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Individual investor behavior and financial advice

Kramer, Marc Michel

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Individual Investor Behavior

and

Financial Advice

Marc M. Kramer

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Voor Anita, Vera, Huub & Amare

Acknowledgements

The idea to write a PhD thesis emerged in 2001 during our world trip when Anita and I stayed in a remote wooden chalet in Barhal, Turkey, near the Georgian border. On the balcony, above a gently flowing river, an American was working on his laptop. He told me he was a PhD candidate both at Princeton and Yale, working on a PhD thesis in Arabic languages. Given that I already considered a career switch from banking to financial research, writing such a PhD thesis had great appeal: it combined doing research, studying, learning, writing, teaching, and traveling with a lot of freedom.

After our trip I made an appointment with Jaap Koelewijn to discuss my ideas. I still knew Jaap from my years as an investment consultant at the Rabobank and he encouraged me to go ahead. Jaap even came up with a topic that eventually became the subject of this dissertation. He suggested combining the growing field of behavioral finance with my previous working experience.

With this topic in mind, I met Frans Tempelaar around 2003. Frans liked the idea from the start. Therefore, in 2005 he arranged my appointment as a lecturer/researcher with a 50/50 allocation to teaching and research. Now, 7 years later, the job has been done.

The reality of writing a PhD thesis was quite different from what I expected based on the experience in Barhal. I must admit that some overconfidence must have entered the decision to start such a project given my personal, very fortunate, circumstances at that time. Huub, our second child, was just born. Vera was born 18 months earlier and 2 years later Amare was born. In the meantime we started a huge renovation of our small and over 100 years old house on the countryside of Groningen, a work that lasted almost three years. Writing a PhD thesis in addition was a bit too much. Now, with the benefit of hindsight, I must admit that I am happy that I persevered, but I am even happier that I finished.

I like to thank all the people that were involved in making this project succeed. I especially thank Frans Tempelaar, my promotor. He had confidence in me, facilitated my entry into the university, and gave me his mental support. I thank Auke Plantinga, my copromotor, for sharing his valuable empirical experience, and Robert Lensink for writing a paper together, a process that taught me a lot on research methodology. I also thank Rob Alessie, Werner De Bondt, and Jaap Koelewijn for being member of the reading committee.

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Groningen,
November 2012,
Marc Kramer

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Chapter 1

Studying Investor Behavior

1.1 Introduction

The aim of this thesis is to enhance insights into the potential value of financial advisors in retail portfolio decisions. This thesis offers four main contributions, three of which are empirical in nature and based on data from a large group of retail investors. The last contribution stems from an extensive review of related literature.

To introduce these four contributions, this first chapter describes a framework with two approaches to the study of retail investor behavior, and discusses both the roles and the environment surrounding financial advice. The economic approach in Section 1.2 deals with the neoclassical economic paradigm of how investors should behave; the behavioral approach in Section 1.3 describes how investors behave in reality. To study the added value of financial advisors, both approaches are equally important: The former provides advisors with a powerful benchmark for "smart" behavior, and the latter offers insights on why investors do not always act normatively. A financial advisor thus faces a daunting task in finding a "meeting of the ways" to help investors make decisions that best serve their interests. This meeting of the ways is nicely illustrated in one of the recommendations[1] to financial advisors that Kahneman and Riepe (1998, p. 62) offer, namely, that advisors should "maximize the client's overall well-being (which includes emotional as well as financial health)." Next, I discuss the role and institutional environment of financial advisors in Section 1.4, then in Sections 1.5 and 1.6, I address the research problem and provide an overview of the thesis, respectively.

1.2 Economic Approach to Investor Behavior

Finance is grounded in neoclassical economics, which also applies to investment decision behavior. Neoclassical economics assumes optimizing agents who make rational decisions, display preferences aligned with expected utility, and use portfolio theory to construct investment portfolios. I briefly define each of these concepts in the following sections.

---

[1] This eleventh recommendation in Kahneman and Riepe (1998) is reproduced in Appendix A to this chapter.

1.2.1 Rationality

Rationality is an idealized, normative, economic decision-making design of individuals. Behavior is rational to the extent to which it is effective, efficient, and consistent; thus, it relates to the quality of the judgment and decision making. Rationality is also a relative concept that depends on the amount of knowledge and the objectives possessed by the decision maker. Economic rationality typically refers to unbounded rationality. This implies that the objectives are known and well-defined, all information is available and used in an unbiased fashion, and choices are consistent.

1.2.2 Expected Utility Theory and Risk Aversion

The concept of rationality in financial decision making is deeply rooted in expected utility theory.[2] This theory, developed by Von Neumann and Morgenstern (1947) is based on earlier work by Bernoulli (1738), and provides a normative model of rational choice under risk. Thus, people maximize their well-being (or utility), given their preferences and constraints, by aggregating the probability-weighted (wealth) outcomes, measured in terms of utility. Utilities are subjective and usually nonlinearly related to money amounts, as displayed in a utility function. People behave rationally if they make choices that maximize their expected utility, so in this framework, economic agents are optimizers (i.e., maximizers, given their constraints).

Generally speaking, the expected utility framework presupposes risk aversion. Those who prefer a certain outcome more than a gamble that provides at least the same expected payoff are risk averse. To accept the gamble, these decision makers have to be compensated. Their risk attitude, induced by the curvature of the utility function, determines the degree of compensation they require. A concave function indicates risk aversion, and the more concave the function is, the more risk averse the person is. Empirical evidence indicates that a majority of people prefer to avoid risk and are prepared to take it on only if they receive compensation.

Expected utility rests on a set of assumptions (or axioms), such as (1) comparability (or completeness), which means that agents have well-defined preferences and thus can rank all prospects; (2) transitivity, such that preferences are consistent (e.g., if a person prefers A over B and B over C, then A must be preferred over C); and (3) invariance, which means that preferences are independent of the context (or framed independently) (Copeland, Weston and Shastri, 2005).

---

[2] Another component of rationality is the updating of probabilities from new information according to the Bayesian theorem. See *e.g.* Ackert and Deaves, 2010, p. 92-93.

1.2.3. Portfolio Theory

Modern portfolio theory, (Markowitz, 1952b), is an important theory in Finance. It assumes that the preferences of investors are solely defined in terms of means and variances of returns.[3] The key insight of this theory is that though the expected return of a portfolio is the weighted average of the returns of its individual components, the portfolio variance is not. Because asset returns typically are not perfectly correlated, combining securities in portfolios leads to a portfolio variance that is lower than the weighted average of the variances of its components. This insight is the core of the diversification principle and guides the investment decisions of many investors.

Combining all possible investments into portfolios using varying weights for each asset can be depicted by a mean and standard deviation diagram of portfolio returns that represents all feasible portfolios. The boundary of this diagram indicates the efficient frontier, which comprises all portfolios that offer the highest expected return for a given amount of risk or else the lowest possible risk given a certain level of expected return. Rationality and maximizing expected utility implies that investors should only choose portfolios that are on the efficient frontier.

The foundations of neoclassical finance provide a useful framework for defining normative behavior. However, it lacks the power to explain the observed decision-making behavior of economic agents in reality. The following section describes how insights from psychology and sociology are better able to explain observed financial decision making.

1.3 Behavioral Approach to Studying Investments

Behavioral finance is an academic field that applies behavioral concepts to the study of portfolio investments, corporate finance, and capital markets. This interdisciplinary approach incorporates insights from economics, psychology, and sociology and departs from the rationality assumption of neoclassical finance discussed in Section 1.2. Whereas neoclassical finance is normative in nature, behavioral finance represents a positive (or descriptive) science studying actual, rather than idealized, behaviors of agents and markets. It starts from the notion that financial decision making typically takes place in complex, opaque, uncertain environments, in which people do not behave as described by rational choice models.

Behavioral finance builds on research into bounded rationality, which relates to two of the building blocks of behavioral finance: framing and heuristics. A third building block involves emotions and self-attributes, a forth to social forces.

[3] MPT also is referred to the use of a mean-variance framework.

1.3.1 Bounded Rationality

The concept of bounded rationality implies that humans are limited in their decision-making capabilities (Simon, 1957). Decision makers therefore should be modeled as satisfiers, seeking a satisfying rather than an optimal solution. March (1994) provides an effective framework for studying investment behavior that relates the role of heuristics and framing to the concept of bounded rationality. March (1994, p. 8) also opposes the rationality assumption because "Studies of decision making in the real world suggest that not all alternatives are known, that not all consequences are considered, and that not all preferences are evoked at the same time." He further introduces bounded (or limited) rationality: "individuals are intendedly rational. Although decision makers try to be rational, they are constrained by limited cognitive capabilities and incomplete information, and thus their actions may be less than completely rational in spite of their best intentions and efforts" (March, 1994, p. 9). March identifies four human "fallacies": (1) limited attention, (2) faulty memory, (3) limited comprehension capacities, and (4) limited communication capacities. As a consequence of these limits, "Decision makers use various information and decision strategies to cope with limitations in information and information-handling capabilities." (March, 1994, p. 11).

The fundamental simplification processes that March (1994) identifies are editing, decomposition, heuristics, and framing. Editing simplifies decisions by ignoring some dimension(s), treating dimensions sequentially rather than simultaneously, or weighing dimensions equally rather than by their importance. Decomposition refers to separating complex problems into manageable partial problems, which often ignores interrelationships. Heuristics are mental rules of thumb; framing, as discussed next, refers to the way people choose to perceive a phenomenon, problem, or outcome.

1.3.1.1 Framing

Framing deals with the way people code events. Framing separates form from substance and thus deals with perceptions. Experimental evidence indicates that the presentation of a decision problem may influence the ultimate decision. Ackert and Deaves (2010) define a decision frame as a decision maker's view of the problem and possible outcomes. March (1994) suggests that decision makers typically do not make choices in a comprehensively inclusive context, which Kahneman and Lovallo (1993) label "narrow framing." Key aspects of framing are reflected in the prospect theory of decision making under uncertainty (Kahneman and Tversky, 1979; Tversky and Kahneman, 1986), in mental accounting (Thaler, 1999) and in path dependence.

a) Prospect Theory

Prospect theory provides a framework for the way people make decisions when dealing with uncertainty. The theory, developed by Kahneman and Tversky (1979), builds on work by Markowitz (1952a). The prospect theory value function is similar in character to that of the utility function. However, one of the major differences is that it evaluates changes in wealth relative to a reference point, not that they evaluate wealth states in absolute levels.

Prospect theory further distinguishes two phases in the decision-making processes: framing and editing, and then evaluation. Outcomes are framed in terms of gains or losses, which in turn affect the decisions being made and the evaluations of the outcomes. In the evaluation phase, framed prospects then get evaluated, such that the most valued prospect is chosen. People are asymmetric in their attitudes toward gains and losses. An important element in this respect is loss aversion: People feel losses more intensely than gains and overweight losses (by an estimated factor of 2.25, according to Tversky and Kahneman, 1991) compared with gains of the same magnitude. The value function is therefore steeper in the loss domain. To avoid a loss or make losses less painful, people apply "techniques" such as hedonic editing (Thaler, 1999).

Another difference with the rational decision making theory is that prospect theory finds that risk tolerance depends on the (framing of the) situation. People tend to be risk averse for gains and risk seeking for losses. In choosing between a sure gain and a gamble with an equal or higher expected value, people tend to select the sure gain. In choosing between a sure loss or gamble with an equal monetary loss, people tend to prefer the gamble. This asymmetric risk attitude is displayed in value functions that are convex for gains but concave in the domain of losses. Risk attitudes also change for outcomes that involve small probabilities. In gain settings, people become risk seeking (e.g., buy a lottery ticket), whereas for losses, they become risk averse (e.g., buying insurance). They tend to pay more for an increase in probability from 90% to 100% than for a jump from 30% to 40%. This tendency is displayed in the probability weighing function, another key aspect of prospect theory. People tend to weight probabilities subjectively, such that low probability events are overweighed, whereas moderate and high probability events are underweighted.

b) Mental Accounting

Mental accounting is the cognitive process of assigning financial events into categories, making financial decisions, and evaluating outcomes (Thaler, 1999). Money in one account appears imperfectly substitutable for money in another, contradicting the economic notion of fungibility. Choices are altered by the introduction of imaginary boundaries. Mental accounting relates to framing and arises when people assign costs and benefits to one object instead of taking the whole into consideration. Typically a mental account contains all costs and benefits related to one decision.

Thaler (1999) identifies three components of mental accounting: (1) how outcomes are perceived and experienced, (2) how activities are assigned to specific accounts, and (3) how often accounts are evaluated. Mental accounting assumes that outcomes are evaluated in terms of prospect theory. Money is typically framed (or labeled) as budget expenditures, wealth accounts, or income categories. This categorization results in different attitudes and behaviors. Following a purchase, a new mental account opens, and people feel emotional pain if they must close the account, without having experienced the pleasure that should have resulted from the purchase. This mechanism also applies to investing. Investors open a new account when buying a new stock. This mental separation inhibits an overall picture of the investment portfolio. Closing a seperate account at a loss is painful. Mental accounting (combined with other behavioral theories) thus predicts that people will be reluctant to sell securities at a loss. In addition, as investments occur over a period of time, investors are free to select the evaluation period. Empirical evidence indicates that investors typically select a rather short period of around one year to evaluate portfolio results, which may lead to "myopic loss aversion," a phenomenon that may drives the equity premium puzzle (Benartzi and Thaler, 1993).

After setting up a scheme of mental accounts, individual decision makers may alter the boundaries between accounts, in a process labeled "hedonic editing." In this process, people strive to attain maximal happiness in evaluating (joint) outcomes by integrating or segregating outcomes. They might integrate a gain with a smaller loss, to "cover" the loss and offset the negative emotion due to loss aversion. In general, through hedonic editing, people (1) segregate gains, (2) integrate losses, (3) integrate smaller losses with larger gains, and (4) segregate small gains from larger losses. evidence on loss integration is contradictory (Thaler and Johnson, 1990).

Arguably, the most important point derived from mental accounting is that "rules are not neutral" (Thaler, 1999, p. 243). The perceived attractiveness of choices and subsequent outcomes depend on how they are framed, how often they are evaluated, and whether or not they are combined with other choices.

c) Path dependence

Prior outcomes influence decisions, in contrast with a normative view that suggests only incremental factors should be taken into account. For example, people are more hesitant to buy a (new) ticket after losing it than they are had they lost the monetary equivalent of that ticket. The willingness to engage in risky activities also depends in part on what happened prior to the decision. Kahneman and Tversky (1979, p. 287) illustrate: "a person who has not made peace with his losses is likely to accept gambles that would be unacceptable to him otherwise." In this respect, three effects emerge: the house money effect, the snake bite effect, and the break-even effect.

