et al's (2009) research.

5.3 Descriptive statistics

In the following chapter, we present descriptive information about the respondents' answers to the overconfidence measures. We present the statistics on miscalibration separately due to its different formulation; we solicit miscalibration by using confidence interval questions and the other measures by using claims. We present the descriptive statistics of the other variables in Appendix 3.2.

Table 19. Descriptive statistics: Illusion of knowledge, Illusion of control, Self-attribution bias.

This table presents descriptive statistics of measures of overconfidence which we ask as claims. We show means, medians and modes in order to describe central tendencies and relative frequencies, thus describing variability. We numerate the answers by using the following scale: 1=Strongly disagree, 2=Somewhat disagree, 3=Do not know, 4=Somewhat agree, 5=Strongly agree.

Panel A

Central tendency	Mean	Median	Mode
Illusion of knowledge (Measure 1: N = 1017, Measure 2: N = 1017)			
Measure 1): I have more useful investment knowledge than the average member of the Shareholders' Association.	3.23	3.00	4.00
Measure 2): I believe that I have had better investment performance than the average member of the Shareholders' Association.	2.95	3.00	2.00
Illusion of control (Measures 1: N = 1015, Measure 2: N = 1013)			
Measure 1): Typically, I have been right when I have had to predict the future price level of investment instruments.	2.92	3.00	2.00
Measure 2): It is very probable that in a situation of economic fluctuation I know how to time my selling point right, i.e. I can sell before the decline of stock market starts.	2.21	2.00	2.00
Self-attribution bias (Measure 1: N = 1006, Measure 2: N = 1013			
Measure 1): Success in investing has happened mainly because of my personal ability and knowledge.	2.95	3.00	4.00
Measure 2): Miss-success in investing has happened mainly because of some external circumstances which have not been dependent on my personal ability or knowledge.	2.80	2.00	2.00

Panel B

Variability	Strongly disagree	Somewhat disagree	Do not know	Somewhat agree	Strongly agree	%
Illusion of knowledge (Measures 1 – 2)						
Measure 1)	5.31	27.73	17.70	36.58	12.68	100
Measure 2)	5.70	35.30	22.03	31.86	5.11	100
Illusion of control (Measures 1 – 2)						
Measure 1)	4.44	45.41	5.23	43.34	1.58	100
Measure 2)	25.91	47.19	7.00	19.31	0.59	100
Self-attribution bias (Measures 1 – 2)						
Measure 1)	7.95	39.26	6.96	41.25	4.57	100
Measure 2)	12.64	40.28	6.12	36.13	4.84	100

Table 20. Descriptive statistics: Miscalibration.

This table presents descriptive statistics of miscalibration variables. The respondents give their predictions about 12-month market return (OMX Helsinki 25 index) and own stock portfolio return. They give their best 12-month return predictions as well as lower and upper bounds of returns in such a way that they are 90% sure the return lies between these bounds. Using those predictions, we calculate the respondents' volatility estimates and skewness of 90% confidence intervals. We construct two separate measures of overconfidence: Measure 1) The difference between the 12-month return prediction of own portfolio and market portfolio, and Measure 2) A dummy variable which gets a value of 1 (0) if the respondent evaluates the 12-month volatility of the OMX Helsinki 25 index to be even smaller (larger) than the 12-month volatility of the OMX Helsinki 25 index calculated as an average among all respondents.

	Mean	Median	Std dev
12 month return prediction, %			
OMX Helsinki 25 index	10.08	9.00	14.27
Own portfolio	11.50	10.00	15.94
12 month volatility prediction, %			
OMX Helsinki 25 index	8.12	6.15	7.03
Own portfolio	8.48	6.15	8.10
Standardized skewness			
OMX Helsinki 25 index	-1.95	-0.27	4.16
Own portfolio	-1.79	-0.21	4.33
Miscalibration (Measure 1: N = 712, Measure 2: N = 712)			
Measure 1): The difference between the 12-month return prediction of the investor's own portfolio compared to that of the market, %-point	1.42	0	8.71
Measure 2): A dummy variable which gets a value 1 (0) if the respondent evaluates the 12-month volatility of the OMX Helsinki 25 index to be even smaller (larger) than the 12-month volatility of the OMX Helsinki 25 index calculated as an average among all respondents.	0.62	1.00	0.49

The results imply that the respondents rely strongly on their investment knowledge relative to other members of the Shareholders' Association. Confidence in one's own skills is also evident in the Self-attribution 1) measure, stating that success in investing has happened mainly because of one's own ability and knowledge. Almost three-quarters of respondents do not believe they can time the selling point right and sell before the decline of stock values starts (Illusion of control 2). The answers to another Illusion of control claim divide strongly: about half of respondents agree they can foresee the price level but the other half do not agree. The same variation in answers occurs also when the respondents evaluate the effect of external issues on their miss-success. The respondents give Do not know answers most often to

Illusion of knowledge claims, but with Illusion of control and Self-attribution bias claims they typically have an opinion.

Some respondents have problems understanding the miscalibration questions, which show as illogical answers: their best return prediction is not situated within the bounds. We drop those answers and use 712 correctly answered ones. The average 12-month return prediction for the Finnish stock market, namely 10.08%, is quite close to the historical mean 12.91% (Nyberg & Vaihekoski 2013, the average value weighted, continuously compounded nominal return in Finland between 1912 – 2009). The respondents underestimate stock market fluctuations: the average cited standard deviation is 8.12%, whereas the historical 12-month standard deviation of the Finnish stock market is 20.76% (Nyberg & Vaihekoski 2013). Prior research documents that volatility estimation is linked with near future volatility, as measured by implied volatility (VIX index), see for example Graham & Harvey (2003) or Glaser & Weber (2007). Because there is no implied volatility calculation for the Finnish stock market, we consider the 12-month implied volatility of the S&P 500 index. We find the VIX index to vary between 16.06 – 20.58% during the data-gathering period, which is a quite typical volatility level. The Finnish stock market is more volatile than U.S. market because of its small size and concentration on export industry companies, which should show as even higher volatility estimates than U.S. volatility. The best return prediction of the investor's own portfolio is 11.50% and the standard deviation is 8.48%, on average. The return prediction difference of 1.42% as regards own portfolio is in line with Graham et al.'s (2009) research. They find the investors' evaluation of own portfolio return to beat the market return on average by 2.3 percentage points.

Like Graham & Harvey (2003), we find the average skewness of confidence intervals to be negative. The respondents evaluate that if their best 12-month return prediction happens to be false, the actual return is lower with a larger interval downwards than higher with a narrower interval upwards. This is in line with observations that investors are prone to see risk more commonly as a possibility of downward rather than upward movement. The negative asymmetry is also seen by De Bondt (1998).

We proceed with measures of overconfidence by running two tests. Firstly, we calculate the correlations between the measures. Secondly, we run a factor analysis to see whether the measures cluster around certain factors. Before running the tests, we drop those investors who have chosen Do not know answers to overconfidence claims. Also, we drop the respondents who have given illogical answers to calibration questions. These actions are in line with the regressions in the empirical results section, Chapter 5.4.

Table 21. Correlation coefficients.

This table presents Spearman correlation coefficients between the separate questions measuring the same manifestation of overconfidence as well as correlations between various manifestations of overconfidence. We have deleted those respondents who have chosen the alternative Do not know to measures of overconfidence which we ask as claims (Illusion of knowledge, Illusion of control and Self-attribution bias). Also, we have deleted the respondents who have had problems understanding the Miscalibration questions, which show as illogical answers, i.e. their best return prediction is not situated between the lower and upper bound. Numbers 1) and 2) after each overconfidence measure refer to Chapter 5.2.1, in which we numerate the measures. The significance levels are presented in parentheses. The lowest number describes the number of respondents.

Measure of overconfidence	Illusion of knowledge 1)	Illusion of knowledge 2)	Illusion of control 1)	Illusion of control 2)	Self-attribution bias 1)	Self-attribution bias 2)	Miscalibration 1)	Miscalibration 2)
Illusion of knowledge 1)	1							
Illusion of knowledge 2)	0.66 (0.00)							
	756	1						
Illusion of control 1)	0.38 (0.00)	0.49 (0.00)						
	804	770	1					
Illusion of control 2)	0.22 (0.00)	0.33 (0.00)	0.38 (0.00)					
	801	766	906	1				
Self-attribution bias 1)	0.47 (0.00)	0.47 (0.00)	0.43 (0.00)	0.26 (0.00)				
	792	760	900	890	1			
Self-attribution bias 2)	0.08 (0.02)	0.12 (0.00)	0.02 (0.43)	0.19 (0.00)	0.09 (0.00)			
	803	766	912	900	906	1		
Miscalibration 1)	0.16 (0.00)	0.18 (0.00)	0.14 (0.00)	0.08 (0.04)	0.14 (0.00)	-0.01 (0.73)		
	597	577	676	670	660	661	1	
Miscalibration 2)	-0.11 (0.01)	-0.05 (0.20)	0.02 (0.60)	0.03 (0.52)	-0.01 (0.75)	0.02 (0.58)	-0.03 (0.41)	
	597	577	676	670	660	661	712	1

There are statistically significant positive correlations between the same manifestations of overconfidence when we do not take into account the Miscalibration measures. Still, the correlation coefficients vary quite much. The strongest rank correlation exists between the Illusion of knowledge measures. Although the rank correlation between Self-attribution bias measures is significant, the coefficient is only 0.09. Measures of Miscalibration do not correlate with each other and their correlation with other manifestations of overconfidence is weak too. When we examine the correlations between the various manifestations, we see a great deal of variability in coefficients. In prior research there is evidence of correlated and non-correlated measures of overconfidence, see for example Klayman & Soll (1999), Glaser & Weber (2007), Deaves *et al.* (2009) or Soll & Klayman (2004). We present the correlations between other variables in Appendix 3.3.

To further analyze the link between the measures of overconfidence, we run a factor analysis by ordering the measures among three factors. We do not include Miscalibration measures in the analysis because their correlation with the measures asked as claims is small.

Table 22. Factor analysis.

This table shows the VARIMAX rotated factor structure matrix from principal factor analysis. Factor loadings of 0.50 at minimum are considered the minimal acceptable level concerning the correlation between overconfidence measure and the factor. Numbers 1) and 2) after each overconfidence measure refer to Chapter 5.2.1, in which we numerate the measures.

Measure of overconfidence	Factor 1	Factor 2	Factor 3	Final communality estimate
Illusion of knowledge 1)	0.882	0.034	0.034	0.781
Illusion of knowledge 2)	0.809	0.278	0.048	0.735
Illusion of control 1)	0.452	0.686	-0.127	0.692
Illusion of control 2)	0.091	0.886	0.192	0.830
Self-attribution bias 1)	0.707	0.232	0.078	0.560
Self-attribution bias 2)	0.080	0.080	0.979	0.972
Variance explained by each factor	**2.155**	**1.395**	**1.022**	

Both Illusion of knowledge measures load strongly on Factor 1. Also, the Self-attribution 1) measure loads on Factor 1. This is in line with the strong correlations between these measures of overconfidence, see Table 21. Because these measures describe respondents' confidence in their own knowledge, abilities or supreme investment performance, we refer to Factor 1 as the *Success caused by own skills* factor. Both Illusion of control measures load on Factor 2. Because these measures describe respondents' confidence in their ability to foresee oncoming market prices, we refer to Factor 2 as the *Market timing ability* factor. A propensity to blame external circumstances for miss-success in investing (Self-attribution bias 2) measure) differs from other measures by loading on its own factor. Regardless it is not a real factor, with only a single variable loading on it, we deem it a third factor. We call it the *Miss-success caused by external circumstances factor*.

5.4 Empirical results

Next we turn to our results on the trading and diversification decisions of common stock portfolios. Firstly, we run regressions by linking the self-perceived, subjective attributes as well as objective attributes describing respondents' demographic and socio-economic characteristics with measures of overconfidence to see which variables explain differences in confidence levels. Then we turn to the potential consequences of overconfidence: too much trading and/or under-diversification. We also test other variables than overconfidence as explanatory variables. Lastly we run robustness checks to test the validity and reliability of the results.

5.4.1 Characteristics explaining confidence in one's own abilities

To examine the characteristics explaining the confidence in the investors' own abilities, we run regressions by using each overconfidence measure as a dependent variable and the investor characteristics that have earlier been linked to overconfidence as explanatory variables. From each measure of overconfidence, we drop those respondents who do not have an opinion to the question being examined, i.e. they have chosen the Do not know answer. We treat similarly those respondents who have given illogical answers to Miscalibration questions. We present the results in Table 23.

Table 23. The relation between measures of overconfidence and investor characteristics.

This tables describes the relation between measures of overconfidence (dependent variable, see their formulations in Chapter 5.2.1) and respondents' objective and subjective attributes (explanatory variables, see their formulations in Appendix 3.1). We drop Do not know answers from Illusion of knowledge, Illusion of control and Self-attribution bias measures of overconfidence and run logistic regression models by using as a dependent variable each overconfidence measure with a four-point scale 1) Strongly disagree, 2) Somewhat disagree, 3) Somewhat agree, 4) Strongly agree. The Miscalibration 1) measure is calculated as the difference between the 12-month return prediction of own portfolio and market portfolio. The regression is a linear regression model. The Miscalibration 2) measure is a dummy variable which gets a value 1 (0) if the respondent evaluates the 12-month return volatility to be smaller (larger) than the average 12-month return volatility calculated from the respondents' answers. The regression is a probit regression model. To simplify the table, we combine some explanatory variables in a fewer categories. The upper values are the estimation coefficients of regressions. The lower numbers in parentheses describe p-values.