Thaler and Johnson (1990) introduce the house money effect, which stipulates that a prior gain stimulates risk seeking within the same mental account. An essential feature is that possible losses are not coded as losses but rather as reductions in gains, which mitigates loss aversion. At first sight, this behavior might seem to contradict prospect theory, which predicts more risk aversion in the gain domain, but prospect theory also describes oneshot gambles only. Sequential gambles are sometimes integrated, and after a large gain, people apparently move away from loss aversion in the value function.

Typically, people become more risk averse after experiencing a loss, a tendency labeled the snake bite effect (Ackert and Deaves, 2010). Experiments by Johnson and Thaler (1990) indicate that participants believed that losing money after an initial loss hurt more than losing money without the prior loss. People were not willing to risk additional losses. After a loss, people become averse to additional losses, such that risk aversion increases. There is one noteworthy exception though: When an opportunity exists to recover the whole loss, that is, to break even, people are willing to accept *more* risk after initial losses. The possibility to close a mental account without any loss is very attractive because of the effects of loss aversion. The preference for long shots at the end of a betting day in horse races may illustrate this effect.

A study of behavior in a large game show provided additional evidence for these results, which previously had relied solely on hypothetical choices in the laboratory. Post *et al.* (2008) analyze the behavior of contestants on the game show *Deal or No Deal*, which requires participants to choose between a sure amount and a gamble repeatedly during the show. The decisions of game contestants appear greatly affected by what happened before, in support of both the house money effect and the break-even effect.

1.3.1.2 Heuristics

Economic agents may use heuristics because they lack the cognitive ability to process and compute the expected utility of all possible actions. Nofsinger (2011, p. 76) characterizes heuristics as "shortcuts the brain uses to reduce the complexity of information analysis." Heuristics refer to the process by which people find out things for themselves, usually by trial and error, which leads to rules of thumb that can be useful in real life, because they allow for decision making without the need of fully digesting all the information. They also can lead to errors though, because they cause misjudgments of probabilities and relationships at the same time. Probability judgment is often essential in financial decision making, so understanding heuristics is critical to understanding financial behavior. Tversky and Kahneman (1974) describe three major heuristics: representativeness, availability, and anchoring and adjustment. The affect heuristic also has gained prominence, and other documented heuristics include the familiarity heuristic.

a) Representativeness

Representativeness refers to judgments based on stereotypes. People tend to estimate probabilities based on comparison with known situations instead of relying on a statistical probability. An illustrative and frequently cited example is the "Linda example" from Tversky and Kahneman's (1982) study. The participants received the following description:

Linda is 31 years old, single, outspoken, and very bright. She majored in philosophy. As a student, she was deeply concerned with issues of discrimination and social justice, and also participated in anti-nuclear demonstrations.

Then they considered a question: "Which is more probable?: A. Linda is a bank teller; B. Linda is a bank teller and is active in the feminist movement." Option B was chosen by 85% of the respondents, apparently because B fits better, or is more representative, of Linda, even though A is less restrictive and thus more probable. This tendency also has been referred to as the conjunction fallacy.

Representativeness also entails the tendency to assign a memory to a random process. Seeing chance as a self-correcting process is the gamblers' fallacy (Tversky and Kahneman, 1994). On a roulette table for example, after a sequence of red outcomes, the perceived probability of black being the next outcome increases above the actual statistical probability of 50%. This fallacy relates to sample size neglect (or the law of small numbers), which occurs when people draw conclusions using too few data points. Representativeness relates to the tendency to perceive causal relationships behind random fluctuations too. Investors perceive trends where there are none. The so-called extrapolation bias is the tendency to make predictions by extrapolating past (perceived) patterns in a naïve fashion. Furthermore, in making predictions, people may forget that outcomes typically regress to the mean. In estimating the grades of college students for example, people put too much weight on high school grades, thereby overrating the successful students and underrating the less successful ones.

b) Availability

People use the availability heuristic when they assign probabilities to outcomes by the ease with which they come to mind. Retrieving information from the mind is easier when instances are more familiar, more salient (if it had more impact), or more recent. Thus people tend to drive more carefully after seeing an accident. The availability heuristic also arises when people use the ease of imagining an outcome in their judgments of probabilities. This bias may lead to ignoring (or underweighing) risks that cannot be imagined or overestimating risks that can be imagined very vividly.

c) Anchoring and adjustment

Through anchoring and adjustment, people make estimates from an initial number but adjust insufficiently (e.g., forecasting a stock index based on the current level, forming new earnings estimates after an earnings surprise) or incorrectly use a random number as the base for their estimation. In prospect theory terms, anchoring relates to the use of a reference point. Anchoring also relates to belief perseverance (or conservatism), such that people cling to their previously formed beliefs. People prefer to search for confirming information (so-called confirmation bias) and are reluctant to search for evidence that contradicts their beliefs. When exposed to contradictory evidence, people typically treat the new information skeptically. This way of dealing with conflicting information has been introduced in a broader sense as cognitive dissonance (Festinger, 1957).

d) Affect

Affect is the immediate emotional response to some stimulus (e.g., the name of a particular firm), which is typically either positive or negative. Relying on such feelings in judgments and decision making is characterized as the affect heuristic. According to Kahneman (2002, p. 470), "the idea of an affect heuristic is probably the most important development in the study of judgment heuristics in the last decades." People's reliance on the affect heuristic certainly offers them some advantages, in that it "is a quicker, easier and more efficient way to navigate in a complex, uncertain and sometimes dangerous world" (Slovic et al., 2002, p. 398). Affective feelings may guide decision making, especially when alternatives are difficult to evaluate (as is the case for many investment choices). Affect is related to mood, which may affect prices in stock markets. Hirshleifer and Shumway (2003) find that nice weather puts investors in a positive mood, makes them more risk tolerant, and thus drives up prices.

e) Ambiguity Aversion and Familiarity

Finally, aversion to ambiguity parallels the familiarity bias, because it implies that people prefer the familiar to the unfamiliar. They are less inclined to gamble if the odds are unknown, compared with a gamble in which the odds are known. People prefer risk to uncertainty, and they prefer gambles that they believe they understand better. Heath and Tversky (1991) relate this finding to the competence effect: When people feel more competent, they prefer to bet on their own judgment.

1.3.2 Emotions and Self-Attributes

Emotions, such as fear, hope, anger, regret, pride, worry, excitement, guilt and mood may also influence investment decision making. According to Nofsinger (2010), the influence of emotions on decision is larger for more complex and uncertain situations. Damasio (1994) even finds that without emotions, reasonable decisions are impossible.

Fear and hope are the key emotions in the two-factor theory of risky choice offered by Lopez (1987). In making decisions in an uncertain environment, people balance their desire for security and potential. They prefer gambles that combine high levels of security (little fear) with some upside potential (a lot of hope). Fear is the dominant emotion for risk-averse people; hope the dominant one for risk seekers. In the behavioral portfolio theory of Shefrin and Statman (2000), these emotions translate into two distinct layers in portfolio composition, focused on the downside or the upside. Aspiration level in turn deals with the probability of falling below a certain level and reflects both opportunities and needs.

The affect heuristic has strong emotional ties. Affective impressions are positive or negative in nature, and thus contrast the visceral factors discussed in Loewenstein (2003). Visceral factors include immediate and typically negative emotions such as fear and anger, and also relate to drive states such as hunger, or feeling states such as pain. Immediate emotions are experienced at the time of the decision. According to Loewenstein (2003), visceral factors play an essential, probably dominant, role in human decision making. Visceral factors may make people behave in conflict with their own self-interest. Loewenstein (2003) argues that most self-control problems involve visceral factors; they also play an important role in decision making under risk and uncertainty, because the evaluation of risk on a cognitive level differs from emotional reactions to that same risk.

Anticipated emotions, such as regret and disappointment, instead are expected to be experienced in the future and not at the time of decision making (Loewenstein, 2003). Although these emotions emerge after an outcome has occurred, they influence decision making, because people anticipate them. Although regret and disappointment are related, regret implies a sense of responsibility for the outcome. Both depend on the degree to which people can imagine another (more desirable) outcome and the salience of that alternative outcome. The pain that occurs from realizing that a previous decision turned out poorly makes people regret averse. Furthermore, regret associated with not acting (i.e., regret of omission) is felt less intensely than the regret resulting from action (i.e., regret of commission). It is easy to imagine that not acting was the better choice.

Emotions typically drive self-attributes such as overconfidence and limited self-control. Psychologists define an overconfident person as one who believes he or she has more accurate information than he or she actually does. People tend to be overconfident in their own predictions and set narrow confidence intervals. Such overconfidence is labeled “miscalibration,” but overconfidence also can relate to a “better than average effect.” When asked about some ability, people generally rate themselves as better than average. The “excessive optimism” type of overconfidence occurs when people assign overly high probabilities to favorable outcomes and low probabilities to unfavorable ones. Two biases drive such overconfidence: self-attribution and hindsight. The former occurs when people relate successful outcomes to their own expertise and/or good judgment and unsuccessful outcomes to bad luck and/or others. The latter relates to the perception people have when they look back at a previously predicted probability. They may assert that they knew a certain outcome was about to happen, which often is not true. An illusion of control also can create overconfidence; people tend to place larger bets on a coin toss before rather than after the toss, even if the outcome has not yet been revealed. This trend indicates that people believe their involvement might change the outcome. Finally, overconfidence stems from the illusion of knowledge, which refers to an incorrect belief that more information leads to more knowledge. Overconfidence is rooted in emotions as it protects someone’s self-esteem, the feeling of one’s own worth, and thus aids in emotional self-preservation.

Limited self-control deals with the difficulty people have executing their will power and their preference for current as opposed to deferred gratification. Limited self-control may lead to procrastination when effort must be expended now to obtain a future benefit. Thus people recognize the need to save money but fail to do so, because other options provide more immediate satisfaction. Such preferences may lead to dynamic inconsistencies, given that preference reversals typically occur in the present, not when the same trade-off refers to sometime in the future. To model such behavior, researchers have introduced the concept of hyperbolic discounting (e.g., Laibson, 1997). Thaler and Shefrin (1981) define self-control as an internal conflict, parallel to that of an organization facing agency problems, though people often adopt similar techniques to cope with such agency problems. Humans appear to have two sets of preferences that are in conflict at some point in time, such that they function as "doers" who are myopically and emotionally short sighted and "planners" who think more rationally in the long term.

1.3.3 Social Forces

Experimental results from ultimatum, dictator, and trust games imply that most people are concerned with issues such as fairness, reciprocity, and trust, even when retaliation or reputation effects are ruled out, which rejects the idea that people are primarily driven by self-interest (Ackert and Deaves, 2010). Conformity also can drive behavior when people give in to real or imagined social pressure (Ackert and Deaves, 2010). Conformity may lead to herding; it implies disregarding one's own information and following the behavior of others. Especially when information acquisition is costly, such behavior may be wise, which implies social learning. Herding also may result from people having similar information, a process in which the media may play an important role.

1.3.4 Overview

Sections 1.2 and 1.3 describe two approaches to the study of investor behavior. The economic approach deals with normative behavior and provides a powerful rational framework that may serve as a benchmark against which to compare actual behavior. Actual behavior appears within the behavioral approach and deals with the impact of framing, heuristics, emotions, and social forces. In categorizing behavior though, it is necessary to recognize that human behaviors are intertwined with cognitive, emotional and social forces. Labels of behaviors are helpful for grasping complex concepts such as human behavior, but readers must recognize the inherent simplification that results from an analytical distinction of categories. Illustrating the existence of interdependencies, Ackert and Deaves (2010) state that cognitively, a person's perception includes affective reactions, and those affective reactions offer cognitive representations of distinct body states. The lack of linearity of the weighing function in prospect theory also may have an emotion basis, and loss aversion may be driven by fear. Although mental accounting is a cognitive operation, the self-control problem it may help solve may be rooted in the fear of outliving the available means.

1.4 The Role of Investment Advice

The core of this thesis pertains to the potential value that investment advisors add to retail portfolio decision making. Assessments of such added value greatly benefit from a sensible benchmark. Portfolios that are independently managed by so-called execution-only investors are a natural candidate for this investigation. Considering the prominence of investment advisors and execution-only investors in this thesis, I start with a brief explanation.

Loonen (2006) positions investment advice between execution-only and discretionary asset management services. He defines execution-only as a transaction-oriented service, primarily aimed at executing trades at low cost, whereas discretionary asset management is a relationship-oriented activity aimed at making investment decisions on behalf of the investor. At their intersection, an investment advisor bridges the asymmetry in experience, knowledge, and means and provides the investor with profitable act–oriented advice. The final decision to act remains with the investor though. Loonen (2006) thus offers a detailed definition of an investment advisor:

> A person, who made it his profession, working for a financial institution or independently, to advise by means of business contact in a (pro)active or reactive way on the composition of an investment portfolio or just on the purchases and sales of securities. This advice is based on an analysis. The fee for this advice consists of a transaction dependent remuneration combined or not with a fixed fee.

Another definition comes from the Dutch Act on Financial Supervision ("Wet op het financieel toezicht" or Wft) that attributes a product-oriented role to the advisor, who engages in the recommendation of products, pension agreements, insurance, or financial instruments (Wft1.1.1).

From these definitions, it appears that the role of financial advisors is to advise on investment portfolios or recommend financial products, but this assertion is more tautological than helpful. I therefore review what others have said about the actual role of financial advisors.

An economic perspective on financial advisors, who often are part of financial institutions, indicates that they act as intermediaries between individuals and capital markets to reduce frictions and transaction costs, as well as transform risks, terms, quantities, and information. Bhattacharya and Thakor (1993) say that financial advisors' core of existence lies in bridging information asymmetry. Using an advisor enables investors to economize on information costs, or the time and money spend to acquire and understand information. In this sense, advisors lower information costs by developing expertise.

From a behavioral viewpoint, the mitigation of behavioral biases and errors (and thus improved investment decisions) offers another reason to hire a professional. This role is the focus of Kahneman and Riepe (1998), who describe financial advice as a prescriptive[4] activity that guides investors to make decisions that best serve their interests. As they state:

> To advise effectively, advisors must be guided by an accurate picture of the cognitive and emotional weaknesses of investors that relate to making investments decisions: their occasional faulty assessment of their own interest and true wishes, the relevant facts that they tend to ignore, and the limits of their ability to accept advice and to live with the decisions they make (p. 52).
>
> Providing timely warnings about the pitfalls of intuition should be one of the responsibilities of financial advisors (p. 53).
>
> The anticipation, diagnosis, and management of investor discomfort and regret are central elements of responsible financial advising and therefore part of the financial advisor's job description (p. 62).