Dependent variable = measure of overconfidence Explanatory variable	(1) Illusion of knowledge 1)	(2) Illusion of knowledge 2)	(3) Illusion of control 1)	(4) Illusion of control 2)	(5) Self-attribution bias 1)	(6) Self-attribution bias 2)	(7) Miscalibration 1)	(8) Miscalibration 2)
Gender	-0.0812	0.2695	0.0247	-0.1693	0.1691	-0.4992	0,3536	-0.1733
(0=Woman, 1=Man)	(0.71599)	(0.2564)	(0.9084)	(0.4134)	(0.4260)	(0.0157)	(0.7637)	(0.3685)
Education (reference category Elementary or Vocational school)								
Gymnasium	0.0754	0.5143	0.3827	0.2261	0.3580	0.1550	-0.0252	-0.0444
	(0.7315)	(0.0219)	(0.0712)	(0.2779)	(0.0897)	(0.4489)	(0.9783)	(0.7976)
Polytechnic or University	0.1271	0.1140	0.1033	-0.2032	0.0999	0.0554	-0.3573	-0.2566
	(0.5243)	(0.5763)	(0.5942)	(0.2830)	(0.6034)	(0.7661)	(0.6589)	(0.0960)
Ln total wealth (value of home	0.0212	0.0366	0.0049	0.0089	0.0196	-0.0025	-0.0687	-0.0019
excluded)	(0.1685)	(0.0247)	(0.7335)	(0.5205)	(0.1756)	(0.8531)	(0.3548)	(0.8666)
Activeness in following	0.7975	0.6965	0.3847	-0.2554	0.4619	-0.3215	1.9702	-0.0222
economic events	(0.0007)	(0.0048)	(0.0907)	(0.2436)	(0.0387)	(0.1366)	(0.0813)	(0.9029)
Self-perceived investment	0.1001	0.0574	0.0489	0.0234	0.0528	-0.0319	0.1942	0.0044
knowledge	(<0.0001)	(<0.0001)	(0.0002)	(0.0665)	(<0.0001)	(0.0102)	(0.0019)	(0.6602)

Dependent variable = measure of overconfidence Explanatory variable	(1) Illusion of knowledge 1)	(2) Illusion of knowledge 2)	(3) Illusion of control 1)	(4) Illusion of control 2)	(5) Self-attribution bias 1)	(6) Self-attribution bias 2)	(7) Miscalibration 1)	(8) Miscalibration 2)
Actual investment knowledge	0.0706	-0.0037	-0.0853	-0.1842	0.0365	-0.1307	0.0543	-0.1654
	(0.2703)	(0.9556)	(0.1734)	(0.0028)	(0.5623)	(0.0299)	(0.8731)	(0.0028)
Risk profile (reference category Very cautious or Cautious)								
Moderate	0.3429	0.4777	0.3934	0.2093	-0.0016	0.2287	0.3075	-0.0929
	(0.1022)	(0.0288)	(0.0520)	(0.2842)	(0.9934)	(0.2375)	(0.6632)	(0.5809)
Return seeking or Very return seeking	0.4875	0.4424	0.2702	-0.2164	-0.0769	0.0128	3.4343	-0.5646
	(0.0233)	(0.0488)	(0.1900)	(0.2790)	(0.7067)	(0.9483)	(0.0078)	(0.0007)
Investment experience (reference category < 5 years)								
5 – 10 years	0.7371	0.3630	0.0300	0.1720	0.1902	-0.1468	-1.1174	-0.1387
	(0.0172)	(0.2783)	(0.9198)	(0.5473)	(0.5060)	(0.6043)	(0.4402)	(0.5504)
10 years -	1.4532	1.1653	0.4082	0.1747	0.8985	0.2530	-0.5198	-0.2264
	(<0.0001)	(<0.0001)	(0.1123)	(0.4806)	(0.0003)	(0.3041)	(0.6773)	(0.2587)
Intercepts (models 1 – 6)								
4	-7.2549	-6.5807	-5.8834	-4.5108	-5.9068	-1.4760		
	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(0.0039)		
3	-4.7906	-3.8292	-1.6461	-0.4336	-2.8708	1.2919		
	(<0.0001)	(<0.0001)	(0.0017)	(0.3910)	(<0.0001)	(0.0099)		
2	-2.1499	-0.8926	1.5106	1.8963	-0.3022	3.5136		
	(<0.0001)	(0.1171)	(0.0045)	(0.0002)	(0.5596)	(<0.0001)		
Intercept (models 7 – 8)							-3.9446	2.3848
							(0.1735)	(<0.0001)
Number of observations	760	721	872	860	848	865	660	655

We find respondents' subjective attributes to have a larger explanatory power than the socioeconomic and demographic variables (objective attributes). The more the respondent feels himself to have knowledge of investment instruments (Self-perceived investment knowledge, question 2), the more he agrees with the measures of overconfidence. In every regression where Actual investment knowledge is significant the coefficient is negative: those having high actual knowledge do not think they can predict the decline of market values, they do not blame external issues on their miss-success and their volatility estimates are not narrower than the average volatility of respondents. Membership in the two most risk-standing profiles contrasted to the two most risk-averse profiles has positive and statistically significant connection with the Illusion of knowledge and Miscalibration variables. Experience gives the respondent confidence that he is more knowledgeable than the average member of the Shareholders' Association and that his success in investing has happened mainly because of his personal ability and knowledge. The same is true with Activeness in following economic events weekly or daily. In unreported regressions we insert the Illusion of knowledge 1) measure (I have more useful investment knowledge than the average member of the Shareholders' Association) as an explanatory variable in other regressions and find it to have statistical significance. This result is in line with the results of Dorn & Huberman (2005), who use relative knowledge as an explanatory variable but not as overconfidence measure. They come to a conclusion that it seems to be "an attractive measure for overconfidence".

Our results do not support the idea of using Gender as a straight proxy for overconfidence. Contrary to some prior research (see, for example, Barber & Odean 2001 or Biais et al. 2005), we do not find statistical significance between measures of overconfidence and male gender. Neither does variety in Education level affect self-confidence (excluding Illusion of knowledge 2). Similarly, our results do not give support to the Background risk effect, as measured by working in a domestic sector or being an entrepreneur (unreported variables).

5.4.2 Drivers of trading

In this chapter we show the results of the relation between trading activity and measures of overconfidence as well as other explanatory variables. To simplify the dependent variable and to meet the proportional odds assumption, we organize the trading activity into a four-class format: 1) Once a year or Biannually, 2) Quarterly, 3) Monthly and 4) Weekly or Daily. We do not take account of respondents who do not trade at least once a year or do not have a stock portfolio. Similarly, we exclude those respondents who do not have an opinion (i.e. they choose Do not know answer) to those measures of overconfidence which we solicit as claims or to the On/off question. In each regression, we include one measure of overconfidence together with other explanatory variables. We organize the regressions according to the factor analysis results, see Chapter 5.3. Our initial goal, i.e. to show the other explanatory variables grouped as subjective and objective attributes, proved to be unnecessary as only subjective attributes (except gender) had statistical significance in explaining trading activity.

Table 24. Drivers of trading activity.

This table describes the relation between trading activity and measures of overconfidence as well as other explanatory variables. The model is ordered logistic regression and has the form $logit[Pr(Y \leq i \mid x)] = \alpha_i + \beta x$. Y is the respondent's trading activity measured as a categorical form: 1) Once a year or Biannually, 2) Quarterly, 3) Monthly and 4) Weekly or Daily. α_i are intercept parameters, β is a vector of regression coefficients and x is a vector of explanatory variables. We define measures of overconfidence in Chapter 5.2.1 and the other explanatory variables in Appendix 3.1. Because the explanatory variables are categorical, we use them by defining a reference category and contrasting the other categories to the reference category. We delete those respondents who trade more seldom than once a year, do not own stock portfolio and those who choose the Do not know answer to the measures of overconfidence which we solicit as claims or On/off question. We also exclude respondents with illogical answers to Miscalibration – questions. In each regression we include one overconfidence measure and keep the other explanatory variables unchanged. We organize the measures of overconfidence according to their factor loadings, see Table 22. The proportional odds assumption does not hold true with Self-attribution bias variables. We report the maximum likelihood estimates and p-values (parentheses). AIC refers to the Akaike information criterion value. Pseudo R-square refers to Nagelkerke Pseudo R-square.

Dependent variable= Trading activity	Drivers of Factor 1: Success caused by own skills, Models 1 – 3		Drivers of Factor 2: Market timing ability, Models 4 – 5		Drivers of Factor 3: Miss-success caused by external circumstances, Model 6		Other measures of overconfidence: Miscalibration, Models 7 - 8	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Illusion of knowledge 1)	Illusion of knowledge 2)	Self-attribution bias 1)	Illusion of control 1)	Illusion of control 2)	Self-attribution bias 2)	Miscali-bration 1)	Miscali-bration 2)
Explanatory variables, measures of overconfidence								
Drivers of Factor 1: Success caused by own skills (Models 1 – 3), reference category Strongly disagree								
Somewhat disagree	0.5636	0.2871	0.5602					
	(0.0932)	(0.3438)	(0.0287)					
Somewhat agree	0.5532	0.6804	0.7610					
	(0.0959)	(0.0264)	(0.0031)					
Strongly agree	0.9394	0.7598	0.7246					
	(0.0106)	(0.0589)	(0.0580)					
Drivers of Factor 2: Market timing ability (Models 4 – 5), reference category Strongly disagree								
Somewhat disagree				0.6062	0.2364			
				(0.0753)	(0.1230)			

Dependent variable= Trading activity	Drivers of Factor 1: Success caused by own skills, Models 1 – 3		Drivers of Factor 2: Market timing ability, Models 4 – 5		Drivers of Factor 3: Miss-success caused by external circumstances, Model 6		Other measures of overconfidence: Miscalibration, Models 7 - 8	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Illusion of knowledge 1)	Illusion of knowledge 2)	Self-attribution bias 1)	Illusion of control 1)	Illusion of control 2)	Self-attribution bias 2)	Miscali-bration 1)	Miscali-bration 2)
Somewhat agree				0.8148	0.2772			
				(0.0176)	(0.1463)			
Strongly agree				1.5389	2.0083			
				(0.0179)	(0.1867)			
Drivers of Factor 3: Miss-success caused by external circumstances (Model 6), reference category Strongly disagree								
Somewhat disagree						0.3313		
						(0.0981)		
Somewhat agree						0.2376		
						(0.2480)		
Strongly agree						0.2395		
						(0.5022)		
Other measures of overconfidence (Models 7 – 8)								
Miscalibration 1) and 2)							-0.0024	-0.0976
							(0.7782)	(0.5251)
Other explanatory variables								
Internet (1) vs. other inform.	0.3996	0.2757	0.4286	0.3269	0.4068	0.3392	0.4343	0.4333
channel (0)	(0.0147)	(0.0991)	(0.0054)	(0.0311)	(0.0080)	(0.0249)	(0.0132)	(0.0134)
Time spent collecting information (reference category 0 – 2 hours / week)								
3 – 5 hours / week	0.8900	0.8352	0.8690	0.8593	0.8265	0.9280	0.8866	0.8851
	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)
6 – 8 hours / week	0.9485	0.9572	1.0044	0.9567	1.0528	1.0522	0.9794	0.9855
	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)
>8 hours / week	1.4986	1.5414	1.6936	1.5882	1.5813	1.7220	1.6397	1.6278
	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)

Dependent variable= Trading activity	Drivers of Factor 1: Success caused by own skills, Models 1 – 3		Drivers of Factor 2: Market timing ability, Models 4 – 5		Drivers of Factor 3: Miss-success caused by external circumstances, Model 6		Other measures of overconfidence: Miscalibration, Models 7 - 8	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Illusion of knowledge 1)	Illusion of knowledge 2)	Self-attribution bias 1)	Illusion of control 1)	Illusion of control 2)	Self-attribution bias 2)	Miscali-bration 1)	Miscali-bration 2)
Importance of being able to make transactions quickly (reference category Not at all important)								
Quite important	1.1466	1.5017	1.4166	1.3461	1.0095	1.0881	1.6889	1.6823
	(0.0813)	(0.0389)	(0.0281)	(0.0370)	(0.0903)	(0.0642)	(0.0498)	(0.0508)
Very important	1.7080	2.1423	1.9750	1.9862	1.5821	1.7207	2.3687	2.3494
	(0.0087)	(0.0029)	(0.0019)	(0.0019)	(0.0072)	(0.0030)	(0.0057)	(0.0061)
Risk profile (reference category Very cautious)								
Cautious	1.0556	1.1106	1.0011	1.1627	1.1856	1.4972	0.8278	0.8102
	(0.1237)	(0.1036)	(0.1503)	(0.0582)	(0.0559)	(0.0265)	(0.2454)	(0.2553)
Moderate	1.5769	1.5280	1.5228	1.6230	1.6958	1.9857	1.0870	1.0717
	(0.0193)	(0.0222)	(0.0259)	(0.0068)	(0.0051)	(0.0028)	(0.1159)	(0.1210)
Return seeking	1.8817	1.7945	1.7935	1.8906	1.9961	2.1744	1.4144	1.3820
	(0.0053)	(0.0073)	(0.0088)	(0.0016)	(0.0010)	(0.0011)	(0.0411)	(0.0453)
Very return seeking	2.1099	2.0371	2.0088	2.1432	2.2538	2.4460	1.5294	1.4899
	(0.0031)	(0.0042)	(0.0052)	(0.0008)	(0.0005)	(0.0005)	(0.0374)	(0.0427)
Willingness to make On/off decisions (reference category Strongly disagree)								
Somewhat disagree	0.2566	0.1312	0.1174	0.1263	0.1729	0.2045	0.1561	0.1533
	(0.0976)	(0.4083)	(0.4193)	(0.3829)	(0.2376)	(0.1571)	(0.3438)	(0.3527)
Somewhat agree	0.3724	0.3333	0.3831	0.3246	0.4262	0.4083	0.5585	0.5479
	(0.0654)	(0.1057)	(0.0426)	(0.0886)	(0.0269)	(0.0288)	(0.0106)	(0.0114)
Strongly agree	1.6168	1.6560	1.5073	1.3789	1.4132	1.4862	1.6933	1.6635
	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)
Gender (0=Woman, 1=Man)	0.5538	0.5798	0.5055	0.5674	0.4697	0.4045	0.6712	0.6626
	(0.0138)	(0.0119)	(0.0161)	(0.0060)	(0.0223)	(0.0468)	(0.0142)	(0.0156)

Dependent variable= Trading activity	Drivers of Factor 1: Success caused by own skills, Models 1 – 3		Drivers of Factor 2: Market timing ability, Models 4 – 5		Drivers of Factor 3: Miss-success caused by external circumstances, Model 6		Other measures of overconfidence: Miscalibration, Models 7 - 8	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Illusion of knowledge 1)	Illusion of knowledge 2)	Self-attribution bias 1)	Illusion of control 1)	Illusion of control 2)	Self-attribution bias 2)	Miscali-bration 1)	Miscali-bration 2)
Intercept 4	-7.1230	-7.2027	-7.4210	-7.4365	-6.7149	-7.1726	-6.7834	-6.6812
	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)
Intercept 3	-5.1385	-5.2488	-5.2410	-5.4436	-4.7248	-5.1951	-4.9009	-4.7985
	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)
Intercept 2	-3.4769	-3.6407	-3.7623	-3.8138	-3.1209	-3.5845	-3.1143	-3.0107
	(<0.0001)	(0.0003)	(<0.0001)	(<0.0001)	(0.0002)	(<0.0001)	(0.0044)	(0.0064)
No. of observations	744	709	846	853	845	867	654	654
AIC	1816	1740	2058	2090	2079	2130	1612	1612
Pseudo R-square	0.2731	0.2666	0.2671	0.2544	0.2455	0.2473	0.2458	0.2462

The results confirm Hypothesis 1: *The more the investor is overconfident, the more actively he trades in his stock portfolio*. The main components of Success caused by own skills factor have a significant effect on trading activity: the more confidently the respondents rely on their investment knowledge, superior past performance in comparison to others, or declare success to have happened mainly because of their personal ability and knowledge, the more actively they trade in their stock portfolios. Also, the other main driver of the Market timing ability factor, i.e. a belief in one's own ability to estimate future price level, shows as more frequent trading. Blaming the external circumstances for miss-success (Self-attribution 2) does not correlate with increased trading activity. The same is true of the Miscalibration measures; they do not have statistical significance. Our results are in line with Glaser & Weber (2007), who find self-perceived investment skills and performance in relation to others to be linked with trading activity. Also Dorn & Huberman (2005) find investors' self-perceived knowledge relative to other investors to show as more active trading. And secondly, our results support Glaser & Weber's (2007) finding that the predictive power of calibration techniques – being the most typical theoretical base to measure overconfidence – has to be treated carefully. The similarity of the results of Glaser & Weber and our results gets more weight because studies use field data, not only experimental tests.

In Appendix 3.4 we run the same regression as above but replace the separate measures of overconfidence with Factors 1, 2 and 3, and combine the factors into single model. Analogously with the above results, we find the Success caused by own skills and Market timing ability factors to explain trading activity. Due to Self-attribution bias 2) not being significant as a separate variable, the Miss-success caused by external circumstances factor is not significant either.

Also the subjective attributes do good work in explaining trading behavior and confirm Hypothesis 3a: *In addition to measures of overconfidence, investor-specific subjective attributes explain trading activity decisions*. Like Dorn & Huberman (2005), we find Risk profile to have a very significant and positive connection with trading activity. Those investors who see themselves as risk-standing and target higher return levels actually trade more actively. We state this observation to be supplementary evidence to our earlier findings (see Chapter 3) that simple questions on risk and return are helpful when explaining variation in investment behavior and risk-taking level. The statistically significant and positive link between trading activity and an Importance of being able to make transactions quickly follows our ex ante assumption. Those who follow economic market events more actively or use the Internet as the most important information channel engage in more trades.

One may consider the causal relationship of these items. Does active market-following via easily accessible channels cause the investors to trade more or does the active trading cause a need to find plentiful information? We suppose the former claim is more likely and agree with the overconfidence literature; investors rely too much on information, especially their own information, which causes differences in opinions and enhances trading.

Experienced investors can be prone to over-active trading, see for example Barber & Odean (2001). According to our results, Experience has no statistical significance in explaining trading activity. Respondents who agree with the claim that "When stock prices start going downwards, it is best to sell the whole stock portfolio, not only a part of it" (On/off variable) trade more frequently. The statistical significance of the On/off variable supports the notion of the Market timing ability factor, i.e. that investors are prone to rely on their ability to foresee market trends. This accelerates their trading activity because they may try to hedge their portfolios by selling them before the market decline.

Excluding Gender, the respondents' demographic or socioeconomic variables (objective variables) do not offer notable explanatory power in our research. We reject Hypothesis 3b: *Investor-specific objective attributes explain trading activity decisions*. Age, Income level and Education play no role in our regressions (we do not show their statistics). Background risk measured by occupation status, i.e. being an entrepreneur or working in a domestic sector, is not significant either. Neither has Actual investment knowledge a link with trading activity. Still, the earlier findings on men's more active trading are supported by our data. Because male gender did not show as a significant variable in explaining the measures of overconfidence (see Chapter 5.4.1, Table 23), we argue men's more frequent trading compared to women's to stem from some other aspect than gender differences in self-confidence.

We have two main messages concerning the trading activity results. The first concerns our hypothesis on overconfidence and trading: those investors who see themselves as competent in investing trade more. The competence is visible through their confidence in better investment success in relation to peers, their assumed superior investment ability and knowledge as well as their market timing abilities. In behaving in this way, they suffer from various manifestations of overconfidence, which leads to active trading. Our results get more weight because of our comprehensive mix of overconfidence measures. Also, we combine the overconfidence measures with actual investor characteristics and portfolio choices – not experimental data. Like the findings of Glaser & Weber (2007), we state that relying on calibration techniques as measures of overconfidence has to be treated with caution. Simple attitudinal questions asked as claims can be easier to understand and can better capture the drivers of overconfidence that can cause variation in trading activity.

Our second message concerns the investor-specific subjective characteristics: in addition to measures of overconfidence, other subjective attributes also have a large role in explaining trading behavior. The trading frequency differences stem from various subjective attributes: activeness in following economic events, willingness to be able to make transactions quickly, internet as a most important information channel, self-perceived risk profile and willingness to make on/off decisions, i.e. to sell the entire stock portfolio instead of selling a part of it. These findings support our earlier findings (see Chapters 3 and 4) on subjective attributes and underline their importance with respect to investment behavior research.

Robustness check

As a robustness check we do not exclude respondents who choose the Do not know answer to the measures of overconfidence which we solicit as claims. We numerate Do not know answers with a number three (3), i.e. we insert them between Disagree – Agree answers. We re-run the regressions and find the results to be robust in the change of method.

As another robustness check, we take one overconfidence claim from each factor and put them into the same regression model. The Illusion of knowledge 1) and Illusion of control 1) variables keep their significances and the Self-attribution bias 2) variable remains insignificant. These results are analogous with the regressions in which we test them individually, i.e. by considering only one at a time in our model.

To control the trading activity caused by larger amount of stocks in portfolio, we include a diversification variable (categorized variable with value of 1: 1-2 stocks, 2: 3-6 stocks, 3: 7-10 stocks and 4: 11 or more stocks) in our regressions. The significances of the explanatory variables do not change and the diversification variable has its own significance with a positive coefficient too. As a last robustness check, we do not combine the trading activity classes when running the regressions. Because the number of cells increases, the proportional odds assumption does not hold at any regression. Depending on the explanatory variable, the significances stay the same or better.

5.4.3 Drivers of diversification

We continue by showing the results of measures of overconfidence as well as other explanatory variables on diversification decisions. We use a rough measure of unsystematic risk reduction by using stock portfolio diversification categories of 1) 1-2 or 3-6 stocks, 2) 7-10 stocks and 3) 11 - stocks. Because the 1 – 2 stocks category contains only about 30 respondents, it is justifiable to combine it with the category of 3 – 6 stocks. Both of these categories represent low degree of diversification. We ignore the respondents who do not own a stock portfolio. We construct the regression models in the same way as with trading activity: we test each measure of overconfidence in a separate regression and show the regressions ordered according to their factor loadings. After measures of overconfidence, we consider the self-perceived, subjective attributes and, lastly, the objective attributes corresponding to the respondents' demographic and socio-economic characteristics. As with trading activity regressions, we exclude those respondents who choose the Do not know answer to the measures of overconfidence which we solicit as claims. We do the same with the On/off variable (= respondent's opinion about total withdrawal from the stock market) and the Familiarity bias variable because there is also a Do not know alternative. We present the results of diversification decision in Table 25.

Table 25. Drivers of diversification.

This table describes the relation between diversification decision and measures of overconfidence as well as other explanatory variables. The model is ordered logistic regression and has the form $logit[Pr(Y \leq i \mid x)] = \alpha_i + \beta x$. Y is the diversification decision of respondent's stock portfolio measured as a categorical form: 1) 1-2 or 3-6 stocks, 2) 7-10 stocks and 3) 11 - stocks. α_i are intercept parameters, β is a vector of regression coefficients and x is a vector of explanatory variables. We define measures of overconfidence in Chapter 5.2.1 and the other explanatory variables in Appendix 3.1. Because the explanatory variables are categorical, we use them by defining a reference category and contrasting the other categories to the reference category. We exclude those respondents who do not own a stock portfolio and those who choose the Do not know answer for the measures of overconfidence which we solicit as claims or for the On/off or Familiarity bias question. We also exclude respondents with illogical answers to Miscalibration questions. In each regression we include one measure of overconfidence and keep the other explanatory variables unchanged. We organize the measures of overconfidence according to their factor loadings, see Table 22. The proportional odds assumption does not hold with Self-attribution bias variables. We report the maximum likelihood estimates and p-values (parentheses). AIC refers to the Akaike information criterion value. Pseudo R-square refers to Nagelkerke Pseudo R-square.

Dependent variable= Diversification	Drivers of Factor 1: Success caused by own skills, Models 1 – 3		Drivers of Factor 2: Market timing ability, Models 4 – 5		Drivers of Factor 3: Miss-success caused by external circumstances, Model 6		Other measures of overconfidence: Miscalibration, Models 7 - 8	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Illusion of knowledge 1)	Illusion of knowledge 2)	Self-attribution bias 1)	Illusion of control 1)	Illusion of control 2)	Self-attribution bias 2)	Miscali-bration 1)	Miscali-bration 2)
Explanatory variables, measures of overconfidence								
Drivers of Factor 1: Success caused by own skills (Models 1 – 3), reference category Strongly disagree								
Somewhat disagree	0.0269	-0.3299	0.1675					
	(0.9351)	(0.3064)	(0.5342)					
Somewhat agree	0.2308	-0.0297	0.3784					
	(0.4895)	(0.9293)	(0.1668)					
Strongly agree	0.3362	-0.1954	0.1697					
	(0.3979)	(0.6774)	(0.7074)					

Dependent variable= Diversification	Drivers of Factor 1: Success caused by own skills, Models 1 – 3		Drivers of Factor 2: Market timing ability, Models 4 – 5		Drivers of Factor 3: Miss-success caused by external circumstances, Model 6		Other measures of overconfidence: Miscalibration, Models 7 - 8	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Illusion of knowledge 1)	Illusion of knowledge 2)	Self-attribution bias 1)	Illusion of control 1)	Illusion of control 2)	Self-attribution bias 2)	Miscali-bration 1)	Miscali-bration 2)
Drivers of Factor 2: Market timing ability (Models 4 – 5), reference category Strongly disagree								
Somewhat disagree				0.2423	-0.3879			
				(0.5181)	(0.0284)			
Somewhat agree				0.0271	-0.6433			
				(0.9429)	(0.0029)			
Strongly agree				-0.0485	-2.9997			
				(0.9460)	(0.0391)			
Drivers of Factor 3: Miss-success caused by external circumstances (Model 6), reference category Strongly disagree								
Somewhat disagree						0.1200		
						(0.5989)		
Somewhat agree						0.3294		
						(0.1633)		
Strongly agree						0.3599		
						(0.3935)		
Other measures of overconfidence (Models 7 – 8)								
Miscalibration 1) and 2)							-0.0080	0.2120
							(0.3994)	(0.2259)
Other explanatory variables								
Willingness to make On/off decisions (reference category Strongly disagree)								
Somewhat disagree	-0.2842	-0.3480	-0.3552	-0.3325	-0.2185	-0.3630	-0.2840	-0.2791
	(0.1029)	(0.0510)	(0.0325)	(0.0446)	(0.1891)	(0.0301)	(0.1341)	(0.1417)
Somewhat agree	-0.6239	-0.6793	-0.5867	-0.5584	-0.4184	-0.6514	-0.5591	-0.5789
	(0.0066)	(0.0038)	(0.0068)	(0.0107)	(0.0557)	(0.0025)	(0.0249)	(0.0193)

Dependent variable= Diversification	Drivers of Factor 1: Success caused by own skills, Models 1 – 3		Drivers of Factor 2: Market timing ability, Models 4 – 5		Drivers of Factor 3: Miss-success caused by external circumstances, Model 6		Other measures of overconfidence: Miscalibration, Models 7 - 8	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Illusion of knowledge 1)	Illusion of knowledge 2)	Self-attribution bias 1)	Illusion of control 1)	Illusion of control 2)	Self-attribution bias 2)	Miscali-bration 1)	Miscali-bration 2)
Strongly agree	-1.1368	-1.3016	-1.4047	-1.4552	-1.4066	-1.4983	-1.5169	-1.5025
	(0.0039)	(0.0020)	(0.0002)	(0.0001)	(0.0003)	(<0.0001)	(0.0002)	(0.0003)
Familiarity bias (reference category Strongly disagree)								
Somewhat disagree	0.0684	0.0672	-0.3193	-0.2742	-0.2935	-0.1819	-0.3177	-0.3275
	(0.7784)	(0.7890)	(0.4009)	(0.2362)	(0.2069)	(0.4317)	(0.2321)	(0.2191)
Somewhat agree	-1.3108	-1.2865	-1.4996	-1.6017	-1.5786	-1.5500	-1.7110	-1.7386
	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)
Strongly agree	-1.8870	-2.0321	-2.1206	-2.2787	-2.1938	-2.0916	-2.1297	-2.1743
	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)
Familiarity of OMX Helsinki 25	0.0235	0.0207	0.0224	0.0267	0.0237	0.0233	0.0236	0.0235
index stocks	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)
Risk profile (reference category Very cautious)								
Cautious	2.2315	2.3993	2.0785	2.0107	2.1370	1.9624	1.7949	1.8265
	(0.0010)	(0.0004)	(0.0020)	(0.0006)	(0.0006)	(0.0011)	(0.0144)	(0.0127)
Moderate	2.7997	2.8679	2.5790	2.4833	2.6997	2.5729	2.4746	2.5008
	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(0.0006)	(0.0005)
Return seeking	2.7811	2.7984	2.6505	2.5302	2.7355	2.6192	2.2687	2.3281
	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(0.0017)	(0.0013)
Very return seeking	2.7909	3.0218	2.6419	2.4988	2.9243	2.5964	2.3677	2.3933
	(0.0001)	(<0.0001)	(0.0002)	(<0.0001)	(<0.0001)	(<0.0001)	(0.0023)	(0.0021)

Dependent variable= Diversification	Drivers of Factor 1: Success caused by own skills, Models 1 – 3		Drivers of Factor 2: Market timing ability, Models 4 – 5		Drivers of Factor 3: Miss-success caused by external circumstances, Model 6		Other measures of overconfidence: Miscalibration, Models 7 - 8	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Illusion of knowledge 1)	Illusion of knowledge 2)	Self-attribution bias 1)	Illusion of control 1)	Illusion of control 2)	Self-attribution bias 2)	Miscali-bration 1)	Miscali-bration 2)
Time spent collecting information (reference category 0 – 2 hours / week)								
3 – 5 hours / week	0.3937	0.4443	0.3991	0.4764	0.3446	0.4025	0.5598	0.5488
	(0.0319)	(0.0174)	(0.0220)	(0.0059)	(0.0458)	(0.0200)	(0.0052)	(0.0062)
6 – 8 hours / week	0.5331	0.6983	0.6509	0.6871	0.6153	0.6772	0.7531	0.7202
	(0.0387)	(0.0093)	(0.0068)	(0.0041)	(0.0103)	(0.0050)	(0.0046)	(0.0066)
>8 hours / week	0.5136	0.6597	0.5660	0.6223	0.6579	0.5917	0.7247	0.7164
	(0.0544)	(0.0145)	(0.0220)	(0.0128)	(0.0086)	(0.0178)	(0.0102)	(0.0107)
Net income, € / month (reference category <3 000 € / month)								
3 000 – 5 000 € / month	0.2614	0.3073	0.2926	0.2272	0.2663	0.3173	0.1355	0.1558
	(0.1211)	(0.0765)	(0.0685)	(0.1525)	(0.0960)	(0.0479)	(0.4558)	(0.3931)
>5 000 € / month	0.9911	0.8330	0.9405	0.9820	0.8628	0.9142	0.8839	0.8962
	(<0.0001)	(0.0009)	(<0.0001)	(<0.0001)	(0.0001)	(<0.0001)	(0.0005)	(0.0005)
Age, years (reference category <40 years)								
40 – 65 years	0.7641	0.9585	0.7652	0.8631	0.7286	0.7984	0.7504	0.7530
	(0.0003)	(<0.0001)	(0.0001)	(<0.0001)	(0.0002)	(<0.0001)	(0.0007)	(0.0007)
>65 years	1.6578	1.7409	1.5017	1.6417	1.6002	1.5812	1.4458	1.4343
	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)
Intercept 3	-5.0936	-4.7908	-4.6838	-4.8463	-4.2979	-4.6520	-4.2735	-4.4159
	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(0.0001)	(<0.0001)	(<0.0001)	(<0.0001)
Intercept 2	-3.6243	-3.2996	-3.2316	-3.3349	-2.8040	-3.2149	-2.6850	-2.8249
	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(0.0015)	(0.0009)
No. of observations	750	713	835	855	842	851	648	648
AIC	1314	1256	1456	1466	1460	1467	1138	1137
Pseudo R-square	0.3253	0.3309	0.3240	0.3429	0.3352	0.3297	0.3167	0.3177

The measures of overconfidence have a more minor role in diversification than with trading activity decision. Thus the results give only little support to Hypothesis 2: *The more the investor is overconfident, the less he diversifies his portfolio*. The only statistically significant measure of overconfidence is the Illusion of control 2) measure: when the respondent agrees he can sell before the stock market decline starts, he diversifies less. The odds of investors strongly agreeing with this claim having a wider diversification are 0.10 times[26] (somewhat agree: 0.53 times) of those strongly disagreeing with this claim, holding other variables constant. When we run a regression by replacing the separate measures of overconfidence as explanatory variables with overconfidence factors (Appendix 3.5), we find the Market timing ability factor to be significant with a negative coefficient as well[27]. The reason for this is the Illusion of control 2) variable which loads strongly on that factor and causes the significance and negative coefficient.