These statements can be operationalized as a comprehensive list of practical recommendations[5] that guide financial advisors in their main tasks. Considering their relevance for this thesis, I regrouped these recommendations into six main categories that may serve as a useful framework for understanding financial advisors' role.

a) *Education and communication*
   Advisors should teach investors about financial markets and the instruments to participate in it, make investors aware of the role of uncertainty, communicate realistic expectations, and provide clear examples.
b) *Framing*
   The presentation greatly affects the perception, choice, and satisfaction of investors. Advisors must make sure to frame as broadly as possible, but also to choose the frame that is relevant for the client. The proper design of the format to present information is part of this task.
c) *Investor characteristics and investment goals*
   Before building a portfolio, the advisor's main goal should be to get as clear a picture as possible of the investor, including the susceptibility to biases.
d) *Personalize*
   Advice should be segmented according to client characteristics, such as sophistication, wealth, and degree of loss aversion.
e) *Sensible policies*
   Advisors should agree on a set of procedures beforehand and make the client feel responsible for any decisions made.
f) *Know your own biases*
   The advisors' knowledge of his or her own susceptibility to biases may help build satisfactory client relationships.

---

[4] Prescriptive is not the same as normative, which implies behavior that follows the axioms of rational choice. Prescriptive is concerned with providing practical advice.

[5] All 44 recommendations are listed in Appendix A at the end of the chapter.

The Dutch Finance Authority (AFM, 2011) implicitly stresses the importance of aspects A and C when it indicates: "the focus on skills in many banks and other financial institutions is primarily aimed at investment skill. In developing professionalism of advisors, the skills needed to get to know and inform the client well during the inventory process receive less attention."

Pompian (2012) also introduces four fundamental characteristics of a successful advisory relationship:

a) *The advisor understands the client's financial goals.*
   To define these goals, an advisor should also understand the psychology and emotions underlying the decisions behind the goal creation.
b) *The advisor maintains a systematic approach.*
   The advisor should bring discipline into the investment process.
c) *The advisor delivers what the client expects.*
   Crucial to this aspect is to fully understand what drives the investor, so that expectations can be addressed.
d) *The relationship benefits both client and advisor.*
   Assuming the advisor benefits most when advisory relationships last, it is crucial to establish a strong bond.

Based on these four aspects, the role of an advisor is to establish a long-lasting relationship aimed at a disciplinary investment approach that rests on a thorough understanding of the client.

Advisors may serve some additional roles as well. As Shefrin (2002) narrates in a hypothetical example of an investor named John, "…the shifting of responsibility from John to his advisor is one of the main services for which John's advisor gets paid. Hand holding may be every bit as important as traditional advice, if no more so" (p. 129), such that, "Having a financial advisor enables the investor to carry a psychological call option. If an investment decision turns out well, the investor can take the credit, attributing the favorable outcome to his/her own skill. If the decision turns out badly the investor can protect his/her ego by blaming the advisor" (p. 130). A survey (ICI, 2007) among U.S. mutual fund investors also provides some support for this view of advisors' roles. Investors indicate that hiring a financial advisor gives them peace of mind about their investments.

Loonen (2006) introduces four roles applicable to a financial advisor: (1) bargain hunter, (2) risk analyst, (3) personal advisor, and (4) fiduciary. The bargain hunter has a good feel for deals in financial markets and makes more profitable trades than the investor would do on her or his own. The risk analyst analyzes the investor's portfolio thoroughly, whereas the personal advisor knows the investor well and incorporates this knowledge into his or her advice. Finally, the fiduciary represents the investors' financial interests. The results of a survey of 1,001 investors and 209 investment advisors regarding their views of the four roles appear in Table 1 (Loonen, 2006). For most investors, the risk analyst role is most important, followed by personal advisor and fiduciary. In contrast, advisors see themselves mainly as a personal advisor, while the role of bargain hunter only fits a few advisors.

Table 1.I Roles of a Financial Advisor
Source: Loonen (2006)

	Investors	Advisors[6]
Bargain hunter	45.1%	7.1%
Risk analyst	79.1%	68.2%
Personal advisor	67.7%	82.9%
Fiduciary	68.2%	67.2%

The evidence presented in this section suggests that financial advisors serve many potential roles. I categorize and summarize them in a six-role framework.

I. Financial economist
The advisor offers investment knowledge, skill, and discipline; lowers information costs; analyzes risks; and is a sounding board.

II. Financial psychologist
The advisor knows how to access and deal with susceptibility to biased reasoning and decision making, including his or her own; she or he can act as a debiaser, stress reliever, comfort bringer and hand holder. Framing effects may help the advisor in this role.

III. Personal advisor
The advisor knows the characteristics, motives, and goals of the investor and incorporates this into her or his advice.

IV. Relationship manager
The advisor knows how to establish and keep long-lasting relationships with clients and acts as a fiduciary.

V. Salesperson
The advisor operates in a commercial environment. The advisor and/or financial institution should also benefit from the advisory relationship.

VI. Teacher
The advisor should help the investor understand, explaining concepts like risk and return, diversification, securities, mutual funds, fee structures, and so forth.

In any advisory relationship, all of these roles are present to some extent. Of course, any advisory relationship is unique; advisors adapt their roles to the specifics of the investor and the context.

[6] Assuming an equal weight of the three size categories in Loonen (2006, p.144)

1.4.1 Moral Hazard Behavior

Investors who engage in advisory relationships may encounter moral hazard risks from the point of their advisors. In as far as professionals operate in an organizational setting, they are subject to agency relationships. In general, such relationships induce incentive-based behaviors (Ross, 1973). These incentives relate to the different financial concerns of financial advisors: (1) generating commissions for the financial institution, (2) performance-based bonuses, and (3) the performance of investors' portfolios (Loonen, 2006). This aspect thus results from the salesperson role. Moral hazard behavior in advisor–investor relationships arises when the advisor engages in activities that are undesirable from the investor's perspective or the advisor has an incentive to hide information. Such behavior is possible, because advisors typically have more information than the investor.

1.4.2 The Environment of Financial Advice in the Netherlands

The empirical research in this dissertation is based on data describing investor behavior in the Netherlands. Therefore, in this final part of Section 1.4, I explain relevant institutional arrangements in the Dutch investment environment.

The number of households in the Netherlands was 7.4 million at the end of 2011. On average, their gross assets amounted €212,000, a large part of which was invested through collective pensions and life insurance arrangements (€152,000). The average household held €49,000 in deposits and €12,000 in individual investment portfolios, though relatively few households invested directly. In 2011, only 17.6% of the households (1.3 million) owned an investment portfolio (Millard Brown, 2011). Survey data from the Dutch Central Bank (De Nederlandsche Bank [DNB], 2008) indicate that the average portfolio (€70,000 in 2007) of Dutch households that owned an investment portfolio contained 54% equity and 25% fixed income securities.

The legal protection of individual investors in the Netherlands stems mainly from the Financial Supervision Act (Wet Financial Toezicht [Wft]), which took effect on 1 January 2007. Starting on 1 November 2007, the European Markets in Financial Instruments Directive (MiFID) also was implemented in the Wft. Supervision of the behavior of financial institutions toward retail investors is the responsibility of the Netherlands Authority for the Financial Markets (Autoriteit Financiële Markten, [AFM]). The legal protection that the Wft provides builds on a "know your customer" principle and differs for asset management, investment advice, and other services, such as Internet or phone-based brokerage (execution-only) services. A financial institution acting as an asset manager or investment advisor must conduct a so-called suitability test (*geschiktheidstoets*) to determine whether a financial product suits the personal characteristics of the investor. Therefore, the advisor must obtain information about a customers' financial situation, investment knowledge, investment experience, investment objectives, and risk willingness, then ensure that all of his or her advice takes this information into consideration. For execution-only services, the requirements are less strict. Advisors only need to conduct a fitness test (*passendheidstoets*) to determine whether the investor has enough investment knowledge and experience to understand a financial product and its risk (Wft 4:23). Finally, the Wft provides a safety net by forbidding churning (BGfo 8.2.2, clause 84)[7], that is, executing transactions with the sole purpose of benefitting the financial institution and/or advisor.

In addition to the Wft, banks are required to follow the banking code (Nederlandse Vereniging van Banken [NVB], 2009), a code of conduct that took effect in 2010. Although this code provides rules on many aspects of bankers' behavior, the customer due care principle (*klant centraal*) is arguably the most relevant for this thesis. Verhoef (2012) provides an overview of dilemmas that banks face in implementing this rule, as aptly illustrated in the conflict between bank profitability and client interests. According to Verhoef (2011), this dilemma is rooted in the focus on product profitability, whereas adopting a customer lifetime value focus could bridge seemingly conflicting aspirations. In a more general setting, this issue relates to conflicts of interest between clients and other stakeholders (e.g., employees, shareholders, bondholders, governments). A relevant additional aspect is the question of which client is relevant to the customer due care principle. If lower commissions or higher interest rates on the investment account for one investment client leads to higher mortgage rates for another, which interests should the bank serve?

Furthermore, Dutch retail banks can signal the competence of their employees through the Dutch Securities Institute (DSI), which sets knowledge, integrity, and experience requirements for security specialists, including asset managers and investment advisors. The DSI also provides a register of professionals who meet its relevant criteria. Individual investors can take their complaints to the DSI complaints committee (Klachteninstituut Financiële Dienstverlening, [Kifid]) which makes binding decisions.[8] The DSI aims to provide an incentive to act in the best interest of clients.

In 2012, some new proposals offered suggestions on ways to improve the financial services provided to retail investors. The Dutch Minister of Finance proposed a new financial market directive (*Wijzingsbesluit Financiële Markten 2013;* Dutch Ministry of Finance, 2012) that includes a ban on commission sales and a bankers' oath (*de bankierseed*). If the law is adopted, the Netherlands will follow the United Kingdom, where the Financial Services Authority (FSA) has also proposed a ban on commission sales starting in 2013. If this legislation gets adopted, financial advisors would charge their clients directly for their services and must be transparent in what they charge, leading to a separation of the trading in and selling of financial instruments and the related advice. So

[7] BGfo stands for *Besluit Gedragstoezicht financiële ondernemingen*; it is part of the Wft.

[8] The complaint committee (*geschillencommissie*) handles only complaints about the financial institution; the financial ombudsman previously handled these complaints.

far, receiving financial advice is supposed to be "free," and advisors are allowed to be paid indirectly, through the products they sell or trade, if some criteria[9] are met (*passendheidseis*). The proposed MiFID II legislation explicitly bans commissions when firms describe their advice as independent. The bankers' oath, applied to all employees of the financial institution, aims to make employees aware of their role in society and provides a moral–ethical obligation to behave appropriately. Taking such an oath is commonplace in other professions. Although the oath might not have much effect, it can provide support to someone faced with an ethical dilemma who must justify her or his behavior to an external party (De Bruin, 2012).

1.5 Research Problem of the Thesis

Given the abundant empirical evidence that individual investors make suboptimal portfolio decisions[10], the question of how to improve the quality of retail investment decisions seems warranted. Various remedies have been proposed, one of which is the introduction of a professional financial advisor.[11] To provide insight into the possible value added of financial advisors, this thesis addresses the following key question:

> *What value, if any, do professional financial advisors provide in the investment portfolio decisions of retail investors?*

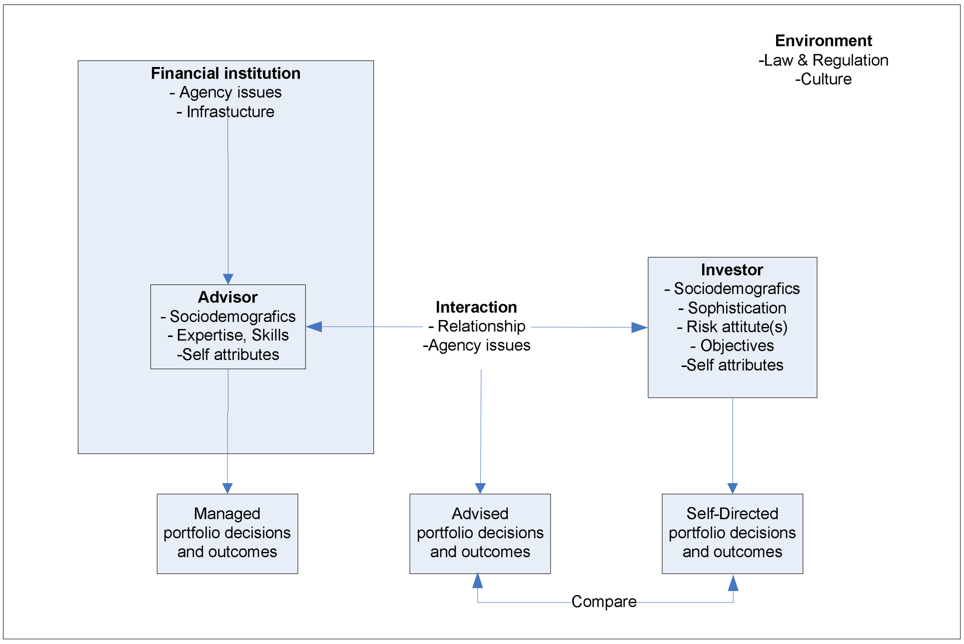
There are many ways to address such a question: I could rely on economic theory, evaluate existing empirical studies, ask investors or advisors about the role they believe advisors serve, study actual advisory meetings between advisors and their clients, consider portfolio decisions and outcomes in a laboratory setting, or do the same using field data. Ideally, all of these approaches should be pursued, but this thesis must choose among them. I review the scarce empirical studies available regarding the impact of financial advisors, but my main results rest on two data sets, one derived from portfolio and transaction records data from a retail bank and the other from a survey of a group of investors.

Figure 1 displays both my key empirical strategy and the specific setting for financial advice.

To summarize, the above mentioned key question of this thesis will be studies trough a comparison of self-directed investors and advised investors and their respective investment performances, their portfolio characteristics and some of their demographic and educational characteristics. Financial advisors are part of a financial institution (with its own policies, rules, and culture) that in turn is part of the Dutch institutional environment.