Our finding on the Illusion of control 2) variable receives support from the results of the On/off variable. When the respondent agrees with the On/off variable that "When stock prices start going downwards, it is best to sell the whole stock portfolio, not only a part of it", he diversifies less. The odds of investors strongly agreeing with this claim having a wider diversification are 0.25 times (somewhat agree: 0.66 times) of those strongly disagreeing with this claim, holding other variables constant. We make a conclusion that investors may think they are capable of hedging their portfolios by timing their selling transactions optimally. Their confidence in their own market timing abilities can be so strong they are willing to even totally withdraw from the stock market, i.e. to make an On/off movement. They can see this kind of behavior as an alternative to proper diversification or as a means to hedge their portfolios. This result is in line with our findings on rebalancing behavior with fund portfolios during stock market crises, see Chapter 4. In behaving this way, the investors ignore the random walk hypothesis of stock prices, which states that market prices cannot be reliably foreseen. The negative coefficient of the On/off variable confirms Hypothesis 4b: *On/off movement, i.e. willingness to totally withdraw from the stock market rather than partially withdraw, shows less diversification of stock portfolio*.

[26] Odds ratios are obtained by exponentiating the parameter estimates in Table 25.

[27] See Appendix 3.5. In addition to the Market timing ability factor, the Success caused by own skills factor is significant but with a positive sign. The sign is due to positive coefficients of those measures of overconfidence which load on that factor. Still, the statistical significance is hard to interpret because measures of overconfidence loading on that factor are not significant.

The results with other subjective attributes are two-fold. These attributes having explanatory power on diversification give support to Hypothesis 3a: *Investor-specific subjective attributes explain diversification decisions*. Still, not all the coefficient signs follow our ex ante assumptions. The Familiarity bias is consistent with our ex ante assumption and shows as narrower diversification: when the respondent agrees with the Familiarity bias variable saying that “I would rather own only a few stocks which I am familiar with than own a diversified portfolio including stocks unfamiliar to me”, he diversifies less[28]. Higher score concerning the respondent’s Familiarity with stocks which belong to the OMX Helsinki 25 index (respondents perceive how well they know the 25 companies by using a scale from 1 to 5 and we sum the scores) follows our ex ante assumption: wider familiarity has positive influence on the magnitude of diversification. Outlining the results of the Familiarity bias and Familiarity – variables, we state that investors have a propensity to see the level of diversification as a concept of familiarity rather than as a mechanism to reduce the portfolio’s unsystematic risk.

Those respondents who belong to more risk-standing Risk profiles diversify their stock portfolios more widely. The result is interesting; the coefficients of Risk profile could have been negative as well and in this sense, our results are opposite to the findings of Dorn & Huberman (2005) and Guiso & Jappelli (2006). However, the reason why comparing the results is difficult, stems from the content of their data and ours. Guiso & Jappelli’s diversification variable is based on the choice between well-diversified mutual funds and directly owned stocks. Dorn & Huberman’s diversification variable is based on calculation of portfolio’s volatility. In Appendix 1.4 we show that Risk profile is closely connected with respondent’s actual portfolio choice: those respondents who classify themselves to belong to higher Risk profiles actually have a larger Risky share[29]. Based on these results, we make a conclusion that the choice of higher Risk profile and larger Risky share does not mean that higher risk taking translates into risky asset portfolio, i.e. to a diversification decision of directly owned stock portfolio.

The respondents who spend more Time gathering financial information diversify their stock portfolios more widely. Large amount of time spent on gathering information can drive investors to rely too strongly on their information,

[28] Familiarity bias is also observed, for example, by Merton (1987), De Bondt (1998), Grinblatt & Keloharju (2001) and Huberman (2001).

[29] The connection between self-perceived risk profile and risky share is analogous with the results of our empirical research *The influence of investor’s subjective attributes on portfolio choice*, see Chapter 3 and Appendix 1.4.

which can result in under-diversification. The results of the trading activity section revealed a positive link between Time spent on information and Trading activity. We argued that relying too much on information causes differences in opinions and increases trading. A nice observation is that time spent with information does not show as narrower diversification even though it shows as more active trading. This is in contrast with Guiso & Jappelli's (2006) results. Also, our results concerning Familiarity with the OMX Helsinki 25 index stocks support the positive link between the level of information and diversification.

Even though we test a large mix of objective attributes, only Age and Income level have statistical significance on diversification. We state that the results of objective attributes only partly support Hypothesis 3b: *Investor-specific objective attributes explain diversification decisions*. Higher age and belonging to upper income groups shows as wider diversification. These findings are analogous with, for example, Goetzmann & Kumar's (2008) results. Gender has no statistical significance. The same is true with Background risk measured as being an entrepreneur or domestic sector worker. Total wealth and Actual knowledge of investment issues are significant as separate variables, but their significance disappears among other variables.

In summary, the various manifestations of overconfidence have a clearly smaller role in explaining diversification decisions of stock portfolios than trading activity decisions. Still, investors are prone to rely on their market timing abilities as a tool for risk control instead of wide diversification. This shows as the Illusion of control, i.e. their self-confidence to be able to foresee the decline of stock prices in time to position their selling transactions optimally. Investors may even think they have the ability to hedge their portfolios by making On/off movements, i.e. by withdrawing totally from the stock market before their self-predicted stock market decline.

In addition to the above findings, we draw the reader's attention to the results of the other subjective attributes. We state that the generalization that higher risk tolerance or overreliance on information causes stock-picking and under-diversification should be handled with caution; those attributes can have the opposite influence as well.

Robustness check

Because we have information on respondents' total wealth calculated to the asset class level as well as inside asset classes (for example, stock instruments = directly owned stocks + stock funds + half of combined funds containing interest and stock instruments), we are able to test whether the investor corrects for the narrow diversification with the help of stock fund portfolio, which represents ownership of widely diversified stock portfolio. We re-run the diversification regressions by inserting fund portfolio ownership as an explanatory variable among other explanatory variables (dummy variable which gets a value 0 is the investor does not own stock fund portfolio and a value 1if the investor owns stock fund portfolio). We do not find ownership of stock fund portfolio to have statistical significance to explain diversification decision.

As another robustness check, we keep the diversification variable in a four-category form by not combining the diversification classes of 1 – 2 and 3 – 6 stocks and re-run the regressions. The results are robust to the formulation of dependent variable.

5.5 Conclusions

In this research we test a comprehensive mix of various manifestations of overconfidence among experienced individual investors in Finland. We test these manifestations as potential reasons for active trading and under-diversification of directly owned stock portfolios. We also test other potential explanations of trading and diversification decisions by focusing especially on investors' self-perceived attitudes and evaluations, which we refer to as subjective attributes. As examples of these attributes, we mention risk tolerance, time spent with investment information, and perception of familiarity with investment instruments.

We make a conclusion that the calibration-based techniques must be used carefully when measuring investors' potential overconfidence. Miscalibration measures are not linked either to trading activity or diversification decision. Also, their link with other measures of overconfidence is weak. We contribute to prior research by stating that simple questions asked as claims seem to work better as measures of overconfidence than more commonly used calibration-based techniques.

Our results show that four out of the six overconfidence measures which we solicit as claims explain more active trading. This result supports the prior research indicating that overconfidence is evidenced through trading activity. Diversification decision is much more loosely connected to confidence in one's own abilities; only one measure of overconfidence explains narrower diversification. Still, this significant overconfidence variable (the Illusion of control variable, measuring the belief in one's own market timing abilities) gains support from our On/off variable. Investors' confidence in their market timing abilities is so strong that they prefer "On/off movements"; they want to totally empty their stock portfolios when they predict a stock market decline to start. We contribute to prior research by bringing evidence that investors can rely on their market timing abilities as a tool to control or hedge the portfolio's risk to the detriment of diversification. In behaving this way, they ignore the random walk of stock prices, which says that market prices cannot be reliably foreseen.

In addition to the measures of overconfidence, the other self-perceived, subjective attributes explain trading and diversification decisions, which underlines their importance with respect to investment behavior research. For that reason, we state that work with subjective attributes is worth continuing; they have explanatory power for investment behavior.

6 Conclusions, implications and discussion

This doctoral thesis aims to contribute to investment behavior modeling by giving new information on the causes which generate differences in investment behavior. As causes to differences in behavior we focus on the influence of investors' self-perceived attitudes, evaluations and judgments. We consider these investor characteristics as *subjective attributes*. The importance of identifying these psychological-based subjective characteristics arises from their predictive power with respect to investors' portfolio choices and actions in their portfolios. We also link variation in investment behavior to investors' demographic and socio-economic characteristics, which we refer to as *objective attributes*.

To fulfill the purpose of our thesis, we conduct three empirical researches which consider investment behavior from various perspectives. As a joint conclusion of the researches, we state that our results confirm the importance of taking into account self-perceived attitudes, evaluations and judgments – subjective attributes – when investigating investment behavior and its variation. These attributes have even more predictive power as regards investors' portfolio choices and actions than more commonly used socio-economic and demographic variables, which we refer to as objective attributes. Better understanding of the attributes which generate differences in investment behavior is important for understanding deviations from standard financial theories and for taking into account the comprehensive mix of attributes when developing behavioral models. Although there is also a need to pay regards to objective attributes, researchers should turn their focus especially to subjective attributes, methods for measuring them, and to how to link them to behavioral models.

Our results gain validity due to the fact that we can test these attributes against investors' actual investment behavior, which is a unique possibility especially with subjective attributes. In the first and second empirical research, we use data gathered from investor questionnaires which the clients of a Finnish financial institution have answered in conjunction with investment negotiations. The questionnaires fulfill European Union legislation requirements which require financial institutions to ensure they understand their clients' investment objectives, risk profiles, experience and ability to understand the risks the products and services contain. The institutions also need to obtain information about clients' regular income, wealth and its breakdown as well as clients' financial commitments. In that way our data consists of clients' self-perceived attitudes and evaluations, and their actual investments. In the third research, we use data which we gather from members of the Finnish Shareholders' Association. We ask them about a variety of subjective and objective attributes, particularly confidence in their own investor abilities. We also ask about their actual investments to be able to contrast their attributes against their real behavior.

Although we can test subjective and objective attributes against actual investments, there exist aspects, which can limit the validity and/or reliability of our results. Investors' responses to subjective questions can be domain-specific, their attitudes can be time-varying or they can understand the questions differently than others. The results should be interpreted in a light of Finnish investors in our data and in a light of wording the subjective questions. Still, we think our results draw attention to very important issue in explaining investment behavior.

The research questions of the first research are the following: 1a: *Does risk profile, asked by simple questions on investor-specific risk-standing ability and return target, allow measurement of an investor's actual risk-standing ability, as shown through his actual portfolio choice?* 1b: *Which investor-specific subjective and objective attributes best explain risk profile?* We contribute by confirming the meaning and importance of European Union regulations aimed at better investor protection. Investor-specific risk-standing ability can be described by using non-complex risk-standing measurement tools: the higher the investor's return target and risk tolerance, i.e. his self-defined risk profile, the larger the relative share he actually invests in risky instruments (we use the term portfolio choice). The predictive power of other subjective attributes – self-perceived investment experience, activeness in following economic events, and willingness to make personal investment decisions – on risk profile and portfolio choice is obvious. We contribute to household finance research by showing that these partly unobservable and non-countable subjective characteristics help explain variation in portfolio choice and therefore, need to be taken into account in portfolio choice models.

The research question of the second research is the following: 2: *Does financial sophistication, measured by subjective and objective attributes, explain differences in rebalancing behavior during the stock market crises?* We investigate investors' rebalancing behavior in their stock and combination fund portfolios during the stock market crises in 2008 – 2009 and again in 2011. We hypothesize that we will find higher financial sophistication, measured by subjective and objective investor attributes, to show as more professional investment behavior: as an ability to understand the long-term character of stock instruments precluding them from selling their portfolios at reduced market values and even encouraging them to buy more fund shares at decreased prices. We show this to hold true only partly.

In contrast to lower sophistication investors, financially sophisticated investors, measured by their subjective attributes (investors considering themselves experienced, following economic events most actively or having a willingness to make their own investment decisions instead of ready solutions from investment advisors) belong to sellers. Also, most typically they sell their entire fund portfolios, not only part of them. We contribute to existing research by showing that financial sophistication – measured by subjective attributes – does not always need to show as more professional investment behavior. We state that, in addition to its very positive effects, financial sophistication can induce the investor to make mistakes like total withdrawal from the stock market, realization of short-term losses or exposure to timing problems of stock portfolio rebuilding. Due to less experience or information on investing, less sophisticated investors can be slower to react to market fluctuations, protecting them from making these withdrawals. Still, we admit that the argument of investment mistake of sophisticated investors can be challenged. We leave the debate, whether the withdrawal from the market is an investment mistake, to discussion between proponents of efficient market theorem (unpredictability of stock prices) and of those who think the stock prices can at least partly be foreseen.

The third research questions are the following: 3a: *Do the following subjective and objective attributes explain trading activity and diversification decisions?* 3a1) *Self-perceived confidence in one's own investment abilities* and 3a2) *Other subjective and objective attributes.* 3b: *Do investors see total withdrawal from the stock market as an alternative to proper diversification or as a means to hedge the portfolio?* We test a large variety of measures of overconfidence (= investors' tendency to be overconfident about the precision of their own knowledge) as generators of active trading and under-diversification of stock portfolio. We also link other subjective and objective investor attributes to trading and diversification. We contribute by showing that simple questions asked as claims seem to work better as measures of overconfidence than more commonly used calibration-based techniques. Our results show several measures of overconfidence to explain trading activity: those investors who rely on their own investment ability and knowledge, prior performance relative to other investors, or their abilities to foresee future price levels, trade more. One single measure of overconfidence, a belief in one's own ability to time the selling point right, clearly predicts narrower diversification. This observation gains support from investors' On/off movements, i.e. willingness to sell their portfolios wholly instead of partly before their self-predicted stock market decline. This total realization of portfolio accords with our empirical research findings on rebalancing. We contribute to prior research by offering evidence that investors can rely on their market timing abilities as a tool to control or hedge portfolio risk to the detriment of diversification. This holds true with two different datasets, see also rebalancing research.

Our thesis has implications for several agents: investors, investment advisors and wealth managers of financial institutions, regulators, authors who attend to people's financial literacy education, and researchers. We go through the main implications and their importance for the various agents in the following paragraphs.

> *1. European Union regulations requiring financial institutions to measure their clients' risk-standing ability is a meaningful mechanism to better investor protection. Measurement of risk-standing ability helps institutions to construct products and services that take into account the different levels of risk-standing ability.*

Risk-standing ability, we name it as risk profile, can be measured by using non-complex methods. Risk profile is closely related to a client's actual risk-taking behavior, which shows through his portfolio choice, i.e. his risky share. Our empirical support of this issue is meaningful to investment advisors. The link between risk profile and actual risky share helps investment advisors to find suitable products and services for clients' personal needs, which in turn betters investor protection. This is a good sign for EU legislation authors; regulation is meaningful and fulfills its targets. In addition to purposes of EU regulation, the financial industry can benefit from risk profile measurement. Institutions can construct new products and services which they tailor to the needs of certain risk profile investors. This benefits the investors themselves too.

> *2. We should pay attention to both financially sophisticated and unsophisticated investors' behavior.*

According to our results on rebalancing behavior, we cannot take for granted that investors with long investment experience, knowledge of investing through active market-following, large wealth etc. are more skilled than other investors to make professional investment decisions. They can carry out short-term decisions like withdrawal from the stock market. Also, they can be cautious to invest in stock instruments despite reduced prices. This finding provides implications for several authors. Financial institutions and authors who attend to people's financial literacy education should take this into account when they co-operate with investors. All types of investors – experienced and less experienced, those making their own decisions and those who want to invest according to ready proposals etc. – need advice and guidance with their investment portfolios.

3. Potential overconfidence should be measured. The measurement should be based on reliable measurement techniques.

Our findings on overconfidence have implications for investors themselves when they make their own decisions, wealth managers when they invest other people's wealth, and researches when they investigate the overconfidence phenomenon. We state that it could be helpful to test investors and wealth managers alike about their confidence in their own investor abilities using the same measures of overconfidence than we use. It could help them to recognize potential signs of overconfidence in their own behavior and to be wary of its likely consequences. Referring to our measurement techniques results, simple questions asked as claims can be easier to understand and can better capture the tendency of overconfidence than calibration-based techniques. Also, researchers should take this into account; they should use a mix of various techniques when they measure overconfidence.

4. It could be meaningful to ask the investors to answer "behavioral questions" in order to reveal their behavioral biases in investing.

To reveal potential behavioral biases and to increase the know-how of investment tasks, the investors could be asked to answer a wider mix of investment behavior questions than the EU regulations require at present. This could further improve the investor protection and investors' abilities to make investment decisions. For example, investors could be made to answer questions on sufficient diversification, the link between risk and return, or their opinion on total withdrawal from the stock market. The resources of modern technology systems could be very useful for this purpose. The questions could be offered through websites to allow the investors to answer them independently, teachers could utilize them in teaching and financial institutions could exploit them with their clients. The responses should be informative and figurative and show with examples what should be done and what should not to be done when making investment decisions. These financial planning systems could hold good potential for identifying behavioral biases and providing advice based on financial theories.

With this final implication for EU regulation authors, financial literacy and financial institution authors and creators of financial planning systems, we close our research on subjective attributes and investment behavior. We hope our research motivates other researches to continue in the same research area.

References

Agnew J, Balduzzi P & Sundén A (2003) Portfolio choice and trading in a large 401(k) plan. The American Economic Review 93(1): 193-215.

Ameriks J & Zeldes S (2004) How do household portfolio shares vary with age? Working paper, Columbia University: 1-87.

Banerjee A (1992) A simple model of herd behavior. The Quarterly Journal of Economics 107(3): 797-817.

Bailey W, Kumar A, Ng D (2011) Behavioral biases of mutual fund investors. Journal of Financial Economics 102(1): 1-27.

Barber B & Odean T (2000) Trading is hazardous to your wealth: The common stock investment performance of individual investors. Journal of Finance 55(2): 773-806.

Barber B & Odean T (2001) Boys will be boys: gender, overconfidence and common stock investment. Quarterly Journal of Economics 116(1): 261-292.

Barber D & Odean T (2002) Online investors: do the slow die first? Review of Financial Studies 15(2): 455-487.

Barberis N, Huang M & Santos T (2001) Prospect theory and asset prices. The Quarterly Journal of Economics CXVI(1): 1-53.

Barsky R, Juster T, Kimball M & Shapiro M (1997) Preference parameters and behavioral heterogeneity; an experimental approach in the health and retirement study. The Quarterly Journal of Economics 112(2): 537-579.

Bernardo A & Welch I (2001) On the evolution of overconfidence and entrepreneurs. Journal of Economics & Management Strategy 10(3): 301-330.

Bernasek A & Shwiff S (2001) Gender, risk and retirement. Journal of Economic Issues 35:345-356.

Bertrand M & Mullainathan S (2001) Do people mean what they say? Implications for subjective survey data. American Economic Review 91(2): 67-72.

Biais B, Hilton D, Mazurier K & Pouget S (2005) Judgmental overconfidence, self-monitoring and trading performance in an experimental financial market. Review of Economic Studies 72(2): 287-312.

Bilias Y, Georgarakos D & Haliassos M (2010) Portfolio inertia and stock market fluctuations. Journal of Money, Credit and Banking. 42(4): 715-742.

Bodie Z & Crane D (1997) Personal investing; advice, theory and evidence. Financial Analysts Journal 53(6):13-23.

Boone D & Boone H (2012) Analyzing Likert Data. Journal of Extension 50(2): 1-5.

Brown S & Goetzmann W (1995) Performance persistence. The Journal of Finance 50(2): 679-698.

Bucher-Koenen T & Ziegelmeyer M (2011) Who lost the most? Financial Literacy, Cognitive Abilities and the Financial Crisis, European Central Bank, discussion paper 1299: 1-40.

Bucks B, Kennickell A, Mach T & Moore K (2009) Changes in U.S. family finances from 2004 to 2007; evidence from the Survey of Consumer Finances. Federal Reserve Bulletin: 1-56.

Calvet L, Campbell J & Sodini P (2007) Down or out; assessing the welfare costs of household investment mistakes. Journal of Political Economy 115(5): 707-746.
Calvet L, Campbell J & Sodini P (2009a) Fight or flight? Portfolio rebalancing by individual investors. Quarterly Journal of Economics 124(1): 301-348.
Calvet L, Campbell J & Sodini P (2009b) Measuring the financial sophistication of households. American Economic Review 99(2): 393-398.
Campbell J (2006) Household Finance. The Journal of Finance LXI(4): 1553-1604.
Campbell J & Viceira L (2002) Strategic assset allocation; portfolio choice for long-term investors. Oxford University Press.
Campello M, Giambona E, Graham J & Harvey C (2011) Liquidity management and corporate investment during a financial crisis. Review of Financial Studies 24(6): 1944-1979.
Carroll CD (2000) Portfolios of the rich. NBER working paper series 7826: 1-43.
Chen P, Finke M. S (1996) Negative net worth and the life cycle hypothesis. Financial Counseling and Planning 7: 87-96.
Cooper A, Woo C & Dunkelberg W (1988) Entrepreneurs perceived chances for success. Journal of Business Venturing 3(2): 97–108.
Daniel K.D, Hirshleifer D & Subrahmanyam A (1998) Investor psychology and security market under- and over-reactions. Journal of Finance 53(6): 1839-1886.
Deaves R, Lüders E & Luo G.Y (2009) An experimental test of the impact of overconfidence and gender on trading activity. Review of Finance 13: 555–575.
Deaves R, Lüders E, Schröder M (2010) The dynamics of overconfidence: Evidence from stock market forecasters. Journal of Economic Behavior & Organization 75: 402–412.
De Bondt W (1998) A Portrait of the Individual Investor. European Economic Review 42: 831-844.
Dohmen T, Falk A, Huffman D, Sunde U, Schupp J & Wagner G (2005) Indicidual risk attitudes; new evidence from a large, representative, experipentally-validated survey. Institute for the Study of Labor, Discussion Paper 1730: 1-56.
Donkers B, Melenberg B & Soest A (2001) Estimating risk attitudes using lotteries; a large sample approach. Journal of Risk and Uncertainty 22(2): 165-195.
Dorn D & Huberman G (2005) Talk and action; what individual investors say and what they do. Review of Finance 9(4): 437-481.
Duchin R, Ozbas O & Sensoy D (2010) Costly external finance, corporate investment, and the subprime mortgage credit crisis. Journal of Financial Economics 97(3): 418-435.
Evans J & Archer S (1968) Diversification and the reduction of dispersion: an empirical analysis. Journal of Finance 23(5): 761-767.
Fama E (1970) Efficient capital markets: a review of theory and empirical work. The Journal of Finance 25(2): 383-417.
Financial Engines. Investment risk tolerance quiz. www.financialengines.com
FinaMetrica. Investment risk tolerance quiz. www.riskprofiling.com
Gervais S & Odean T (2001) Learning to be overconfident. Review of Financial Studies 14(1): 1-27.

Gilliam J, Chatterjee S & Grable J (2010) Measuring the perception of financial risk tolerance; a tale of two measures. Journal of Financial Counseling and Planning 21(2): 30-43.

Glaser M & Weber M (2007) Overconfidence and trading volume. Geneva Risk and Insurance Review 32(1): 1-36.

Goetzmann WN & Kumar A (2008) Equity portfolio diversification. Review of Finance 12(3): 433-463.

Grable J (2000) Financial risk tolerance and additional factors that affect risk taking in everyday money matters. Journal of Business and Psychology 14(4): 625-630.

Grable J & Lytton RH (2003) Development of a risk assessment instrument; a follow-up study. Financial Services Review 12(3): 257-274.

Grable J & Lytton RH (1999) Financial risk tolerance revisited; the development of a risk assessment instrument. Financial Services Review 8(3): 163-181.

Grable J & Lytton RH (2001) Assessing the concurrent validity of the SCF risk tolerance question. Association for Financial Counseling and Planning Education: 43-53.

Graham J, Campbell R & Hai H (2009) Investor competence, trading frequency and home bias. Management Science Volume 55(7): 1094–1106.

Graham J & Harvey C (2003) Expectations of equity risk premia, volatility and asymmetry. NBER working papers 8678: 1-20.

Graham J, Harvey C & Huang H (2009) Investor competence, trading frequency and home bias. Management Science 55(7): 1094–1106.

Griffin D & Tversky A (1992) The weighting of evidence and the determinants of confidence. Cognitive Psychology 24: 411-435.

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

Grinblatt M & Keloharju M (2001) How distance, language, and culture influence stock-holdings and trades. Journal of Finance 56(3): 1053-1073.

Grinblatt M & Keloharju M (2009) Sensation seeking, overconfidence, and trading activity. The Journal of Finance 64(2):549–578.

Guiso L, Jappelli T & Terlizzese D (1996) Income risk and portfolio choice. The American Economic Review 86(1):158-172.

Guiso L, Haliassos M & Jappelli T (2002) Household stockholding in Europe; Where do we stand and where do we go? Discussion Paper, University of Cyprus: 1-53.

Guiso L & Jappelli T (2005) Awareness and stock market participation. Review of Finance 9(4): 537-567.

Guiso L & Jappelli T (2006) Information acquisition and portfolio performance. CEPR discussion paper 5901: 1-63.

Guiso L & Paiella M (2008) Risk aversion, wealth, and background risk. Journal of the European Economic Association 6(6): 1109-1150.

Guiso L & Jappelli T (2009) Financial literacy and portfolio diversification. Centre for Studies in Economics and Finance, working paper 212: 1-41.

Guiso L, Sapienza P & Zingales L (2013) Time varying risk aversion. Booth working paper 13-64: 1-52.

Haliassos M & Bertaut C (1995) Why do so few hold stocks? Economic journal 105(432): 1110-1129.
Halko M, Kaustia M & Alanko E (2012) The gender effect in risky asset holdings. Journal of Economic Behavior and Organization 83(1): 66-81.
Hallahan T, Faff R & McKenzie M (2004) An empirical investigation of personal financial risk tolerance. Financial Services Review 13(1): 57-78.
Hanna S & Lindamood S (2004) An improved measure of risk aversion. Association for Financial Counseling and Planning Education 15(2): 27-38.
Heath C & Tversky A (1991) Preferences and beliefs: Ambiguity and competence in choice under uncertainty. Journal of Risk and Uncertainty 4(1): 5-28.
Heaton J & Lucas D (2000a) Portfolio choice in the presence of background risk. Economic Journal 110(460): 1–26.
Heaton J & Lucas D (2000b) Portfolio choice and asset prices; The importance of entrepreneurial risk. Journal of Finance 55(3): 1163-1198.
Hoffmann A, Post T & Pennings J (2011) Individual Investors and the Financial Crisis: How perceptions change, drive behavior, and impact performance. Netspar discussion paper 41: 1–51.
Hoffmann A, Post T, Pennings J (2013) Individual Investor Perceptions and Behavior During the Financial Crisis. Journal of Banking and Finance 37: 60–74.
Huberman G (2001) Familiarity breeds investment. Review of Financial Studies 14(3): 659-680.
Humodiet P, Kezdi G & Willis J (2011) Stock market crash and expectations of American households. Journal of Applied Econometrics 26(3): 393-415.
Ivashina V & Scharfstein D (2010) Bank lending during the financial crisis of 2008. Journal of Financial Economics 97(3): 319-338.
Kahneman D & Tversky A (1973) On the psychology of prediction. Psychological Review 80(4): 237-251.
Kapteyn A & Teppa F (2002) Subjective measures of risk aversion and portfolio choice. Rand working paper: 1-40.
Kapteyn A & Teppa F (2011) Subjective measures of risk aversion, fixed costs and portfolio choice. Journal of Economic Psychology 32(4): 564-580.
Keefer D & Bodily S (1983) Three-point approximations for continuous random variables. Management Science 29(5): 595-609.
Klayman J & Soll J (1999) Overconfidence: It depends on how, what, and whom you ask. Organizational Behavior and Human Decision Processes 79(3): 216-247.
Langer EJ (1975) The illusion of control. Journal of Personality and Social Psychology 32(2): 311-328.
Langer EJ & Roth J (1975) Heads I win, tails it's chance: The illusion of control as a function of the sequence of outcomes in a purely chance task. Journal of Personality and Social Psychology 32(6): 951-955.
Likert R (1932) A technique for the measurement of attitudes. Archives of Psychology 22(140): 1-55.

Lucarelli C & Brighetti G (2010) Errors in individual risk tolerance. Social Science Research Network, working paper series 23: 1-28.