[9] BGfo 149a, clause 2 states that commissions must be reasonable, transparent and not inhibit the obligation to act in the best interest of the client.
[10] This statement is mainly inferred from research discussed in Chapter 2.
[11] Throughout this thesis, in accordance with prior literature, the terms "financial advisor" and "investment advisor" are used interchangeably. A financial advisor might serve a broader role, advising on many financial issues, whereas investment advisors often limit themselves to investment portfolio advice. Advisors in this thesis typically serve the more specialized role.

Figure 1.1: Key Empirical Strategy and Setting



1.6 Overview of the Thesis

The remainder of this thesis is organized into the following five chapters.

Chapter 2 provides an overview of literature on retail investor behavior, which serves as a useful introduction for determining when a financial advisor may or may not help. The focus is on portfolio composition, trading behavior, and buying and selling securities. The last sections investigate the role of sophistication, which appears prominent for understanding the described behaviors.

In Chapter 3, I provide the results from a comparison of advised and self-directed investment behavior. This research is based on a large data set that contains portfolio holdings and transaction records from a group of Dutch retail investors. The focus is on the differences in portfolio performance and portfolio composition between the two groups.

Chapter 4 addresses a critical issue for evaluating the impact of advisory intervention. In comparing the behavior and outcomes of advised versus non-advised investors, self-selection bias could cause some noise. This chapter therefore introduces the Hausman-Taylor estimation as a potential remedy, considering the data available, such that Chapter 4 offers primarily a methodological improvement over Chapter 3.

Chapter 5 determines the potential relationship among financial literacy, cognitive abilities, and the propensity to seek financial advice. It models the choice to hire an advisor, using financial literacy, cognitive abilities, and many other socio-economic variables as explanatory variables.

In Chapter 6, I provide a summary of the main results and discuss their implications.

A final note on the nature of chapters 3, 4 and 5: these chapters are directly derived from work that has been published or is in the process of going to be published. Therefore, each of these chapters is "self-contained", and – as a consequence – will contain introductions and explanations that overlap with material from previous chapters. Also, each chapter may follow a different editorial format.

Appendix 1.A: Recommendations to financial advisors

Taken from Kahneman and Riepe (1998); these recommendations have been regrouped by topic.

A. Know your own biases

1. Keep track of instances of your own confidence.
2. Be mindful of your propensity for overconfidence when making statement to clients.
3. Resist the natural urge to be overoptimistic and think, for example, of things that can go wrong.
4. Because you are more likely to remember your successes, keep a list of past recommendations you made that were not successful.
5. Ask yourself whether you have real reason to believe that you know more than the market.
6. Before making an active decision, consider the possibility that the trade is based on random factors. List the reasons why it isn't before making the trade.

B. Education and communication

7. Make clients aware of the uncertainty involved with investment decisions.
8. Communicate realistic odds of success to your clients.
9. Provide client with real-life examples of where it was better to "let the winners run" or "cut losses."
10. In the education process, be careful not to inadvertently reinforce the tendency toward overreaction to chance events.
11. Drawing the investor's attention to the role of statistical aggregation is perhaps the best remedy to unreasonable loss aversion (i.e. you win a few and lose a few, but in the long run, you come out ahead).
12. Teach the investor the importance of taking a long-term view.
13. If the investor drastically alters a portfolio based on short-term considerations, tactically point out the consequences of these actions the next time the urge arises.

C. Framing

14. When presenting historical data to clients, resist the tendency to focus on the upside.
15. When presenting alternative courses of action to clients, do so using the broadest possible frame.
16. Make sure the frame chosen has relevance for the client (e.g., wealth).
17. For clients whose primary goal is retirement, consider converting the level of wealth into the amount of annuity that can be expected during retirement.
18. Alert the client to the costs of narrow frames (e.g., simultaneous borrowing and saving).

19. Broad frames are preferable, but using mental accounts is probably the better option for those investors who use mental accounting as an instrument of self-control or who would suffer undue stress over losing money from a "safe" account.
20. Design statements that give less prominence to the most recent quarter, and more to what has happened over the lifetime of the account.
21. Redesign account statements to give greater prominence to the performance of the overall portfolio. Downplay what happened to each piece of the portfolio.
22. When developing a client's investment policy, follow a top-down process that accounts for all the investor's objectives simultaneously. Avoid the common bottom-up approach in which a separate policy is set up for each investor's objective

D. Investor characteristics and investment goals

23. Optimists who are also regret prone have the worst combination of traits. Early identification of such tendencies is therefore useful.
24. Some individuals may be more loss averse than others. Assess how loss averse each client is.
25. Risk of loss is an important aspect of risk for most investors, but loss is a relative term. Determine the reference point from which a gain will be calculated.
26. Identify the degree of aversion to different aspects of risk (e.g. shortfall risk, volatility, risk of loss).
27. Pay more attention to what investors have done in the past than what they say they will do in the future.
28. Recognize early which clients find it most difficult to stay the course and live with a long-term commitment.
29. Maximize the client's overall well-being (which includes emotional as well as financial health).
30. Objective factors (e.g., investment horizon, liquidity needs) as opposed to emotional factors (e.g., aversion to risk, irrational fear of certain asset classes, propensity for regret) should receive the greater weight, but relative weights need not to be the same for all clients.
31. When there is an extreme mismatch between the client's goals and what actions the client's emotional state will allow, consider ending the relationship.
32. Encourage investors to confront their propensity for regret.
33. Determine the type of regret to which your client is most susceptible (omission/commission).
34. If clients are particularly prone to regrets of commission, a radical change in the investment policy or a decision that is out of character for them should prompt special caution.

E. Personalize

35. Do not recommend very risky investments to loss-averse clients. They will accept such investments only if they optimistically underestimate risk.
36. Sophisticated investors should consider using derivative overlays that limit the downside while retaining some upside participation.
37. Higher net worth clients are also likely receptive to equity-linked structured notes.
38. For lower end clients, equity-linked annuities can be an attractive option.

F. Sensible policies

39. Advisors should of course shop around to compare prices for these instruments.
40. Before a purchase decision is made, discuss conditions in which a sale would be made.
41. Encouraging clients to adopt and follow a sensible risk policy is one of the important tasks of financial advisors.
42. Agree ahead of time on a set of procedures to follow in the event that the investor is tempted to make a portfolio alteration based on a hunch.
43. Involve the client in the decision process so that decisions are "ours" and not the advisor's alone.

Chapter 2

A Review of Individual Investor Behavior Literature[1]

2.1. Introduction

This chapter provides an overview of literature pertaining to individual investor behavior.[2] The study of individual (or retail) investors is important for two main reasons (de Bondt, 1998). First, from a micro-level perspective, individual investment behavior affects the well-being of households. Households increasingly are responsible for their own financial future, so the question of how they fare is more relevant than ever. Second, from a macro-level perspective, retail behavior appears systematic (Barber *et al.*, 2009a) and therefore affects prices (Barber *et al.,* 2009b).

Given this importance, it is not surprising that the number of studies on retail investor behavior and performance is vast.[3] Although these studies indicate substantial heterogeneity in both retail investor behavior and performance, some stylized facts emerge. This chapter details the research findings related to portfolio composition (Section 2.2), trading behavior (Section 2.3), buying behavior (Section 2.4), and selling behavior (Section 2.5).

Many of these behaviors have negative impacts on outcomes. Odean (1999) shows that the stocks U.S. investors buy underperform the stocks they sell, in line with Grinblatt and Keloharju's (2001) report that stocks that Finnish investors buy exhibit weak future performance. Barber and Odean (2000) also find that the average U.S. individual investor earns meager risk-adjusted returns. Barber *et al.* (2009c), who analyze all stock market trades in Taiwan, indicate that whereas retail investors lose as much as 3.8% per year, professional parties gain from trading. Bauer *et al.* (2009) similarly provide evidence that Dutch online traders underperform, especially those who trade in options.

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[1] A previous version of this chapter which was co-authored with Frans Tempelaar has been published in Risk Magazine (see volume 15, no 4, p. 30-35)
[2] Other papers that review retail investor behavior are De Bondt (1998), Barberis and Thaler (2003), and Barber and Odean (2011).
[3] A search on Scopus using "individual investor" or "retail investor" indicates almost 600 publications in peer-reviewed journals since 1998.

But it also is important to note that though weak (long- term) performance may be a stylized fact, it ignores two additional findings. First, across four studies (Barber *et al.*, 2009a; Kaniel *et al.*, 2008; Kaniel *et al.*, 2010; Kelley and Tetlock, 2012), there is "intriguing evidence that individual investors' trades positively predict returns at short horizons in the US"[4] (Barber and Odean, 2011, p .10), which implies retail investors might perform well in the short run (up to one month). Second, significant heterogeneity has been documented in individual investor behavior. Many of the behaviors discussed have a negative impact on portfolio outcomes, though not for all investors.[5] For example, mounting evidence suggests that sophistication drives good financial decision making, so mechanisms to increase investor sophistication might have the potential to benefit investors. Financial advice could introduce more sophistication to retail portfolios. Therefore, in Section 2.6, evidence about the impact of financial sophistication and professionalism on portfolio behaviors and outcomes will be discussed.

2.2. Portfolio Composition

Studies of portfolio composition mainly deal with how people diversify. Generally speaking, diversification in retail portfolios is limited, naïve, and significantly influenced by proximity considerations.

2.2.1. Limited Diversification

Choices about diversification arguably are among the most important portfolio decisions investors must make. Campbell (2006) calls diversification the "second major topic in household finance,"[6] and using data from 100,000 Swedish households, he estimates that approximately half of the volatility in retail portfolios is non-systematic, due to a lack of sufficient diversification. Blume and Friend (1975) were perhaps the first to identify a lack of diversification in U.S. retail portfolios; more than half the investors in their sample held only one or two stocks, and only a small minority of investors held more than ten.[7] More recent studies confirm widespread underdiversification. In their sample of U.S. online brokerage investors, Barber and Odean (2000) find the median (mean) number of stocks to be only 2.6 (4.3).

Using this same data set Goetzmann and Kumar (2008) analyze the lack of diversification more thoroughly. Almost 30% of the investors held only one stock, and only 9% held

[4] Evidence from Taiwan indicates retail investors suffer losses in both the long and the short run though.

[5] Barber and Odean (2000) find that approximately 43% of individual investors outperform the market after transaction costs. Approximately 25% do so with an excess return of 6% a year, whereas another 25% earn a negative excess return of 9% annually. Coval *et al.* (2005) document strong performance persistence among individual investors.

[6] The first is financial market participation.

[7] Campbell *et al.* (2001) note that a portfolio of 20-30 stocks attains a large fraction of the total benefits of diversification; Statman (1987) shows that an optimally diversified portfolio must include at least 30 stocks. Statman (2002) also has indicated that at least 120 stocks may be needed for an optimal level of diversification, using the rules of mean-variance portfolio theory.

more than ten. The level of diversification improves over time though: The average number of stocks held increased from four to seven during a six-year interval. Although holding more stocks generally improves diversification, the authors find no evidence of sophisticated diversification improvement (i.e., by holding less correlated stocks). In their study of 21,500 German online investors, Dorn and Huberman (2005) confirm a lack of diversification in German stock portfolios, in that the average portfolio in their sample contains four to five positions. Especially young and active traders tend to under-diversify. Anderson (2007) finds underdiversification in a sample of Swedish (online, small, very active) investors. The median (average) investor holds two (three) stocks, and the author suggests that the degree of diversification is related to skill.

Various explanations for limited diversification have been advocated. For example, transaction and search costs or small portfolio sizes may be hurdles to diversified portfolios, or perhaps behavioral factors are needed to explain the empirical findings. Odean (1999) indicates that overconfidence leads to underdiversification when investors hold unrealistic views about specific stocks. Goetzmann and Kumar (2008) confirm that the degree of underdiversification relates positively to overconfidence, as well as holding local stocks and trend chasing. Thus underdiversification appears at least partly driven by behavioral factors, a finding further supported by evidence that shows underdiversified investors typically underperform. In general, better diversified investors seems to have better stock picking abilities, and risk preferences also may play a role. Goetzmann and Kumar (2008) find that underdiversified investors prefer risky (higher volatility, higher beta) stocks and stocks with more skewed returns.

Although this evidence on underdiversification is rather robust, some additional remarks are necessary to provide a complete story. Campbell (2006) notes that measuring an investor's total portfolio is not easy, considering the lack of comprehensive data on each household or individual investor. In addition, evidence about limited diversification is limited itself, in that it tends to be based only on common stocks. Polkovnichenko (2005) finds that many investors simultaneously hold well-diversified mutual funds and underdiversified portfolios of common stock. Thus a singular focus on common stock understates the degree of diversification, because mutual funds generally provide investors with well-diversified portfolios. The huge size of the retail mutual fund market might imply that the limited diversification of individual investors is not as big a problem as many studies suggest. Calvet *et al.* (2007) confirm this view with another sample of Swedish households: 76% of Swedish households that own individual stocks also hold mutual funds. Thus, many Swedish households are well diversified, even though the authors still can identify a group that selects highly concentrated portfolios.

Portfolio concentration is generally considered an investment error. Goetzmann and Kumar (2008) find that underdiversified investors typically underperform, though a small subset of active, underdiversified investors outperforms. Ivkovic *et al.* (2008) suggest that investors hold concentrated portfolios to exploit informational asymmetries and that concentrated portfolios actually outperform diversified portfolios. In particular portfolios of wealthy investors or concentrating in non-S&P500, local stocks, and stocks with low analyst coverage outperform others, which suggests that informational asymmetries drive concentration.

Insufficient diversification becomes manifest in more forms than just holding a limited number of individual stocks. The next sections offer more evidence of limited diversification among retail investors, as a result of naïve diversification and a concentration of portfolios in local, domestic, own-industry, or own-company stocks .

2.2.2. Naïve Diversification

Benartzi and Thaler (2001) find a remarkable framing effect when retirement contribution participants construct an investment portfolio. In various experimental survey designs, final asset allocations depend greatly on the funds being offered. Participants apparently use a naive diversification heuristic—or in its most extreme form, a 1/n heuristic—in which they evenly divide their money over the choice alternatives. When more stock funds are presented, participants increase their equity allocation; when more bond funds are presented, the same happens for their fixed income allocation. In one experimental condition, four out of five funds were fixed income funds and the other was a stock fund, equity exposure was 43%. When the choice option included four stock funds and one fixed income fund, the equity exposure rose to 68%.