Lusardi A & Mitchell O (2005) Financial literacy and planning: Implications for retirement wellbeing. Michigan Retirement Research Center, working paper 108: 1-29.

Lusardi A & Mitchell O (2009) How ordinary consumers make complex economic decisions: Financial literacy and retirement readiness. NBER working paper 15350: 1-46.

Manski C (2004) Measuring expectations. Econometrica 72(5): 1329-1376.

Markowitz H. M (1952) Portfolio selection. Journal of Finance 7(1): 77-91.

Mellan O (2009) Reassessing risk. Independent Advisor (November 1): 1-4.

Merton RC (1969) Lifetime portfolio selection under uncertainty; The continuous-time case. Review of Economics and Statistics 51(3): 247-257.

Merton R (1987) A simple model of capital market equilibrium with incomplete information. Journal of Finance 42(3): 483-510.

Milgrom P & Stokey N (1982) Information, trade and common knowledge. Journal of Economic Theory 26(1): 17-27.

Nyberg P & Vaihekoski M (2013) Equity premium in Finland and long-term performance of the Finnish equity and money markets. Forthcoming in Cliometrica.

Odean T (1998) Volume, volatility, price and profit when all traders are above average. Journal of Finance 53 (6): 1887-1934.

Odean T (1999) Do investors trade too much? American Economic Review 89(5): 1279-1298.

OP-Pohjola Group. Investment risk tolerance quiz (in Finnish). https://www.op.fi/op/henkiloasiakkaat/saastot ja sijoitukset/sijoittajakuva

OP-Pohjola Group. Mutual funds (in Finnish). https://www.op.fi/op/henkiloasiakkaat/saastot ja sijoitukset/rahastot

Peress J (2004) Wealth, information acquisition, and portfolio choice. The Review of Financial Studies 17(3): 879-914.

Peress J (2011) Erratum, wealth, information acquisition, and portfolio choice. The Review of Financial Studies 24(9): 3187-3195.

Powell M & Ansic D (1997) Gender differences in risk behaviour in financial decision-making; An experimental analysis. Journal of Economic Psychology 18(6): 605-628.

Quadrini V (2000) Entrepreneurship, saving and social mobility. Review of Economic Dynamics 3(1): 1-40.

Riley W & Chow K (1992) Asset allocation and individual risk aversion. Financial Analysts Journal 48(6): 32-37.

Rooij M, Lusardi A & Alessie R (2011) Financial literacy and stock market participation. Journal of Financial Economics 101(2): 449-472.

Rooij M, Lusardi A & Alessie R (2012) Financial literacy, retirement planning, and household wealth. Economic Journal 122(560): 449-478.

Roszkowski M & Davey G (2010) Risk perception and risk tolerance changes attributable to the 2008 Eeconomic crisis: A subtle but critical difference. Journal of Financial Service Professionals 64(4): 42-53.

Rui Y, Hanna S & Lindamood S (2004) Changes in financial risk tolerance 1983-2001. Financial Services Review 13(4): 249-266.
Russo JE & Schoemaker P.J (1992) Managing overconfidence. MIT Sloan Management Review 33(2): 7-17.
Rutgers University. Investment risk tolerance quiz by Grable & Lytton. http://njaes.rutgers.edu/money/riskquiz/.
Samuelson P (1969) Lifetime portfolio selection by dynamic stochastic programming. Review of Economics and Statistics 51(3): 239-246.
Santacruz L (2009) Effect of general economic mood on investor risk tolerance – implications for financial planning. The Finsia Journal of Applied Finance (1): 35-42.
Selcuk E, Altinoklar A & Aydin G (2010) Financial Risk Tolerance, Scale Development and Analysis of Determinants. Journal of American Academy of Business 15(2): 89-98.
Shefrin H (2005) A behavioral approach to asset pricing. Elsevier Academic Press
Shefrin H & Statman M (1985) The disposition to sell winners too early and ride losers too long: Theory and Evidence. Journal of Finance 40(3): 777-790.
Shefrin H & Thaler R.H (1988) The behavioral life-cycle hypothesis. Economic Inquiry 26(4): 609-643.
Shiller R (2003) From efficient markets theory to behavior finance. The Journal of Economic Perspectives 17(1): 83-104.
Soll J & Klayman J (2004) Overconfidence in interval estimates. Journal of Experimental Psychology: Learning, Memory, and Cognition 30(2): 299-314.
Statistics Finland (2007) Financial assets of households 1997-2007.
Statman M (1999) Foreign stocks in behavioral portfolios. Financial Analysts Journal 55(2): 13-16.
Statman M, Thorley S & Vorkink K (2006) Investor overconfidence and trading volume. The Review of Financial Studies 19(4): 1531-1565.
Sung J & Hanna S (1996) Factors related to risk tolerance. Financial Counseling and Planning 7: 11-19.
Thaler RH (1985) Mental accounting and consumer choice. Marketing Science 4(3): 199-214.
Tirole J (1982) On the possibility of speculation under rational expectations. Econometrica 50(5): 1163-1182.
Wachter JA & Yogo M (2010) Why do household portfolio shares rise in wealth? Review of Financial Studies 23(11): 3929-3665.
Wang C & Hanna S (2007) The risk tolerance and stock ownership of business owning households. Financial Counseling and Planning 18(2): 3-18.
Weber E & Milliman R (1997) Perceived risk attitudes; Relating risk perception to risky choice. Management Science 43(2): 123-144.
Vissing-Jorgensen A (2002) Towards an explanation of household portfolio choice heterogeneity; Nonfinancial income and participation cost structures. NBER Working Paper 8884: 1-60.
Yang Y (2004) Measuring risk preferences; Re-examination of Grable and Lytton's 13-item questionnaire. Consumer Interest Annual 50: 19-122.

Appendix 1
The influence of investor's subjective attributes on portfolio choice (Chapter 3)

Appendix 1.1, Citations from Article 19(4) of Directive 2004/39/EC, Article 3

Assessment of suitability;

1. Member States shall ensure that investment firms obtain from clients or potential clients such information as is necessary for the firm to understand the essential facts about the client and to have a reasonable basis for believing, giving due consideration to the nature and extent of the service provided, that the specific transaction to be recommended, or entered into in the course of providing a portfolio management service, satisfies the following criteria:

– (a) it meets the investment objectives of the client in question;
– (b) it is such that the client is able financially to bear any related investment risks consistent with his investment objectives;
– (c) it is such that the client has the necessary experience and knowledge in order to understand the risks involved in the transaction or in the management of his portfolio.

3. The information regarding the financial situation of the client or potential client shall include, where relevant, information on the source and extent of his regular income, his assets, including liquid assets, investments and real property, and his regular financial commitments.

4. The information regarding the investment objectives of the client or potential client shall include, where relevant, information on the length of time for which the client wishes to hold the investment, his preferences regarding risk taking, his risk profile, and the purposes of the investment.

5. Where, when providing the investment service of investment advice or portfolio management, an investment firm does not obtain the information required under Article 19(4) of Directive 2004/39/EC, the firm shall not recommend investment services or financial instruments to the client or potential client.

(Official Journal of the European Union, 2/9/2006, 1–33. Comission Directive 2006/73/EC of 10 August 2006 implementing Directive 2004/39/EC of the European Parliament and of the Council as regards organizational requirements and operating conditions for investment firms and defined terms for the purposes of that Directive. Page 25)

Appendix 1.2 Investment view survey questionnaire (www.op.fi)

I am interested in saving or investing money:

- To improve my financial situation for retirement
- Saving for a home
- For my children / grandchildren
- Saving for a car, a boat, a leisure apartment etc.
- For future needs
- To invest already acquired wealth

How would you describe yourself as a saver and as an investor?

- I aim at the best possible return in the long run and I am ready to take large risks.
- I aim at good long term return and I am ready to take risks.
- I aim at good value growth and I am ready to take some risk.
- I aim at steady value growth and I am ready to take some risk.
- I aim at small value growth and I want my invested capital to be safe.

How do you react to value fluctuations of your savings and investments?

- I understand value fluctuations belong to investments and I accept even large fluctuations with my investments.
- I understand value fluctuations belong to investments and I accept that the value of my investments can fluctuate quite a lot.
- I understand value fluctuations belong to investments and I accept that the value of my investments can temporarily decrease to some extent.
- I don’t like value fluctuations but I accept that the value of my investments can temporarily decrease a little.
- I do not accept value fluctuations with my investments under any circumstances.

What is your education?

- Elementary school
- Vocational school
- Gymnasium
- Polytechnic
- University

How much experience (in years) do you have with the following instruments?

Product	**Experience in years**
Bank accounts	________________
Money market instruments	________________
Bonds	________________
Structured products (index-linked bonds etc.)	________________
Interest funds	________________
Stock or combination funds	________________
Stocks	________________
Warrants	________________
Derivatives	________________
Saving insurances	________________
Other (specify)	________________

Appendix 1.3, Investment plan questionnaire

How long is your estimated investment time?

- More than 7 years or for the foreseeable future
- More than 6 years
- More than 5 years
- More than 4 years
- More than 3 years
- More than 2 years
- More than 1 year
- Less than 1 year

How actively do you follow economic events?

- Infrequently
- Weekly
- Daily

Do you want to make your own investment decisions?

- I want to use time to take care of my investments and I want to make the decisions myself
- I want to get a ready solution proposal from an investment advisor
- I am interested in having a wealth manager

How would you describe your investment experience?

- I am a novice
- I have some experience
- I have much experience

What is your main source of income?

- Salary or pension
- Investment income
- Other

What is your monthly net income?

- < 1 000 €
- 1 000 – 3 000 €
- 3 000 – 5 000 €
- 5 000 – 8 000 €
- 8 000 € -

What are your regular monthly expenses?

- < 500 €
- 500 – 1 000 €
- 1 000 – 2 000 €
- 2 000 – 5 000 €
- 5 000 € -

How large is your wealth in euros and how have you divided it in various instruments?

	Assets within this bank	Elsewhere
Short term interest instruments		
Bank accounts		
Saving insurance, stake in short term interests		
Interest funds, short term		
Money market instruments (firms responsible)		
Combination funds, stake in short term interests		
Long term interest instruments		
Saving insurance, stake in long term interests		
Bonds		
Interest funds, long term		
Combination funds, long term		
Stock instruments		
Stock funds		
Saving insurance, stake in stock instruments		
Directly owned stocks		
Derivatives		
Combination funds, stake in stock instruments		
Other property		
Home		
Investment apartment		
Leisure apartment		
Land and forest property		
Other real property (private business etc.)		

Appendix 1.4: Re-running of risk profiles

In this appendix we re-run the risk profiles of Chapter 3: *The influence of investor's subjective attributes on portfolio choice* by using another dataset. In Figure 1 we use the same database as in the original data used in Chapter 3 but have collected it among different investors and during another time period. In Figure 2 the database is different. In each case we have measured the risk profiles in the same manner. The profiles are measured according to investors' answers to two questions about their self-perceived risk-taking level and return target. Also, we have gathered the information on investors' wealth in the same manner and calculated the risky shares identically. The risky share is calculated by summing the value of stock-related investments (directly owned stocks, stock funds, half of combination fund assets, insurance savings which are invested in stock-related instruments) and dividing it by the value of total wealth the investor owns (excluding the value of the primary domicile e.g. home).

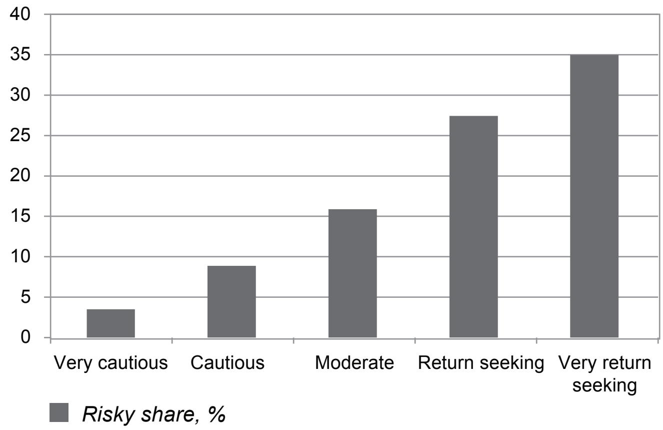


Figure 1. Risky share by risk profiles, data from Chapter 4.

This figure shows the relative weights of stock instruments (=risky share) by risk profiles among clients of a Finnish financial institution, N = 3,408 investors. We use this data in the empirical research of Chapter 4: *Rebalancing behavior during the stock market crises 2008 – 2009 and 2011*.

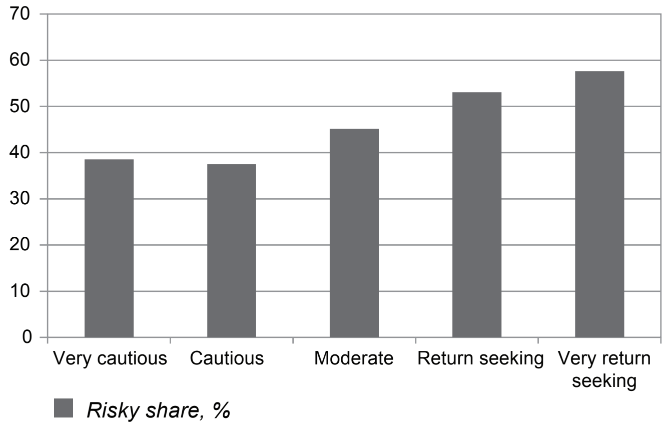


Figure 2. Risky shares by risk profiles, data from Chapter 5.

Relative weight of stock instrument by risk profiles among investors belonging to the Shareholders' Association in Finland, N = 838 investors. We use this data in the empirical reseach of Chapter 5: *Investor-specific trading and diversification decisions: due to overconfidence or something else?*

Appendix 1.5: Re-running the regressions on the connection between risk profile and subjective and objective investor attributes

In this appendix we re-run the regressions on the connection between risk profile and subjective and objective investor attributes (see empirical research *The influence of investor's subjective attributes on portfolio choice*, Chapter 3) with year 2011 data taken from the same database as our original data from year 2008, which we use in Chapter 3. The estimation method and variables used are identical with those in the original empirical research.

Table 1. The influence of subjective attributes on Risk profile choice, year 2011 data.

This table describes the influence of subjective attributes on Risk profile choice. The model is ordered logistic regression and has the form $logit[Pr(Y \leq i \mid x)] = \alpha_i + \beta x$. *Y* is Risk profile classified into three categories (1= Very cautious or Cautious, 2 = Moderate and 3 = Return seeking or Very return seeking), α_i are intercept parameters, β is a vector of regression coefficients and x is a vector of explanatory variables. Explanatory variables are Investment experience (1 = Novice, 2 = Some experience, 3 = Experienced), Activeness in following economic events (1 = Infrequently, 2 = Weekly, 3 = Daily) and Investment decisions (dummy variable, 0 = The investor wants to get a ready solution which is taken care of by an investment advisor or wealth manager, 1 = The investor wants to use time to take care of investments and wants to make his own decisions).The table contains maximum likelihood estimates and p-values (parentheses below). AIC refers to the Akaike information criterion value. Pseudo R-square refers to Nagelkerke Pseudo R-square.