These experimental results were confirmed using data from 162 real retirement savings plans. In the low equity group (on average, 37% of the investment options were equity funds), the allocation to equity was 49%. For two other groups (medium equity, with 65%, and high equity, with 81%, of the alternatives in equity funds) equity allocation rose to 60% and 65%. These authors also tested whether own-company stocks were mentally separated from other equity investments. In plans in which the sponsor's stock was not offered as an option, contributions were evenly split between stocks and bonds. When company stock was an option, employees allocated 42% of their contributions to company stock; the rest of the contribution was evenly split between stock and bond funds. That is, employees appear to place own-company stock in a different mental account than equity investments in general; see also Section 2.2.3.

In a longitudinal study of a single firm, Benartzi and Thaler (2001) further show that adding and removing funds greatly influences investor's decisions. When offered a balanced and a bond fund, participants allocated 18% of their contributions to equity. When the company added three stock funds, equity allocation increased to 41% right after the introduction, then rose to 62% in the following two years. When the bond fund was removed, the average equity allocation was 71%. These changes appeared within a period of less than four years, so changing preferences were unlikely to drive the results.

Huberman and Jiang (2006) test the robustness of these findings using data from more than half a million 401(k) participants in the United States and find further evidence of a so-called conditional 1/n diversification heuristic. Most investors only select about three to four funds, irrespective of the number of funds offered. Then having chosen the funds, investors use the 1/n heuristic and evenly spread their allocations across funds. The relation between equity exposure and the number of equity funds offered is more complex than Benartzi and Thaler (2001) suggested though; it also depends on the amount of funds offered. Only when the menu of available funds is relatively small (<10) does equity exposure depend significantly on the number of equity funds offered, and the effect is not as strong as suggested by Benartzi and Thaler (2001). For plans with more choice options (>10), they find no effect on equity allocation.

Baltussen and Post (2011) conduct a laboratory experiment that confirms the conditional 1/n heuristic. The participants limit their choice set by selecting assets that appear attractive in isolation and then divide their wealth evenly over the remaining assets. Only a few participants evenly distribute their wealth over all options, though when they were told about the benefits of diversification, they considerably improved the quality of their decisions. Financial education or advice thus might be enable people to avoid an overly simple diversification strategy.

Vast literature has indicated that applying naïve diversification strategies does not automatically imply that portfolios are inefficient. DeMiguel *et al.* (2007) formally test the quality of a 1/n strategy and show that it outperforms many more advanced allocation mechanisms for selecting a portfolio of individual stocks. Although naïve diversification may not result in inefficient portfolios, the inherent framing effect may create a portfolio that does not match the risk preferences of the investor.

2.2.3. Impact of Proximity

Investors exhibit a clear preference for stocks to which they feel close. Evidence reveals an overweighing of own-company, own-industry, domestic, and local stocks. This preference may be driven by behavioral phenomena, such as the familiarity heuristic, the affect heuristic, myopia, or (perceived or real) informational asymmetries.

2.2.3.1. Own-Company and Own-Industry Stock

Traditional finance theory has a clear implication for employees investing in own-company stock: It's unwise. Evidence from the 2001 defaults of firms such as Enron and Global Crossing exemplified the risk of this strategy: When a firm fails, employees lose both their retirement savings and their job (Poterba, 2003). Yet investing in own-company stock remains widespread in U.S. defined contribution[8] retirement saving plans. These

[8] For defined benefit (DB) plans, U.S. legislation caps holdings of own-company stock at 10%, but for defined contribution (DC) plans, this is not the case. Therefore, most literature deals with DC plans.

plans, many of them 401(k) plans, are of central importance, because in 2012, they had \$2.8 trillion invested by more than 50 million active workers.

Choi *et al.* (2002) report that participants invest more than 35% of their portfolio in own-company stock. Similarly, Benartzi and Thaler (2001) find that on average 42% of the wealth in 162 retirement plans is invested in company stock; Benartzi (2001) reports that around one-third of employees' retirement savings is invested in company stock in a sample of 135 S&P 500 firms. As an extreme case, Coca-Cola employees allocate 76% of their discretionary contributions to company shares. Mitchell and Utkus (2002) estimate that 5.3 million employees (out of 23 million) in the United States hold more than 60% in own-company stock in their 401(k) plan, while 8 million have zero exposure to company stock.

Benartzi *et al.* (2007) explain own-company stock in retirement portfolios as a result of bounded rationality by both employees and employers. Huberman (2001) instead relates investing in own-company stock to the familiarity heuristic. In a good review of company stock in retirement plans, Mitchell and Utkus (2002) evaluate the rationale for the high fraction of company stock, for both employers and employees. Employers believe it boosts efficiency, worker productivity, employee morale, and eventually firm value by aligning interests more closely, though empirical evidence of these effects offers only mixed results. The appeal of having stock in "friendly hands" also may motivate employers to encourage employee stock ownership. Employees hold high fractions of company stock partly because of myopia; they perceive their own company stock as less risky than a well-diversified equity fund. Survey data indicate that only a small fraction of investors (16%) realize that company stock actually is riskier than the overall stock market. Greater own-company stock holdings also relate to past stock performance, because employees extrapolate past performance. Benartzi (2001) finds that the allocation of discretionary contributions to company stock relates strongly and positively to past returns; employees thus apply the representativeness heuristic[9] (in particular, excessive extrapolation) to company stock.

Huberman and Sengmueller (2004) analyze active changes to own-company stock investments in 401(k) plans. Although few employees make active changes to their retirement portfolios, when they do, inflows to employer stock relate to salient information such as past returns and business performance; thus the availability heuristic may play a role. This reaction to past performance is asymmetric. The strongest and most robust reactions occur with positive absolute and market-adjusted returns. Past positive return sensitivity extends as far back as three years, whereas bad past performance does not have any effect. In addition, employees allocate more to own-company stock when firms match employee contributions with additional own-company stock.

[9] Please also see Section 2.4.2, "Buying Based on Representativeness."

There is no evidence suggesting investments in own-company stock are driven by informational advantages. Mitchell and Utkus (2002) show that portfolios that overweigh own-company stocks exhibit deteriorating performance, and Benartzi (2001) finds that allocations to company stock do not predict future performance.

Finally, overweighing own-company stock may be related to the so-called endorsement effect, which posits that employees interpret matching plans by the employer as an implicit advice. This effect is substantial: Plans in which employers match employee investments in company stock lead to company holdings that are more than twice as large as plans in which employees make all allocation decisions themselves. This finding may have relevance for this thesis, because when an employer's allocation decision is perceived as implicit investment advice, it is widely followed.

Related to the trend of excess holdings of own-company stock is overweighting of stocks based on professional proximity. Investors appear to prefer investments in the same industry in which they work. Doskeland and Hvide (2011), using all trades of individual investors in Norway over a 10-year period, find that they overweigh professionally close stocks with an average allocation to professionally close stocks of 11%, an excess of 7%. This overweighting is not driven by informational benefits, because professionally close portfolios and trades do not provide superior returns. Doskeland and Hvide (2011) thus confirm previous results about local investments[10] that do not seem information driven. Their results are consistent both with overconfidence and familiarity. Familiarity has also been proposed as a potential driver of home country bias.

2.2.3.2. Home-Country Bias

Home- Country bias refers to the tendency of investors to overweigh domestic securities in their portfolios. This behavior is inconsistent with standard models that highlight the benefits of international diversification, due to the relatively low correlation among stock returns of various countries.

French and Poterba (1991) were among of the first to report a strong home-country bias in security selection:[11] U.S. investors hold 92% domestic equity; Japanese investors hold 96%, U.K. investors hold 92%, German investors 79%, and French 89%. This overweighting of domestic stocks has been declining though. Dorn and Huberman (2005) find a domestic equity allocation of 46% for German online investors in a 2000 sample, and French (2008) shows that the degree of U.S. aggregate home bias has gradually declined over time, such that investors allocated only 2% to foreign stocks in 1980, 8.5% in 1990, 14% in 2000, and 28% to 2007.

[10] Section 2.2.3.3. offers more discussion of the so-called local bias.
[11] Home country bias is traditionally calculated as the deviation between the actual weights and the weights based on a country's market capitalization within the world equity market.

Solnik and Zuo (2012) provide an overview of the degree of home bias in many countries. Especially in emerging markets, the home bias is large, with an average of approximately 95%, compared with 70% for developed countries, averaged over 2001–2008. Across developed countries, the differences also are large: In the Netherlands, the home bias (37%) is the lowest of the 21 developed counties listed, but Greek investors overweigh domestic securities by 92%.

Home bias has been explained using both rational and behavioral arguments. Karlsson and Nordén (2007) relate home bias to the mutual fund allocations of 4.4 million Swedish individuals in a new defined contribution plan. The degree of home bias can be explained by inflation hedging, a lack of sophistication, and overconfidence. In an overview of literature on the home bias, Lewis (1999) concludes that hedging against domestic-specific risks and transaction costs are not enough to explain the empirical findings. Cooper and Kaplanis (1994) concur that home bias cannot be explained by investors hedging against inflation risk.

Behavioral explanations focus on familiarity, optimism (about future returns on the domestic market), pessimism (about future returns on foreign equity), and perceived risks of foreign equity. French and Poterba (1991) assert that risk perceptions largely drive home bias, because investors perceive foreign securities as more risky than domestic securities due to their limited knowledge of foreign markets. Aversion to ambiguity drives the relative unpopularity of foreign securities. Statman (1999) also posits that foreign stocks are unpopular because of a lack of familiarity. According to behavioral portfolio theory (BPT), foreign stocks will be unattractive if their past returns are low, given that they are placed in the upside potential layer.[12]

Bailey *et al.* (2008) find that investors who diversify more domestically also invest internationally more often, which may suggest that behavioral factors play a role. The overconfident investors invest more abroad, but investors who display the local bias or the disposition effect invest less in foreign assets, resulting in a detrimental performance effect.

2.2.3.3. Local Bias

Local bias is another example of how geographical proximity drives asset allocations. It implies a “home bias at home” (Coval and Moskowitz, 1999) that might induce unjust feeling of competence or make valuable information acquisition easier. Specifically, local bias refers to the tendency of investors to tilt their portfolios toward locally headquartered stocks. One of the first investigations of a preference for geographical proximity, by Coval and Moskowitz (1999), shows that U.S. investment managers prefer firms with headquarters near where they live. In a subsequent study, Coval and Moskowitz (2001)

[12] Within the BPT, correlations between layers are ignored, and thus the diversification benefits of foreign holdings get overlooked.

note that preference for geographic proximity may be driven by informational advantages, because local holdings really do outperform various benchmarks. Although this study examines the portfolios of professional money managers, it prompted similar studies among retail investors, which ask whether overweighing local stocks is a bias that arises from feeling more comfortable with local stocks and opposing diversification theory, or if it is rooted in a rational explanation, such as exploiting informational asymmetries or hedging again price increases in local services or goods.

Huberman (2001) finds that shareholders of regional telephone companies tend to live in the same area in which the companies operate. Each of the regional telephone companies is equally accessible, so transaction costs (as have been proposed to explain home bias) are not valid. Overweighing local telephone companies may provide a hedge against price increases, though Huberman (2001) finds a stronger argument from the opposite direction. Because households' financial welfare is closely linked to the success of local companies, nonregional asset allocation would be more rational. These results are in line with a preference for the familiar. Grinblatt and Keloharju (2001) provide further evidence about how familiarity drives individual investment decisions. Using data from Finland, they report that retail investors exhibit a preference for holding and trading nearby firms that share the same language and culture. Ivkovic and Weisbenner (2005) confirm this strong preference for holding local stocks among U.S. individual investors, who overweight local firms by a factor of three on average. Local holdings outperform non-local holdings considerably, suggesting retail investors may be able to exploit information asymmetries. The excess returns on local holdings are 3.2% per year and mainly driven by non-S&P500 stocks, for which information asymmetry is more likely.

Massa and Simonov (2006) also provide evidence of the impact of proximity. Their data set is unique, in that it covers all wealth components (cash, real estate, equity holdings, bonds) of almost all Swedish households during 1995–2000. Proximity is operationalized by professional and geographical proximity, as well as the holding period. Because investors tilt their portfolios toward stocks that correlate positively with their nonfinancial (e.g., labor) income, hedging motives can be ruled out as an explanation. In line with Ivkovic and Weisbenner (2005), they reject the view that familiarity is a bias: Investors benefit from overweighting close stocks. Proximity apparently provides a cheap information acquisition route and thus allows investors to improve their returns.

Seasholes and Zhu (2010) question the information-based hypothesis though and assert that previous findings are econometrically flawed. Using the same data as Ivkovic and Weisbenner (2005) but correcting for cross-sectional dependence (using calendar-time portfolios), these authors find that the performance differences between local and non-local portfolios, though positive, are no longer significant. They even find a negative performance of –1.7% per year for trades rather than portfolios, formed on the basis of geographical proximity. This negative effect increases for trades of stocks with more information asymmetries (non-S&P stocks). The authors thus conclude that retail investors do not exploit information asymmetry through geographic proximity.

2.2.4. Volatility Specialization

Dorn and Huberman (2010) test the so-called preferred risk habitat hypothesis, with a prediction that investors engage in narrow framing and select stocks one-by-one based on individual stock volatility. Using a data set of 20,000 German discount broker clients, they find that stocks in individual portfolios have remarkably similar volatilities. Apparently investors match the average volatility of stocks to their risk aversion, rather than to portfolio volatility, and thus they ignore the return correlations proposed by portfolio theory. More volatility-specializing investors expose themselves to more idiosyncratic risk with lower Sharpe ratios. The volatilities of less experienced investors and those with more concentrated portfolios exhibit the most pronounced volatility specialization, suggesting a behavioral explanation (in particular, narrow framing).

2.2.5. Behavioral Portfolio Theory

Many of these behaviors temped Shefrin and Statman (2000) to develop a descriptive approach to portfolio composition, opposing the normative mean-variance approach proposed by Markowitz (1952). Their behavioral portfolio theory (BPT) explicates actual portfolio compositions of individuals by incorporating elements from mental accounting (Thaler, 1985) and Lopes's (1987) SP/A theory to address the impact of emotions (i.e., hope and fear). In BPT, investors build portfolios as pyramids of layers, with layers associated with particular goals, time horizons, and attitudes toward risk. Typically, investors built a bottom layer to avoid the risk of poverty and a top layer to achieve wealth aspirations. These layers represent distinct mental accounts, and covariances between them are overlooked. Investors first label securities as "bonds" or "stocks" or "domestic" or "foreign," which may inhibit a clear overall (frame-independent) picture of the portfolio. Also, "foreign" may be perceived as more risky, leading to more funds allocated to domestic stocks. Behavioral investors also may prefer securities framed in a way to guarantee a minimum payoff, which would explain the popularity of some structured products.

The finding that people take more factors into consideration than just risk and return motivated Fisher and Statman (1997a) to focus on the differences in the mean variance between optimal and actual portfolio decision making. They compare investments and food portfolios: Just as people assess the attractiveness of meals by considering various factors, beyond nutrition value and cost, investors care about more than risk and expected return. Food has other goals than to be fed at low cost and is therefore judged on palatability, variety, prestige, and cultural aspects. Similarly, investments are judged on criteria that make them intuitively appealing, which leads to a preference, for example, for socially responsible companies. These authors conclude that optimization techniques dictate how investors should behave, but prescriptions should fit investor preferences, as in BPT.

In another study, Fisher and Statman (1997b) evaluate investment advice from mutual fund companies using the insights of BPT. Mutual fund companies address such mental accounting in the labels of their funds, which designate specific goals (a bond fund is sold as an “income” or “high yield” fund; a stock fund as “growth” fund). They frame their portfolios as layered pyramids of mutual funds, just as described by BPT. They advise investors to assign particular funds to particular goals, essentially advising them to ignore correlations between funds or asset classes. Although the portfolio recommendations of mutual fund companies may deviate from MPT-efficient portfolios, the authors conclude that the costs of ignoring the prescriptions of the mean-variance framework are small.

In summary, diversification by retail investors appears suboptimal: The average investor owns only a few stocks, divides money evenly over investment options, and bases allocation decisions on proximity. In many cases, it seems likely that behavioral phenomena are at the root of observed allocation decisions. Behavioral portfolio theory addresses these issues and offers a descriptive approach to explain how portfolios are constructed.

2.3. Trading Behavior

A long-standing anomaly in financial research has been the excessively large volume of trading in securities markets. In 2009 annualized turnover of the New York Stock Exchanges was 129%, though it declined to 86% over 2011 (NYSE, 2011). Black (1986) introduced the concept of noise trading in this context. He defines noise as anything that is not information, so noise traders cannot expect to profit from their trades. Although trading on noise may be irrational, there are many rational motives to trade: liquidity, lifecycle considerations, rebalancing, private information signals, or taxes, for example.[13] Barber *et al.* (2009) estimate a 3.8% market-adjusted loss as a consequence of trading by individual investors, using all transaction of the entire Taiwanese market for a five-year period. Linnainmaa (2011) also posits that investor trade to learn, so return reductions as a result of excessive trading is the price that investors pay to learn, in which case it would be rational. But many other scholars believe that behavioral explanations are needed for observed trading volumes. Overconfidence (one source of noise) is widely cited as a possible driver of excessive trading. In this case, overconfidence refers to an irrational, excessive belief in one’s own abilities (the “better than average effect” or “hubris”) or an overestimation of the precision of information (“miscalibration”).

Odean (1999) and Barber and Odean (2000) test an overconfidence-based trading hypothesis using data from a U.S. discount brokerage firm and find a large penalty for

[13] In many tax systems, realized gains and losses have tax consequences. Realizing losses is beneficial in these systems, because it lowers the taxes to be paid.

active trading, mainly due to transaction costs. Although the least active traders perform reasonably in line with the market, net performance is monotonically decreasing with trading activity. The quintile of most active traders thus generates a negative three-factor alpha of –0.86% per month, whereas the least active investors generate an alpha of around 0. Although alternative explanations, including liquidity trading, rebalancing, tax-motivated selling, or the joy of gambling, may explain some trading activity, the authors believe trading is mainly explained by overconfidence.

Barber and Odean (2001) test the robustness of the overconfidence hypothesis using gender as a proxy for the degree of overconfidence. The underlying assumption that men tend to be more overconfident than women has been supported by many psychological studies, especially in domains considered "masculine," such as finance. Barber and Odean (2001) confirm that men trade significantly more actively than women (annualized turnover = 77% vs. 53%), which also means they underperform women (annualized net return difference = 0.94%). The differences between single men and single women are even more pronounced, suggesting that overconfidence is a cause of excessive trading.

To further explore the overconfidence-based trading hypothesis, Barber and Odean (2002) investigate the change in trading behavior after investors move from telephone-based to online trading. Before going online, these investors outperformed both the market and a size-matched control group. Once online though, they traded more frequently (average annual turnover before switching = 70%, after switching = 120%) and perform worse than they previously did, as well as compared with a control group. These findings support the overconfidence hypothesis, because the switchers likely are more overconfident than non-switchers due to their self-attribution bias (i.e., their previous investment success was due to their own skill), the illusion of control (due to their active involvement in the trade), the illusion of knowledge (due to vast amount of data available to them), and cognitive dissonance (time and effort spent on information leads to the perceived necessity to trade).

Further support for the overconfidence hypothesis comes from Statman *et al.* (2006), who explore the relationship between overconfidence and trading volumes at the macro level. Trading volume relates positively to lagged stock returns, consistent with increased overconfidence as a result of past success and biased self-attribution. Their finding especially holds for subsamples in which individual investors have more impact. Also, Barber *et al.* (2009) propose that the 300% turnover in the Taiwanese stock market is caused by overconfidence and the desire to gamble.

Although Odean (1999), Barber and Odean (2000, 2001, 2002) and Statman *et al.* (2006) find evidence in support of overconfidence-based trading, a major limitation of these studies is that they infer overconfidence from observed behavior. Many authors therefore question whether other reasons, apart from (or instead of) overconfidence, may be relevant for explaining trading behavior. These authors thus try to measure psychological attributes that proxy for or are related to overconfidence.

Glaser and Weber (2007) combine trading records and survey responses from German online investors and find that investors who (incorrectly) perceive themselves as above average exhibit greater trading activity, whereas the degree of miscalibration has no effect. Although this finding supports the impact of the better-than-average form of overconfidence, it still seems surprising, given the vast literature that explains overconfidence as a manifestation of overestimations of the precision of information.

Although Dorn and Huberman (2005) confirm substantial trading using data from German online investors, their two proxies for overconfidence (self-attribution bias and the illusion of control) are not related to trading activity. They instead claim that self-reported risk aversion is the main determinant of trading: More risk-tolerant investors trade more aggressively. The reported differences are large, such that the monthly portfolio turnover of the most risk-averse investors is less than 10% compared with more than 30% for the least risk-averse.

The finding that men trade more because of their higher degree of overconfidence is also disputed by Grinblatt and Keloharju (2009), who claim that instrumenting overconfidence by gender fails to recognize that gender is associated with many other investor attributes (e.g., sensation seeking) that also affects trading. Sensation seeking is a psychological attribute linked to gambling behavior. Kumar (2008) relates trading to gambling motives. Sensation seekers are driven by intensity, novelty, and the variety of experiences. To proxy for sensation seeking, Grinblatt and Keloharju (2009) use the number of speeding tickets received by an investor and find that it is strongly related to trading, in addition to overconfidence. In line with Glaser and Weber (2007), Grinblatt and Keloharju (2009) find overconfidence related to the better-than-average effect, not to miscalibration.

Related to sensation seeking is entertainment seeking. Dorn and Sengmueller (2009) show a strong effect of entertainment and gambling motives on trading behavior. Their research is motivated by responses to a survey that called investing “a nice pastime” (Hoffman, 2007). In this view, the direct utility derived from trading may compensate for the performance deterioration that results from trading excessively. The most enjoyment- or gambling-prone investors turn their portfolio over twice as often. Dorn and Sengmueller (2009) estimate that more than half of the turnover in their sample is driven by irrational explanations, and their findings do not change even when they include proxies for overconfidence, which actually appear unrelated to turnover. Bauer *et al.* (2009) report results consistent with these findings. Option traders, in their sample of Dutch online investors, are affected most by entertainment and sensation-seeking motives, and these investors incur the largest portfolio losses, resulting from a combination of poor market timing and high trading costs. Dorn and Sengmueller (2009) conclude with a relevant observation: Financial economists often evaluate behavior in terms of effects on wealth, but they may ignore the impact of that behavior on welfare.

Graham *et al.* (2009) estimate the impact of the competence effect, which posits that people are more willing to rely on their own judgment when they feel more competent (Heath and Tversky, 1991). They find that perceived competence positively affects trading behavior. Specifically, when their competence measure increases by one standard deviation, the propensity to trade more than once a week almost doubles. Their measure of overconfidence is not related to trading though.

Although excessive trading may be a stylized fact for a specific group within the retail investor population, many studies document completely different behavior, namely, strong inertia by many households. Inert behavior may relate to the status quo bias (Samuelson and Zeckhauser, 1988), that is, a person's preference to leave matters unchanged. People generally have a deep aversion to regret, and making active (portfolio) changes that turn out to be inferior, relative to having kept the status quo, are painful. Choi *et al.* (2002) find that a majority of investors (55% in one plan, 59% in another) in 401(k) plans never trade during a three-year period. Similarly, Linnainmaa (2011) reports that in her sample of 1.1 million Finnish households, 48% of the people that own stocks never trade during an eight-year sample period, and 60% of the trades during that same period originate from the 5% most active traders. Dahlquist *et al.* (2011) document strong inertia in their sample of Swedish investors in retirement accounts. Again a large majority of them make virtually no changes: 68% of investors made no changes in their portfolios during 2000–2010, and an additional 16% made only one change. Inertia cannot be explained by transaction costs, which are absent in these samples. Contrary to Barber and Odean (2000, 2001, 2002), trading activity was actually beneficial in this case, in that Dahlquist *et al.* (2011) show that performance increases monotonically with activity as a result of successful mutual fund picking.

This overview of trading activity by retail investors exhibits two stylized facts: Some investors trade excessively, and others do not trade at all. Excessive trading has mainly been observed in online accounts and relates to the behavior of only a fraction of the investor population.[14] Because inertia typically has been found in retirement accounts, it is necessary to distinguish inert behavior from rational buy-and-hold considerations, which is not easy.

2.4. Selecting Securities to Buy

Grinblatt and Keloharju (2000) investigate the behavior of different investor classes in Finland over a two-year interval using the buy ratio.[15] They find that Finish retail investors follow a contrarian strategy.[16] Using the buy–sell ratio may obscure the possibility of

[14] Campbell (2006, p. 1571) states for example, "discount brokerage customers tend to be households with a particular interest in equity trading.

[15] The buy ratio is calculated as the number of buys divided by the number of buys plus sells.

[16] In a contrarian strategy, the investor buys stocks that have performed badly and sells stocks that have done well, or the opposite of a momentum strategy.

different drivers of buying and selling decisions though. Barber and Odean (2011) find that investors both buy and sell stocks that have performed well, which they relate to different thought processes involved when buying or selling. According to them, retail investors exhibit contrarian behavior only when they sell and momentum behavior when they buy. Although retail investors may pursue some sort of deliberate strategy in their buying decisions, many studies find that buying is influenced by the attention, representativeness, and affect heuristics.

2.4.1. Buying Based on Attention and Availability

Merton (1987) notes that certain stocks grab investors' attention and are thus considered for purchase. For a typical individual investor, the buying decision is far more complex than the selling decision. Most people do not sell short and therefore only need to focus on the (few) stocks that they already own when they sell. In buying though, they can select from thousands of stocks. Barber and Odean (2008) therefore hypothesize that attention influences the buying decision of individual investors to a greater extent than does the selling decision. The availability heuristic relates to attention in that it deals with the degree to which information is readily available.

Lee (1992) finds a relation between buying behavior and earnings announcements that likely attracts investor attention. Lee assigns trades to individual and professional investors according to trade size (trades below $10,000 proxy for individual investor trades) and finds a remarkable difference in their reactions to earnings news. Trades by professionals react to the type of news: Good news creates net buying, bad news generates net selling. For trades by individuals though, the direction of the news does not matter. Around earning releases in general, good or bad, buying dominates, in support of the proposition that attention drives the trading behavior of individual investors.

Hirshleifer *et al.* (2008) also find an earnings attention effect. They identify individual traders and focus on extreme earnings surprises as proxy for attention-grabbing news. The extreme earnings surprises trigger bigger trading activity and greater net buying for three weeks after the extreme earnings announcement. Abnormal trading is higher after extreme negative earnings surprises than for positive earnings surprises. Apparently, bad news is more salient. People are net buyers after both negative and positive earnings surprises.

Barber and Odean (2008) investigate the existence of attention-based buying among both individual and institutional investors. Their proxy for attention-grabbing information is abnormally high trading volume, extreme previous day returns, and companies being in the news. On high volume days, individual investors are large net buyers, but on low volume days, this group consists of net sellers. Institutional investors engage mainly in buying on low volume days. On days following high negative or high positive returns, people mainly buy. For institutional investors, the behavior depends on style: Momentum investors sell after negative returns and buy after positive returns, but value investors do the opposite.

When firms are in the news, individual investors also buy more of this stock than they sell. To test if the imbalance is caused by a constraint on short-selling, the stocks already in the portfolio are taken into consideration. In that case, selling dominates, but the same relative buy–sell imbalance is visible. Attention-based buying harms individual investors, because stocks bought underperform stocks sold.

Seasholes and Wu (2007) support the attention hypothesis in their study of the trading behavior of arbitrageurs and individual investors. On the Shanghai Stock Exchange, stocks cannot rise above or below a daily price limit (for most stocks, ±10%). Stocks that hit their price limit are reported in the news and therefore more likely to be noticed by individual investors. The authors find active individual investors buying the day after an upper price limit has been hit. The effect is even stronger for first-time buyers in the particular stock, supporting the attention-based buying hypothesis.

Da *et al.* (2011) proxy for retail attention using Google search frequency for particular stocks. Although these Google searches correlate weakly with the proxies for attention used by Barber and Odean (2008), their results strongly support the retail attention hypothesis. Greater investor attention measured by Google search frequency leads to positive price pressures for the following two weeks, followed by a reversal during the rest of the year, especially for stocks traded mainly by retail investors. Higher search volume also leads to large first-day IPO returns.

Bae and Wang (2012) also support the investor attention hypothesis by investigating Chinese firms listed in the United States, which may include “China” in their name or not. China-named stocks significantly outperform non–China-named stocks during a boom period in the Chinese stock market, but they exhibit greater price reversal during downturns. In Hong Kong, they find no China-named effect, which suggests that attention drives the U.S. findings. Although the authors do not mention it, the representativeness heuristic also may play a role. The “China” label may easily be linked to positive news about the growing Chinese economy.