Dependent variable = Risk profile			
		Model	
Explanatory variable	(1)	(2)	(3)
Investment experience (reference category Novice)			
Some experience	0.7569	0.4649	0.4568
	(<0.0001)	(<0.0001)	(<0.0001)
Experienced	2.3067	1.5781	1.4408
	(<0.0001)	(<0.0001)	(<0.0001)
Activeness in following economic events (reference category Infrequently)			
Weekly		0.8382	0.7509
		(<0.0001)	(<0.0001)
Daily		1.2960	1.1321
		(<0.0001)	(<0.0001)
Investment decisions			0.4511
0 = Ready solution,			(<0.0001)
1 = Own decisions			
Intercept 3	-2.0647	-2.3809	-2.4460
	(<0.0001)	(<0.0001)	(<0.0001)
Intercept 2	-0.2585	-0.4796	-0.5290
	(<0.0001)	(<0.0001)	(<0.0001)
Number of observations	3429	3429	3429
AIC	6852	6645	6617
Pseudo R-square	0.0883	0.1511	0.1598

Table 2. The influence of subjective and objective attributes on Risk profile choice, year 2011 data.

This table describes the influence of subjective and objective attributes on Risk profile choice. The model has the form $logit[Pr(Y \leq i \mid x)] = \alpha_j + \beta x$, where Y is Risk profile classified into three categories (1= Very cautious or Cautious, 2 = Moderate and 3 = Return seeking or Very return seeking), α_j are intercept parameters, β is a vector of regression coefficients and x is a vector of explanatory variables. Subjective attributes as explanatory variables are the same than in Table 1. Objective attributes are Income (= Monthly net earnings classified into four categories), Education (= Education classified into three categories), Gender (dummy variable, 0 = Woman, 1 = Man) and Age in years. The table contains maximum likelihood estimates and p-values (parentheses below). AIC refers to the Akaike information criterion value. Pseudo R-square refers to Nagelkerke Pseudo R-square. Proportional odds assumption doesn't hold from Model 3 onwards. The reason for that is the Investment decisions variable. By deleting it, there is no problem with proportional odds assumption in any model.

Dependent variable = Risk profile							Model
Explanatory variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Investment experience (reference category Novice)							
Some experience	0.7569	0.4649	0.4568	0.4333	0.4219	0.4154	0.6209
	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)
Experienced	2.3067	1.5781	1.4408	1.3499	1.3253	1.2994	1.6949
	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)
Activeness in following economic events (reference category Infrequently)							
Weekly		0.8382	0.7509	0.7269	0.7120	0.5932	0.5744
		(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)
Daily		1.2960	1.1321	1.1052	1.1061	0.9629	1.0187
		(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)
Investment decisions			0.4511	0.4313	0.4172	0.3589	0.3420
(0 = Ready solution, 1 = Own decisions)			(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)
Net income / month, € (reference category < 1000 € / month)							
1 000 – 3 000 € / month				-0.0341	-0.0845	-0.0832	0.3343
				(0.7441)	(0.4235)	(0.4329)	(0.0034)
3 000 – 4 999 € / month				0.2030	0.0990	0.0074	0.4213
				(0.1125)	(0.4538)	(0.9556)	(0.0026)
5 000 € / month –				0.4756	0.3629	0.1914	0.6488
				(0.0265)	(0.0974)	(0.3857)	(0.0043)
Education (reference category vs. lower than Polytechnic)							
Polytechnic					0.2877	0.3170	0.0700
					(0.0011)	(0.0003)	(0.4433)
University					0.1963	0.2721	0.1309
					(0.0182)	(0.0012)	(0.1268)

Dependent variable = Risk profile	Model						
Explanatory variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Gender (0 = Woman, 1 = Man)						0.6007	0.5040
						(<0.0001)	(<0.0001)
Age							-0.0297
							(<0.0001)
Intercept 3	-2.0647	-2.3809	-2.4460	-2.4429	-2.4919	-2.1409	-13951
	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)
Intercept 2	-0.2585	-0.4796	-0.5290	-0.5203	-0.5637	-0.1765	0.6553
	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(0.1182)	(<0.0001)
Number of observations	3429	3429	3429	3429	3429	3422	3422
AIC	6852	6645	6617	6611	6603	6519	6314
Pseudo R-square	0.0883	0.1511	0.1598	0.1632	0.1668	0.1866	0.2428

Appendix 2, Rebalancing behavior during the stock market crises 2008 – 2009 and 2011 (Chapter 4)

Figure 1. Stock market crises 2008 – 2009 and 2011.

S&P 500 index Jan. 1, 2008 – Jan. 25, 2013 (500 large cap firms in U.S. markets). The stock market crises under research are June 30, 2008 – Mar. 31, 2009 and May 31 – Sept.30, 2011.

Table 1. Rebalancing behavior, stock and combination fund portfolios.

Rebalancing behavior (=active change) of stock and combination fund portfolios. We divide investors into sellers, no rebalancing and buyers. As a no rebalancing group we use a range from -1% to +1% (see Descriptive statistics Chapter 4.4, Table 14) as well as a range from -10% to +10% (we use this range in probit regressions in Chapter 4.5, Tables 15-17). Panel A describes the data from the stock market crisis in 2008 – 2009 and Panel B the data from the crisis of 2011. Table consists of investors with fund ownership min. 1,000 euros.

Panel A: Crisis 2008 – 2009

Stock fund owners	Sellers, %	No rebalancing, %	Buyers, %	Total, %
No rebalancing -1 - +1 %	14	37	49	100
No rebalancing -10 - +10 %	10	49	41	100
Stock and combination fund owners				
No rebalancing -1 - +1 %	18	36	46	100
No rebalancing -10 - +10 %	14	53	33	100

Panel B: Crisis 2011

Stock fund owners	Sellers, %	No rebalancing, %	Buyers, %	Total, %
No rebalancing -1 - +1 %	11	50	39	100
No rebalancing -10 - +10 %	10	74	16	100
Stock and combination fund owners				
No rebalancing -1 - +1 %	11	50	39	100
No rebalancing -10 - +10 %	10	75	15	100

Appendix 3 Investor-specific trading and diversification decisions: due to overconfidence or something else research (Chapter 5)

Appendix 3.1, Definition of variables

Trading

We ask the respondent to relate his trading activity:

How actively do you trade with your stock portfolio?
1 = More seldom than once a year
2 = Once a year
3 = Biannually
4 = Quarterly
5 = Monthly
6 = Weekly
7 = Daily

Diversification

We ask the respondent to relate the diversification of his actual stock portfolio:

How many company's' stocks do you own?
1 = 0 stocks
2 = 1–2 stocks
3 = 3–6 stocks
4 = 7–10 stocks
5 = 11 or more

Demographic and socioeconomic variables (we refer to these as objective attributes)

Gender
0 = Woman
1 = Man

Age
Investor's age in years

Total wealth
We ask the respondent to relate the value of total wealth (€) he owns himself or together with his spouse:

Deposits, stocks, mutual funds with various investment policies, bonds, investment apartment(s), an apartment which is used as a home, other property (land, forest, own business, leisure home etc.)

Risky share
By using the answer to the Total wealth question we calculate the respondent's risky share:

Wealth invested in stock-related instruments / Total wealth excluding the value of home (this takes into account the takes into account the unique nature of the home compared to other wealth instruments)

Net income, € / month
1 = <1 000 €
2 = 1 000 – 2 999 €
3 = 3 000 – 4 999 €
4 = 5 000 – 7 999 €
5 = > 8 000 €

Capital income, € / year
1 = <1 000 €
2 = 1 000 – 2 999 €
3 = 3 000 – 4 999 €
4 = 5 000 – 7 999 €
5 = > 8 000 €

Education
1 = Elementary school
2 = Vocational school
3 = Polytechnic
4 = University of applied sciences
5 = University

Occupation
1 = Working in the public sector
2 = Working in the private sector
3 = Entrepreneur
4 = Student
5 = Retired
6 = Other life situation

Self-perceived characteristics of respondents (we refer to these as subjective attributes)

We collect the respondent's self-perceived knowledge of investment issues by asking the following questions (1–2):

Question 1:

How would you describe the financial information you have?
1 = I have very little information
2 = I have quite a little information
3 = I have an average amount of information
4 = I have quite a lot of information
5 = I have a lot of information

Question 2:

Please, imagine how well you could describe the following financial instruments to your friend: stocks, bonds, stock funds, interest funds, index funds, derivatives, index bonds.
1 = Very poorly
2 = Quite poorly
3 = Averagely
4 = Quite well
5 = Very well

The respondent evaluates his knowledge on a scale of 1 – 5 and we sum his scores.

We ask about the amount of time the respondent spends gathering financial information:

How much time do you spend gathering information to help you make your investment decisions (reading newspapers or Internet, visiting investor meetings or advisor etc.)?
1 = < 1 hour / week
2 = 1 – 2 hours / week
3 = 3 – 5 hours / week
4 = 6 – 8 hours / week
5 = > 8 hours / week

We ask about the respondent's activity to follow economic events:

How actively do you follow economic events?
1 = Infrequently
2 = Weekly
3 = Daily

We ask about the respondent's investment experience:

How long is your experience as an investor?
1 = < 5 years
2 = 5 – 10 years
3 = 10 years -

We ask the respondent to specify his most important information channel when making investment decisions:

What is your most important information channel when you make your investment decisions?
1 = Relatives, friends or other acquaintances
2 = Newspapers
3 = Internet
4 = Personal counseling of banks or financial institutions

We ask the respondent the following question about the importance of being able to make transactions quickly:

How important is it to you to be able to make transactions quickly?
1 = Not at all important
2 = Quite important
3 = Very important

We ask the respondent's willingness to make his own decisions or use a wealth manager:

How independently do you want to make your investment decisions?
1 = I want to get a ready solution from an investment advisor
2 = I want to use time and to make my own decisions
3 = I want to mandate the wealth manager to make the decisions

We construct Risk profile by asking the following questions (1 – 2). The respondent's risk profile is determined by the level of risk inherent in the responses.

How would you describe yourself as a saver and as an investor?

- I aim at the best possible return in the long run and I am ready to take large risks.
- I aim at good long term return and I am ready to take risks.
- I aim at good value growth and I am ready to take some risk.
- I aim at steady value growth and I am ready to take some risk.
- I aim at small value growth and I want my invested capital to be safe.

How do you react to value fluctuations in your savings and investments?

- I understand value fluctuations belong to investments and I accept even large fluctuations with my investments.
- I understand value fluctuations belong to investments and I accept that the value of my investments can fluctuate quite a lot.
- I understand value fluctuations belong to investments and I accept that the value of my investments can temporarily decrease to some extent.
- I don't like value fluctuations but I accept that the value of my investments can temporarily decrease a little.
- I do not accept value fluctuations with my investments under any circumstances.

We create an On/off variable by asking the respondent's opinion about the following claim:
When stock prices start going downwards, it is best to sell the whole stock portfolio, not only a part of it.

We create Familiarity bias variable by asking the respondent's opinion about the following claim:
I would rather own only a few stocks which I am familiar with than own a diversified portfolio including stocks unfamiliar to me.

The scale for answering the On/off and a Familiarity bias variable is as follows:
- Strongly agree
- Somewhat agree
- Somewhat disagree
- Strongly disagree
- Do not know

We numerate the answers to the On/off and Familiarity bias variables in the following way:

1=Strongly disagree, 2=Somewhat disagree, 3=Do not know, 4=Somewhat agree, 5=Strongly agree

When we run the factor analyses and regressions, we drop the Do not know answers and numerate the answers in a new way: 1=Strongly disagree, 2=Somewhat disagree, 3=Somewhat agree, 4=Strongly agree

We create a Familiarity variable by asking the respondents opinion about how well he knows the stocks which belong to the OMX Helsinki25 index (25 most traded stocks on the NASDAQ OMX Helsinki exchange). The scale is:
1) I know the company very poorly
2) I know the company quite poorly
3) I know the company somewhat
4) I know the company quite well
5) I know the company very well

We sum the scores the respondents give to the 25 stocks.

Questions measuring actual investment knowledge

Six questions from Lusardi (see Lusardi & Mitchell 2005, 2009 or Lusardi 2011 or 2012):

1) Suppose you had €100 in a savings account and the interest rate was 2% per year. After 5 years, how much do you think you would have in the account if you left the money to grow? You do not need to take into account taxes or inflation. (The last sentence is our own modification)

(i) More than €102
(ii) Exactly €102
(iii) Less than €102
(iv) Do not know

2) Imagine that the interest rate on your savings account was 1% per year and inflation was 2% per year. After 1 year, how much would you be able to buy with the money in this account?

(i) More than today
(ii) Exactly the same
(iii) Less than today
(iv) Do not know

3) If somebody buys the stock of firm A in the stock market:

(i) He owns a part of firm A
(ii) He has lent money to firm A
(iii) He is liable for firm A's debts
(iv) None of the above
(v) Do not know

4) When an investor spreads his money among different assets, does the risk of losing money:

(i) Increase
(ii) Decrease
(iii) Stay the same
(iv) Do not know

5) If somebody buys a bond of firm B:
(i) He owns a part of firm B
(ii) He has lent money to firm B
(iii) He is liable for firm B's debts
(iv) None of the above
(v) Do not know

6) If the interest rate falls, what should happen to bond prices?
(i) Rise
(ii) Fall
(iii) Stay the same
(iv) None of the above
(v) Do not know

Three own questions:

7) P/E ratio describes the relation between a share price and its per-share earnings
(i) Right
(ii) False
(III) Do not know

8) The Helsinki Stock Exchange belongs to Frankfurt Stock Exchange.
(i) Right
(ii) False
(III) Do not know

9) Euribor is a daily announced, a reference interest of all euro currency -countries. Its' level is decided by European Central Bank (ECB).
(i) True
(ii) False
(III) Do not know

We give one point when the respondent chooses the right answer and zero points if he chooses the wrong answer or the Do not know response. We then sum his scores.

Appendix 3.2, Descriptive statistics

Table 1. Descriptive statistics.

This table presents the descriptive statistics of our data.

Variable	Mean	Median	Std dev	Min	Max	Frequency
Age in years	56.2	59.0	13.81	20	93	
Wealth, €						
Total wealth	833 000	546 000	1 017 000	5 000	11 440 000	
Total wealth, value of home excluded	569 000	305 000	882 000	5 000	11 440 000	
Wealth distribution, % (calculated without the value of home)						
Interests	19.51	12.69	20.23	0	100	
Stocks	48.16	45.45	28.71	0	100	
Other investments	20.24	8.75	25.18	0	100	
Investment apartment	12.07	0	21.83	0	100	
Gender						
Woman						12.55
Man						87.45
Net income, € / month						
<1 000 €						3.09
1 000 – 2 999 €						44.74
3 000 – 4 999 €						36.29
5 000 – 7 999 €						20.93
8 000 € -						4.95
Capital income € / year						
< 1 000 €						13.58
1 000 – 2 999 €						18.84
3 000 – 4 999 €						19.15
5 000 – 7 999 €						14.29
8 000 € -						34.14
Education						
Elementary school						4.36
Vocational school						13.56
Polytechnic						24.65
University of applied sciences						10.69

Variable	Mean	Median	Std dev	Min	Max	Frequency
University						46.73
Occupation						
Working in a public sector						11.76
Working in a private sector						28.66
Entrepreneur						13.74
Student						1.78
Retired						39.82
Other life situation						4.25
Trading intensity, times / year						
More seldom than once a year						2.95
Once a year						8.06
Biannually						15.23
Quarterly						29.37
Monthly						32.02
Weekly						10.61
Daily						1.77
Diversification of stock portfolio						
0 stocks						1.49
1 – 2 stocks						4.08
3 – 6 stocks						18.29
7 – 10 stocks						23.76
11 – stocks						52.39

Appendix 3.3, Correlations

Table 2. Correlation coefficients.