2.4.2. Buying Based on Representativeness

In buying decisions, the representativeness heuristic may play a role. Representativeness enables people to perceive systematic patterns in recent stock price movements or earnings, even when these patterns are random. Using perceived patterns, investors might extrapolate in a naïve fashion and buy stocks that recently increased in value. When investors naively extrapolate past returns and exhibit the so-called extrapolation bias, they are positive feedback traders.

In a survey of individual investors, De Bondt (1993) finds that the typical non-expert expects trends to continue. The average percentage gap between the fraction of investors that is bullish and the fraction that is bearish increases by 1.3% for every percentage point that the Dow Jones rises during the week prior to the survey.

A previous section detailed how employees increase company stock allocations in their retirement portfolio, especially when it performs well (Benartzi, 2001; Huberman and Sengmueller, 2004). Bange (2000) provides additional evidence of positive feedback trading among small equity investors through survey data. Investors increase their exposure to equity after positive market returns and decrease equity allocations after market downturns. Bange (2000) finds no evidence that these allocation changes reflect superior market timing ability. The findings are consistent with evidence from Barber *et al.* (2009b), who document the positive relation of aggregate buying by retail investors with past returns.[17] In analyzing trades of online investors, Odean (1999) also shows that individual buys follow positive market-adjusted returns. Retail investors buy securities that have outperformed the market in the previous two years. Although Chen *et al.* (2007) confirm evidence of representativeness-based buying in China, they also find, contrary to Odean, that individual investors typically focus on recent (past four months) returns.

Whether incorporating past returns in investment decisions is really a bias likely depends on the investors' estimated holding period. Jegadeesh and Titman (2001) provide evidence of short-term momentum (stocks that have done well recently yield abnormal returns in the near [3–12 months] future), but de Bondt and Thaler (1985) find long-term reversals (winners underperform losers over a three- to five-year horizon). This so-called winner–loser effect appears driven by investors becoming too optimistic about stocks that have increased in price and overly pessimistic about stocks that have decreased.

Beyond the naïve extrapolation, stereotyping, based on the same representativeness heuristic, may influence investors' buying decisions. Stereotyping may lead investors to confuse stock attributes with company characteristics. Solt and Statman (1989) show that investors can confuse a growth company (high growth opportunities in sales or earnings) with a growth stock (high expected return). Using Tobin's q as a measure of growth opportunities and data from 1960 to 1977, they find that growth companies earn much lower returns. Companies in the highest Tobin's q quintile (i.e., highest growth opportunities) exhibit an annual return that is 5.9% less that the firms in the lowest quintile. In a similar vein, Chan and Lakonishok (2004) look into return differences between so-called growth (or glamour) stocks (high past growth rates in sales) and value stocks. The average five-year return difference was more that 60% in favor of the value stocks. This finding implies that many investors erroneously believe past performance is representative of future performance.

[17] Because the disposition effect (Section 2.5.1.) posits that investors preferably sell winners, both buying and selling should follow rising stock prices.

2.4.3. Buying Based on Affect

The impact of the affect heuristic on investment decision making has not been studied as extensively as attention or representativeness. Affect may be defined as the immediate emotional response to some stimulus (e.g., stock of a particular firm). As Kahneman (2002) stated in his Nobel Prize lecture, "the idea of an affect heuristic is probably the most important development in the study of judgment heuristics in the last decades."

Affective feelings may guide decision making, especially when alternatives are difficult to evaluate (as is the case in many investment choices). Affect relates mood, which can affect prices in stock markets. Hirshleifer and Shumway (2003) find that nice weather puts investors in a positive mood, makes them more risk tolerance, and drives up prices.

Cooper *et al.* (2001) find that during the late 1990s (when positive sentiment about Internet businesses likely triggered positive affect), firms that added "dotcom" to their names experienced tremendous increases in market value (average abnormal returns of 74% within 10 days of an announcement), but in the early 2000s (when Internet businesses likely triggered negative affect), similar market reactions were observed for firms that removed "dotcom" from their names (Cooper *et al.*, 2005).

Statman *et al.* (2008) report that firms with positive affect are associated with both high returns and low risk. They relate affective responses for firms to subsequent returns and find that a portfolio of admired firms' stock underperforms a portfolio of stocks of less admired (or spurned) firms. Aspare and Tikkanen (2011) also provide survey evidence that people's affect toward a company provides an extra motivation to invest in its stock. The impact of affect does not relate to many of the investor characteristics studied, except for education; for investors holding a university degree, affect plays a lesser role.

Kuhnen and Knutson (2011) built on neurological evidence that relates affective responses to financial judgment and decision making. In an experimental setting, these authors provide evidence that excitement and anxiety—which relate to different regions of the brain—modify risk preferences. Risk aversion is diminished by excitement but increased by anxiety. Affect can be introduced exogenously or result from past outcomes, and it relates positively to confidence in one's ability to evaluate risky investments, which in turn provides further evidence in support of the overconfidence hypothesis.

2.5. Selecting Securities to Sell

Selling decisions by individual investors typically relate only to stock they already own. Combined with a typical individual investor holding only a few stocks, it makes the selling decision relatively easy compared with the buying decision. The disposition effect is the most prominent description of how individuals decide to sell.

2.5.1. Disposition Effect

The disposition effect is a preference to sell winning security positions rather than losing positions; it is remarkably robust. Shefrin and Statman (1985) predict the disposition effect from elements of prospect theory (Kahneman and Tversky, 1979) and mental accounting (Thaler, 1999). In making investment decisions, it implies that (1) investors evaluate outcomes of individual securities rather than portfolio returns, (2) investors label the outcomes of their investments in terms of gains and losses related to a reference point (e.g., buying price), and (3) due to loss and regret aversion, most investors prefer not to realize losses and close the mental account they opened by buying the security, such that they can leave open the possibility that the purchase was a wise decision after all.

Odean (1998) tests the disposition effect hypothesis using a large data set of 10,000 online investor accounts during 1987–1993 and finds strong support. Odean (1998) compares the proportion of gains realized (PGR) with the proportion of losses realized (PLR) and finds that a larger part (by a factor of 1.5) of the wining positions gets sold compared with losing positions. This disposition behavior is not justified ex post. By having sold the loser and holding on to the winner, investors could have earned a much larger return (3.4% for a one-year horizon). Selling losers and holding winners would also be more rational, considering the tax effects of these transactions in some systems. Alternative explanations for the disposition effect include a belief in mean reversion, portfolio rebalancing, liquidity demands, or a reluctance to sell at low prices due to higher transaction costs. But when investors believe in mean reversion, they seemingly should tend to buy past losers, which they do not do. If investors rebalanced their portfolio due to changed risk characteristics, we should expect that only part of the positions would be liquidated, which again is not the case. Liquidity motives do not drive the effect; the disposition effect is not dampened for a subsample of stocks sold for which the proceeds are reinvested within three weeks of the sale.

Weber and Camerer (1998) find evidence of the disposition effect through an experimental approach. People are 50% more likely to realize gains than losses. In line with Odean's (1998) findings, investors' possible belief in mean reversion can be ruled out, because the disposition effect was greatly reduced when stocks were automatically sold after each round.

In a large-scale study of investor behavior in Finland, Grinblatt and Keloharju (2001) also find evidence of the disposition effect for five investor groups (non-financial corporations, financial and insurance institutions, governmental organizations, nonprofit institutions, and households). Especially for large losses, there is a strong reluctance to take a loss, yet in December, investors accept losses to realize tax benefits.

Kaustia (2004) finds support for the disposition effects by analyzing a data set of initial public offerings (IPOs). An advantage of IPOs is the availability of a relatively unambiguous reference price, the offering price, which is shared among many investors. That study showed that stocks trading below the offering price since their IPO exhibit significantly more trading volume when the offering price is exceeded, especially when it happens for the first time.

Whereas Feng and Seasholes (2005) document a disposition effect among Chinese investors, Barber *et al.* (2007) study the disposition effect in aggregate using a database of all trades in Taiwan. These authors report strong evidence in favor of the disposition effect. Investors in Taiwan are twice as likely to sell a stock for a gain as for a loss. A large majority of investors in Taiwan (84%) exhibit a disposition effect.

2.6. Relevance of Investor Sophistication and Financial Advice

The preceding sections documented many typical individual investor behaviors. For some of these behaviors, rational-economic explanations cannot be excluded, but they mostly appear rooted in human psychology: driven by heuristics and emotions, and frame dependent. The role of intuitive decision making by retail investors should come as no surprise though. Financial decision making is complex, made in opaque and uncertain environments, and the feedback is slow and often hard to interpret. Although "quick and dirty" judgment and decision rules may not always lead to optimal outcomes, they are often an efficient and good enough way to make decisions.

An interesting question thus is whether greater guidance of retail investors would improve their financial decision making. Such guidance can take many forms: financial education, the use of sensible default choice options, or the use of a financial advisor. Guidance generally implies greater (financial) sophistication added to the decision-making process. The impact of sophistication has been widely studied, so it may serve as a useful introduction to the main question of this thesis: whether and how retail financial advisors add or detract value.

To review prior literature on financial sophistication and guidance, this section offers (1) a comparison of portfolio performance and the behavior of various classes of markets participants that may be assumed to differ in level of sophistication (e.g., financial institutions, retail investors); (2) a discussion of the impact of various proxies for sophistication (e.g., experience, wealth, occupation, education, financial literacy, cognitive abilities) among retail investors; and (3) a review of the (scarce) literature available related to the impact of financial advisors.

2.6.1. Performance and Behavior of Various Investor Classes

A comparison of the performance of various investor classes typically aims to address the question of the extent to which wealth transfers take place across various participants. Estimating these wealth transfers preferably requires data that cover a whole market, considering the adding-up constraint on trading. In empirical literature on investor behavior, two data sets cover a whole market and can identify participants. Grinblatt and Keloharju (2000) use all stock market transactions in Finland over a two-year time span. They find that stocks that individuals buy exhibit weak future performance, whereas sophisticated investors (e.g., foreign, professionally managed funds, investment banking houses) take the other side of the trade and exhibit strong performance. Barber *et al.* (2009) analyze all stock market trades in Taiwan. A similar and clear pattern emerges: Retail investors lose while professional parties gain. Comparing the buys and sells of individuals, they reveal that stocks sold outperform stocks bought by 75 basis points per month. The net market adjusted returns of Taiwanese individual investors in aggregate are –3.8%, which reflect the combination of bad stock picking, commissions, taxes, and bad market timing. Hvidkjaer (2008) analyzes all trades in the United States and finds that small trades offer a good proxy for retail behavior. His findings are in line with the two other studies: Small trades underperform the market by 89 basis points per month. He also finds that stocks with strong retail buying are growth stocks with high past returns and high advertising expenses.

Other studies compare the behavior (rather than the performance) of individuals against that of professionals. Generally speaking, many of the behaviors discussed in Sections 2.1–2.5 exist among both retail and professional investor classes, but the most biased behavior occurs among individuals. Barber *et al.* (2007) find that most investors in Taiwan (84%) exhibit a disposition effect, but mutual funds and foreign investors do not. Although many investor classes are driven by preferences for familiar firms, this effect is less prominent for institutions (Grinblatt and Keloharju, 2001). Barber and Odean (2008) note that attention-based buying is only observable among retail investors and not (or much less so) among institutional investors.

2.6.2. Impacts of Sophistication and Learning on Retail Behavior

An interesting question remains, namely, whether behavioral biases and errors are mainly a beginner's phenomenon, such that experience reduces or even eliminates deviations from micro-economic predictions. List (2003) finds that the degree of market experience tends to correlate with the degree of rationality of in people's decision making. De Bondt (1998, p. 832) is less positive though: "What is surprising is the failure of many people to infer basic investment principles from years of experience."

In addition to experience, investor sophistication might result from education, financial literacy, cognitive ability, occupation, or wealth. Most studies show that higher levels of sophistication are associated with better decision making and better outcomes. Bailey *et al.* (2008) find that wealthier, more experienced investors are more likely to hold foreign equity. In addition, behavioral factors play a role. Whereas overconfident investors invest more abroad, investors who display a local bias or the disposition effect invest less in foreign assets, resulting in detrimental effects on performance. Bailey *et al.* (2011) further note that investors with higher income or education and more experience make better mutual fund investment decisions.

Feng and Seasholes (2005) study the disposition effect as a function of experience and investor sophistication for a group of 1,511 investors in the People's Republic of China. On average these investors exhibit a disposition effect, but sophisticated and experienced investors have fewer problems with selling losing stocks. Dhar and Zhu (2006) also document a negative relationship among financial literacy, trading experience, and the disposition effect.

According to Loewenstein (2003), emotions have a strong impact on decision making, and experience relates to the level of these emotions. Lo and Repin (2002) observe significant differences in emotional responses between experienced and less experienced foreign exchange and derivatives dealers. More experience leads to lower emotional responses.

Goetzmann and Kumar (2008) look into investor characteristics and diversification and find that the least diversified portfolios are held by young, low income, less educated, less sophisticated, and non-professional groups. Graham *et al.* (2009) find that (perceived) competence mitigates home bias. In their whole sample, 38% of the investors hold foreign assets, but among those who feel more competent, 52% invest internationally. For investors with the highest degree of competence, the probability of holding foreign assets increases to more than 73%. In support of these findings, Abreu *et al.* (2011) show that after gaining experience in the home market, investors start investing abroad and improve their portfolio performance. Kimball and Shumway (2010) use survey data and find that sophisticated investors invest more internationally, suggesting that home bias is an issue, especially for the less financially literate.

Another branch of literature looks into the effects of financial literacy and cognitive abilities. Generally, a lack of financial literacy or low cognitive abilities adversely affect the quality of financial decision making: Less literate people are less likely to participate in the stock market (Van Rooij *et al.*, 2011) and tend to diversify their portfolios insufficiently (Christellis *et al.*, 2010). Grinblatt *et al.* (2011a) first find a positive relation between IQ and stock market participation, and then they report that high-IQ investors show significantly better portfolio performance (Grinblatt *et al.*, 2012). Korniotis and Kumar (2012) also reveal that portfolio distortions such as concentration, excessive trading and holding local stocks must be conditioned on cognitive abilities.

2.6.3. Impacts of Financial Advice

Although the performance and behavior of professional market participants and the role of sophistication in the retail investor class provides some useful insights regarding the role of professionalism, related research has ignored the specific setting in which financial advice usually gets organized. Insofar as professionals operate in an organizational setting, they are subject to agency relationships, which tend to induce particular, incentive-based behaviors (Ross, 1973). The incentives for financial advisors pertain to various financial concerns, such as producing commissions for their financial institution, generating a performance-based bonus, or enhancing the performance of investors' portfolios (Loonen, 2006). Therefore, in professional investment decision making, behaviorally based effects might be less prominent, because the professional decision environment and sophistication are augmented by agency-based effects from the organizational setting in which investment counseling and decision making takes place.