This table presents Spearman correlation coefficients between the variables. See Appendix 3.1 for variable definitions. When calculating the correlations concerning On/off and Familiarity bias variables we exclude those respondents who choose the Do not know answer to those variables. Then we numerate On/off and Familiarity bias variables in the following way: 1=Strongly disagree, 2=Somewhat disagree, 3=Somewhat agree, 4=Strongly agree. We calculate Log total wealth variable by excluding the value of home.

	Trading activity	Diversi-fication	Man (1), Woman (0)	Age	Edu-cation	Ente-preneur (1), else (0)	Domestic sector worker (1), else (0)	Net income	Inv. income	Log total wealth	Active-ness in following economic events	Self-perceived invest-ment know-ledge	Actual invest-ment know-ledge	Risk profile	Invest-ment experi-ence	Trade speed	Internet (1), else (0)	On/off	Fami-liarity bias	Fami-liarity of OMX25 index stocks
Trading activity	1																			
Diversi-fication	0.22	1																		
	(<0.00)																			
Man (1), Woman (0)	0.16	0.04	1																	
	(<0.00)	(0.19)																		
Age	-0.05	0.17	0.00	1																
	(0.12)	(<0.00)	(0.92)																	
Education	0.00	0.08	-0.05	-0.18	1															
	(0.96)	(0.00)	(0.11)	(<0.00)																
Entepreneur (1), else (0)	0.04	0.01	0.02	-0.02	-0.03	1														
	(0.16)	(0.74)	(0.56)	(0.29)	(0.35)															
Domestic sector worker (1), else (0)	-0.05	-0.08	0.03	-0.21	0.09	-0.14	1													
	(0.09)	(0.00)	(0.30)	(<0.00)	(0.00)	(<0.00)														
Net income	0.10	0.15	0.07	0.06	0.22	0.09	-0.06	1												
	(0.00)	(<0.00)	(0.03)	(0.07)	(<0.00)	(0.00)	(0.07)													
Investment income	0.22	0.36	0.09	0.25	-0.01	0.22	-0.10	0.30	1											
	(<0.00)	(<0.00)	(0.00)	(<0.00)	(0.73)	(<0.00)	(0.00)	(<0.00)												

Log total wealth	0.07	0.09	0.13	0.09	-0.02	-0.03	-0.03	0.05	0.16	1									
	(0.02)	(0.00)	(<0.00)	(0.00)	(0.58)	(0.28)	(0.28)	(0.10)	(<0.00)										
Activeness in following economic events	0.28	0.19	0.18	0.04	-0.02	0.04	-0.03	0.11	0.19	0.06	1								
	(<0.00)	(<0.00)	(<0.00)	(0.17)	(0.46)	(0.23)	(0.36)	(0.00)	(<0.00)	(0.05)									
Self-perceived investment knowledge	0.18	0.06	0.02	-0.36	0.32	0.06	0.05	0.19	0.06	0.00	0.12	1							
	(<0.00)	(0.07)	(0.49)	(<0.00)	(<0.00)	(0.06)	(0.14)	(<0.00)	(0.07)	0.76)	(0.00)								
Actual investment knowledge	0.19	0.12	0.16	-0.22	0.25	0.03	0.01	0.12	0.11	0.11	0.16	0.47	1						
	(<0.00)	(0.00)	(<0.00)	(<0.00)	(<0.00)	(0.38)	(0.75)	(0.00)	(0.00)	(0.00)	(<0.00)	(<0.00)							
Risk profile	0.31	0.12	0.12	-0.29	0.07	0.04	0.03	0.07	0.10	0.12	0.19	0.36	0.27	1					
	(<0.00)	(0.00)	(0.00)	(<0.00)	(0.03)	(0.25)	(0.28)	(0.02)	(0.00)	(0.00)	(<0.00)	(<0.00)	(<0.00)						
Investment experience	0.29	0.14	0.10	0.40	-0.06	0.02	-0.12	0.16	0.29	0.06	0.11	0.03	0.07	-0.04	1				
	(<0.00)	(<0.00)	(0.00)	(<0.00)	(0.04)	(0.56)	(0.00)	(<0.00)	(<0.00)	(0.07)	(0.00)	(0.40)	(0.02)	(0.20)					
Trade speed	0.32	0.04	0.03	-0.14	0.02	0.03	0.02	0.00	0.05	0.05	0.16	0.17	0.07	0.25	-0.02	1			
	(<0.00)	(0.20)	(0.34)	(<0.00)	(0.45)	(0.38)	(0.57)	(0.93)	(0.09)	(0.15)	(<0.00)	(<0.00)	(0.03)	(<0.00)	(0.48)				
Internet (1), else (0)	0.25	0.03	0.14	-0.23	0.00	-0.00	0.04	0.03	-0.02	-0.00	0.13	0.14	0.15	0.16	-0.11	0.18	1		
	(<0.00)	(0.43)	(<0.00)	(<0.00)	(0.88)	(0.98)	(0.23)	(0.37)	(0.47)	(0.78)	(<0.00)	(<0.00)	(<0.00)	(<0.00)	(0.00)	(<0.00)			
On/off	0.12	-0.18	0.05	0.06	-0.02	-0.01	0.05	-0.02	-0.02	0.00	-0.03	0.02	0.02	-0.01	0.02	0.09	0.04	1	
	(0.00)	(<0.00)	(0.11)	(0.06)	(0.57)	(0.72)	(0.11)	(0.63)	(0.54)	(0.96)	(0.28)	(0.50)	(0.46)	(0.64)	(0.56)	(0.00)	(0.16)		
Familiarity bias	-0.05	-0.36	0.00	0.00	-0.05	-0.00	0.06	0.03	-0.06	-0.2	-0.05	-0.03	-0.04	0.02	-0.04	-0.00	0.05	0.20	1
	(0.15)	(<0.00)	(0.84)	(0.94)	(0.14)	(0.84)	(0.06)	(0.34)	(0.08)	(0.49)	(0.10)	(0.29)	(0.19)	(0.60)	(0.16)	(0.91)	(0.12)	(<0.00)	
Familiarity of OMX25 index stocks	0.23	0.25	0.11	-0.06	0.12	0.04	-0.00	0.13	0.16	0.15	0.22	0.39	0.22	0.22	0.10	0.16	0.13	0.00	-0.06
	(<0.00)	(<0.00)	(0.00)	(0.06)	(0.00)	(0.26)	(0.99)	(<0.00)	(<0.00)	(<0.00)	(<0.00)	(<0.00)	(<0.00)	(<0.00)	(0.00)	(<0.00)	(<0.00)	(0.90)	(0.05)

Appendix 3.4, Trading activity

Table 3. Drivers of trading activity.

This table describes the relation between trading activity and overconfidence factors as well as other explanatory variables. The model is ordered logistic regression and has the form $logit[Pr(Y \leq i \mid x)] = \alpha_i + \beta x$. Y is the respondent's trading activity measured as a categorical form: 1) Once a year or Biannually , 2) Quarterly, 3) Monthly and 4) Weekly or Daily. α_i are intercept parameters, β is a vector of regression coefficients and x is a vector of explanatory variables. The regression model is identical with Table 24 in Chapter 5.4.2 but as a measure of overconfidence we use the overconfidence factors defined in Chapter 5.3. The other explanatory variables are defined in Appendix 3.1. We exclude those respondents who trade more seldom than once a year, do not own a stock portfolio and those who choose the Do not know response to those measures of overconfidence which we solicit as claims or to On/off questions. We report the maximum likelihood estimates and p-values (parentheses). AIC refers to the Akaike information criterion value. Pseudo R-square refers to Nagelkerke Pseudo R-square.

Dependent variable= Trading activity Explanatory variables	
Measures of overconfidence	
Factor 1: Success caused by own skills	0.2211 (0.0079)
Factor 2: Market timing ability	0.1885 (0.0176)
Factor 3: Miss-success caused by external circumstances	-0.0813 (0.3022)
Other explanatory variables	
Internet (1) vs. other information channel (0)	0.3067 (0.0916)
Time spent collecting information (reference category 0 – 2 hours / week)	
3 – 5 hours / week	0.9162 (<0.0001)
6 – 8 hours / week	1.0088 (<0.0001)
>8 hours / week	1.4845 (<0.0001)

Dependent variable= Trading activity	
Explanatory variables	
Importance to be able to make transactions quickly (reference category Not at all important)	
Quite important	2.0078 (0.0182)
Very important	2.5859 (0.0021)
Risk profile (reference category Very cautious)	
Cautious	0.8794 (0.2161)
Moderate	1.3812 (0.0465)
Return seeking	1.7837 (0.0105)
Very return seeking	2.0620 (0.0056)
Willingness to make On/off decisions (reference category Strongly disagree)	
Somewhat disagree	0.1894 (0.2819)
Somewhat agree	0.2805 (0.1976)
Strongly agree	1.4554 (0.0002)
Gender (0=Woman, 1=Man)	0.6942 (0.0077)
Intercept 4	-7.0861 (<0.0001)
Intercept 3	-5.2302 (<0.0001)
Intercept 2	-3.5615 (0.0010)
Number of observations	619
AIC	1516
Pseudo R-square	0.2951

Appendix 3.5, Diversification of stock portfolio

Table 4. Drivers of diversification.

This table describes the relation between diversification decision and overconfidence factors as well as other explanatory variables. The model is ordered logistic regression and has the form $logit[Pr(Y \leq i \mid x)] = \alpha_i + \beta x$. *Y* is the diversification decision of respondent's stock portfolio measured as a categorical form: 1) 1-2 or 3-6 stocks, 2) 7-10 stocks and 3) 11 - stocks. α_i are intercept parameters, β is a vector of regression coefficients and *x* is a vector of explanatory variables. The regression model is identical with Table 25 in Chapter 5.4.3 but as a measure of overconfidence we use the overconfidence factors defined in Chapter 5.3. The other explanatory variables are defined in Appendix 3.1. We delete those respondents who do not own a stock portfolio and those who choose the Do not know response to those measures of overconfidence which we ask as claims, to the Familiarity bias or On/off question. We report the maximum likelihood estimates and p-values (parentheses). AIC refers to the Akaike information criterion value. Pseudo R-square refers to Nagelkerke Pseudo R-square.

Dependent variable = Diversification Explanatory variables	
Measures of overconfidence	
Drivers of Factor 1: Success caused by own skills	0.2231 (0.0242)
Drivers of Factor 2: Market timing ability	- 0.2331 (0.0090)
Drivers of Factor 3: Miss-success caused by external circumstances	0.0829 (0.3599)
Other explanatory variables	
Willingness to make On/off decisions (reference category Strongly disagree)	
Somewhat disagree	-0.2303 (0.1266)
Somewhat agree	-0.4660 (0.0640)
Strongly agree	-1.3188 (0.0027)
Familiarity bias (reference category Strongly disagree)	
Somewhat disagree	-0.0021 (0.9938)
Somewhat agree	-1.3508 (<0.0001)
Strongly agree	-2.1596 (<0.0001)

Dependent variable = Diversification Explanatory variables	
Familiarity of OMX Helsinki 25 index stocks	0.0209 (<0.0001)
Risk profile (reference category Very cautious)	
Cautious	2.0567 (0.0040)
Moderate	2.5362 (0.0003)
Return seeking	2.5325 (0.0003)
Very return seeking	2.6306 (0.0007)
Time spent collecting information (reference category 0 – 2 hours / week)	
3 – 5 hours / week	0.5243 (0.0102)
6 – 8 hours / week	0.7223 (0.0128)
>8 hours / week	0.6691 (0.0255)
Net income, € / month (reference category <3 000 € / month)	
3 000 – 5 000 € / month	0.2236 (0.2390)
>5 000 € / month	0.9576 (0.0004)
Age, years (reference category <40 years)	
40 – 65 years	0.7730 (0.0017)
>65 years	1.5920 (<0.0001)
Intercept 3	-4.5456 (<0.0001)
Intercept 2	-3.0233 (0.0003)
Number of observations	617
AIC	1072
Pseudo R-square	0.3538

51. Juntunen, Mari (2011) Corporate rebranding processes in small companies : a multiple case study from the B2B software industry
52. Ainali, Saara (2011) Alueiden työllisyyden rakenne ja kehitys tavarantuotannon ja palvelujen vuorovaikutuksessa
53. Juho, Anita (2011) Accelerated internationalisation as a network-based international opportunity development process
54. Vilmi, Lauri (2012) Studies in the macroeconomic implications of firm entry and exit
55. Orjasniemi, Seppo (2012) Studies on the macroeconomics of monetary union
56. Kauppinen, Antti (2012) The event of organisational entrepreneurship : disrupting the reigning order and creating new spaces for play and innovation
57. Mäkimurto-Koivumaa, Soili (2012) Effectuation in embedded and enquiry-based entrepreneurship education : essays for renewing engineering education at Kemi-Tornio University of Applied Sciences
58. Ruopsa, Jukka (2013) Laatu ja työprosessi : diskurssien taistelu rakennustyömaalla
59. Pernu, Elina (2013) MNC making sense of global customer relationships
60. Lehtimäki, Tuula (2013) The contextual nature of launching industrial new products
61. Palo, Teea (2014) Business model captured? : variation in the use of business models
62. Lim, Cheryl (2014) What's in it for me? : organizational commitment among faculty members in UAE business schools
63. Almarri, Jasem (2014) Social entrepreneurship in practice : the multifaceted nature of social entrepreneurship and the role of the state within an Islamic context
64. Lantto, Anna-Maija (2014) International Financial Reporting Standards adoption in a continental European context: perspectives of preparers
65. Kantola, Hannele (2014) Management accounting change in public health care
66. Khan, Asadullah (2014) Improving Performance of Construction Projects in the UAE : multi cultural and decent work perspectives
67. Tolonen, Pekka (2014) Three essays on hedge fund performance
68. Jansson, Noora (2014) Discursive practices in organizational change

Book orders:
Granum: Virtual book store
http://granum.uta.fi/granum/

UNIVERSITY OF OULU P.O. Box 8000 FI-90014 UNIVERSITY OF OULU FINLAND

ACTA UNIVERSITATIS OULUENSIS

ISBN 978-952-62-0576-2 (Paperback)
ISBN 978-952-62-0577-9 (PDF)
ISSN 1455-2647 (Print)
ISSN 1796-2269 (Online)

UNIVERSITY of OULU
OULUN YLIOPISTO