Some interesting studies adopt an explicit focus on the role and impact of financial advice. For example, studying role of professionalism in retail portfolios, Shapira and Venezia (2001) report that compared with investors who made independent investment decisions, professionally managed portfolios are better diversified and exhibit a lesser disposition effect, better market timing, and better round-trip performance. The managed group also exhibits more trading activity, which may be due to a status quo bias for the independent group, agency-related problems (churning), or more overconfidence in the managed group.

Laboratory evidence supports the claim that financial advisors are not free of bias. Glaser *et al.* (2010) document that even when all participants are overconfident to some extent, financial professionals tend to be more overconfident than laypeople. Kaustia and Perttula (2011) confirm overconfidence among financial advisors, as well as the positive effects of debiasing measures, such as training or written warnings. Kaustia *et al.* (2009) indicate strong framing effects among a group of financial advisors, such that the advisors relate higher risk to higher required returns but lower expected returns. Thus, retail investors suffer from misconceptions related to risk and return (De Bondt, 1998), but advisors may not do much better. Kaustia *et al.* (2008) also find that financial experts exhibit significant anchoring effects in forming stocks market return expectations, though to a lesser extent than laypeople.

Bergstresser *et al.* (2009) compare the aggregate performance of various mutual fund classes sold through intermediary and direct distribution channels in the United States. They find that broker-sold funds underperform direct-sold funds,[18] on a risk-adjusted basis. Therefore, brokers must deliver clients unobserved intangible benefits, or else conflicts of interest inhibit brokers from providing value for their clients

Hackethal *et al.* (2012) similarly paint a rather negative picture of the value of financial advisors, based on a comparison of advised and self-directed portfolios in Germany from 2003–2005. Advised portfolios achieved a net return 5% per year lower than the independent group, but its risk also was lower. Monthly risk and investor characteristic

[18] Broker-sold funds are sold through intermediaries; direct-sold funds are marketed directly to the retail investor. Vanguard is a typical example of a supplier of direct-sold funds, and American Funds offers funds through financial advisors. However, direct-sold funds are sometimes also used by fee-based financial advisors. The same fund also might be offered to direct customers and broker customers simultaneously.

adjusted returns were 0.4% per month lower for the advised group; turnover and mutual fund allocations were higher.

In an interesting audit study, Mullainathan *et al.* (2010) analyze whether advisors tend to debias their clients. They find that though advisors match portfolios with client characteristics, they fail to debias customers and, in some cases, even exacerbate client biases. Advisors promote return chasing behavior, encourage holding of actively managed funds, and fail to discourage holdings of own company stock. In general, advisors tend to support strategies that result in more transactions and higher fees.

In a laboratory choice experiment, Hung and Yoong (2010) expose participants randomly to three conditions: (1) advice, (2) no advice, or (3) the choice to receive advice. The random assignment to different treatments has the clear advantage that self-selection bias plays a much lesser role.[19] Some interesting results emerge. First, less financially literate people seek advice more often. Second, though unsolicited advice is generally ignored, participants who choose to receive advice improve their investment performance significantly, which implies a positive causal effect of advisory intervention. Bhattacharya *et al.* (2012) similarly offered 8,200 execution-only investors in Germany the option to receive free and unbiased advice in a financial advice choice experiment. A large majority of investors chose not to accept the offer; of those who accepted it offer, many chose not to follow the advice. However, investors who accepted the advice and followed it significantly improved their portfolio efficiency. In contrast with Hung and Yoong (2010), Bhattacharya *et al.* (2012) find that less financially literate participants are *less* likely to take advice; that is, those who most need advice opt not to receive it.

Karabulut (2011) indicates that though advisors mitigate home bias and underdiversification and reduce trading activity, they do not improve risk-adjusted returns. Bluethgen *et al.* (2008) confirm that advisors are associated with better diversified portfolios, more in line with predefined model portfolios but also higher fee expenses.

2.7. Conclusion

Retail investor behavior is a widely studied phenomenon. Empirical evidence typically indicates deviations from normative recommendations among individual investors. For example, diversification is typically limited, trading is excessive for some but other investors never trade, and buying decisions are heuristically based while selling decisions are narrowly framed and influenced by loss and regret aversion. Retail investors as a group exhibit portfolio performance that is inferior to that of more sophisticated investor classes. Within the group of retail investors, increased sophistication positively affects the quality of portfolio decision making.

[19] In the advice-choice treatment, investors still self-select to receive advice or not.

A related question is whether guidance, in the form of financial advice, can improve the investment decision-making quality exhibited by retail investors. Existing evidence on the effect of advisory intervention in retail portfolio decision making is mixed, to say the least. Laboratory experiments indicate that financial advisors are not free from biased judgments. Sometimes advisors are less (anchoring) and sometimes more (overconfidence) biased than laypeople. In combination with possible moral hazard behavior, this influence implies that debiasing efforts by advisors should not be taken at face value; in some cases, advisors even may exacerbate investment mistakes. Other experimental studies indicate that financial advisors positively affect portfolio outcomes, but only when investors accept and follow their advice, which is not obvious. Finally, studies that use transaction and portfolio data outside experimental settings find positive, negative, and zero effects on risk-adjusted returns, though diversification generally improves as a result of advisory intervention.

Whether advisory interventions have any effect on the portfolio decisions of retail investors thus remains an open question. This thesis aims to contribute to the discussion on the possible added value offered by financial advice.

Chapter 3

Financial Advice and Individual Investor Portfolio Performance[1]

3.1. Introduction

This paper attempts to address the question whether financial advisors add value to individual investor portfolio performance by comparing the portfolio performance of advised and self-directed investors, using a large data set of Dutch investors.[2] Although many individual investors rely on financial advisors to make portfolio investment decisions, until recently, existing literature has largely ignored the added value of financial advice.[3] Recent theoretical and empirical literature suggests an ambiguous contribution of advisors on retail portfolios. In line with predictions of Stoughton, Wu, and Zechner's (2011) model, Bergstresser, Chalmers, and Tufano (2009) suggest a negative relationship between advisor involvement and investor performance in U.S. mutual funds. In addition, Hackethal, Haliassos, and Jappelli (2012) find that risk-adjusted returns are lower for advised portfolios, partly as a result of higher trading costs. Other studies indicate that advisors fail to debias their customers or even exacerbate client biases that are known to hurt returns (Mullainathan, Nöth, and Schoar, 2010). In contrast, Bluethgen, Gintschel, Hackenthal, and Muller (2008) find that advisors are associated with better diversified portfolios that are more in line with predefined model portfolios, but with higher fee expenses. Bhattacharya, *et al.* (2012) find that advice taking is associated with an improvement in portfolio performance, though only a fraction of investors are willing to accept and follow advice. Finally, Shapira and Venezia (2001) report that compared with

[1] In a slightly modified form, this chapter has been accepted for publication in Financial Management (see volume 41 (2012), issue 2, p. 395-428).

[2] Advised investors have an advisory relationship with the bank that provided the data; self-directed (or execution-only) investors do not have such a relationship. This division is overly simple in that advised investors likely make some investment decisions independent of their advisors, and self-directed investors might hire advisors through different channels. However, on average, the decisions of advised investors in this data set should be influenced more by an advisor than the decisions by the group of self-directed investors.

[3] In the U.S., for example, 81% of the households investing in mutual funds, outside a retirement plan, rely on a financial advisor (Investment Company Institute, 2007). Similarly, Bluethgen *et al.* (2008) indicate that roughly 80% of individual investors in Germany rely on financial advice for their investment decisions, and Hung, Clancy, Dominitz, Talley, Berrebi, and Suvankulov (2008) find that 75% of U.S. investors consult a financial advisor before conducting stock market or mutual fund transactions. In the Netherlands, the domain of the current research, 51% of households with an investment portfolio rely on financial advice (Millward Brown, 2010).

investors who made independent investment decisions, professionally managed portfolios were better diversified and showed better round trip performance due to better market timing. Thus, whether financial advisors improve or worsen portfolio decision making remains an open question to which this paper tries to make a contribution.

Research regarding advised portfolio behavior may be positioned at the intersection of individual and professional portfolio behavior, two research streams that are well established. In early research on the portfolio performance of retail investors, Schlarbaum, Lewellen, and Lease (1978a, 1978b) report risk-adjusted returns of approximately 0% and reasonable levels of skill, though recent empirical studies indicate that average individual investors perform poorly.[4] Within these findings, however, a large heterogeniety in performance can be observed.[5] In addition, the added value of professional money managers has been debated ever since Jensen (1967) first demonstrated that mutual funds do not outperform a buy-and-hold strategy on average (Barras, Scaillet, and Wermers, 2010; Busse, Goyal, and Wahal, 2010; Fama and French, 2010). Yet Binay (2005) argues that institutional investors, including investment advisors, generate excess returns based on their style and stock picking. Other studies that explicitly compare the portfolio performance of individual households with that of professionals find that professionals significantly outperform less sophisiticated investors (Grinblatt and Keloharju, 2000; Barber, Lee, Liu, and Odean, 2009).

This paper differs from the extant literature in several ways. First, in addition to providing a rich set of descriptives that distinguish advised from self-directed investors, I combine analysis of the role of advisors on risk, return, portfolio composition, and timing skills. Additionally, my results likely rely on a more representative data set than previous studies.[6] Moreover, by comparing pre- and post-advice seeking behavior, I am able to identify effects from advisory intervention and, at least partly, circumvent endogeneity problems that may hinder previously reported results.

Despite differences in investor and portfolio characteristics between advised and self-directed investors, I cannot reject the hypothesis of no return differentials between the two groups. Less ideosyncratic risk exists in advised portfolios because of their greater diversification resulting from more investments in mutual funds, the use of more asset classes, and a lesser focus on domestic equity. The potential for selection effects leaves me to question whether these findings reflect the advisor's influence alone. Less sophisticated

[4] Their method is based on realized returns, however, causing a positive bias in performance measurement due to the disposition effect (Shefrin and Statman, 1985; Kaustia, 2010).

[5] For other papers on retail investor performance, see Barber *et al.*, 2009; Bauer, Cosemans, and Eichholtz, 2009; Ivkovic, Sialm, and Weisbenner, 2008; Coval, Hirshleifer, and Shumway, 2005; Ivkovic and Weisbenner, 2005; Barber and Odean, 2000, 2001; and Odean, 1998, 1999.

[6] Bergstresser *et al.* (2009) use aggregated holdings of mutual funds. Hackethal et al (2012) use data from 10,000 accounts over a 34-month period with an average account value of less than €13,000, which is unlikely to represent the whole portfolio of the investors in their sample. Bluethgen *et al.* (2008) use data from less than 4,500 accounts.

investors, for example, may be more inclined to seek advice (Hung and Yoong, 2010). If sophistication and portfolio performance are positively correlated, selection effects may understate the reported results. Evidence from an additional analysis of investors who switch from being self-directed to advised, however, indicates that the results (at least in part) reflect the effect of advisory intervention.

The remainder of this paper is organized as follows. Section 3.2 presents the potential costs and benefits of financial advice. After describing the data and summary statistics in Section 3.3, I present the methods and empirical results in Section 3.4 and 3.5. I provide my conclusions in Section 3.6.

3.2 Investment Advice and Individual Investor Performance

3.2.1 Potential Costs of Investment Advice

When professionals operate in an organizational setting, they are subject to agency relationships that induce incentive-based behaviors (Ross, 1973). The incentives for financial advisors often pertain to different financial concerns, such as producing commissions for their financial institution, generating a performance-based bonus, or enhancing the performance of investors' portfolios (Loonen, 2006). Several theoretical studies model behavioral responses to these incentives and predict that exploitation of unsophisticated clients may occur (Ottaviani, 2000; Krausz and Paroush, 2002; Inderst and Ottaviani, 2009; Stoughton *et al.*, 2011). Bergstresser *et al.* (2009) provide empirical evidence regarding conflicts of interest between brokers and their clients in the mutual funds market. Broker-sold funds underperform direct-sold funds (before costs). Zhao (2003) reports similar findings. Funds with higher loads tend to receive higher inflows.

Although research indicates that financial professionals tend to be less biased in some ways than laypeople (discussed in the next section), they may be more biased in some other fashion or, given the agency relationship discussed previously, may have an incentive to exacerbate their clients' biases. For example, overconfidence hurts returns (Odean, 1999), but correcting it may be difficult. Overconfidence likely reduces an investor's propensity to seek advice (Guiso and Japelli, 2006). Even when he or she hires an advisor, it is questionable whether that will help. Shapira and Venezia (2001) find more trading activity in professionally managed accounts, which they relate, among other issues, to a possible higher degree of overconfidence for the managed group. Glaser, Weber, and Langer (2010) document that although all participants are overconfident to some extent, financial professionals tend to be more overconfident than laypeople. Kaustia and Perttula (2011) also find overconfidence among a group of financial advisors and some positive effects from debiasing measures. In addition, Kaustia, Laukkanen, and Puttonen (2009) find strong framing effects among a group of financial advisors. Advisors relate higher risk to higher required returns, but to lower expected returns. Thus, while retail investors may suffer from misconceptions related to risk and return (De Bondt, 1998), advisors may not do much better.

Mullainathan *et al.* (2010) analyze whether advisors tend to debias their clients. They find that although advisors tend to match portfolios to client characteristics, they fail to debias their customers and, in some cases, even exacerbate client biases. That is, the authors find that advisors promote return chasing behavior, encourage holding of actively managed funds, and fail to discourage the holding of their own company stock. In general, advisors tend to support strategies that result in more transactions and higher fees. In addition, Karabulut (2011) indicates that advisors have no influence on stock market participation, but are associated with lower degrees of home bias and less turnover.

3.2.2. Potential Benefits of Investment Advice

Hackethal *et al.* (2012) indicate that economies of scale in portfolio management and information acquisition, as well as advisors' potentially better investment decision making abilities, may help investors improve portfolio performance. Stoughton *et al.* (2011) rationalize the use of financial advisors by noting that they facilitate small investor market participation by economizing on information costs. It seems likely that, on average, financial advisors are more financially sophisticated than individual investors in terms of investment experience, financial education, and financial knowledge, characteristics linked to improved decision making. Kaustia, Alho, and Puttonen (2008) report that financial market professionals are still biased in their return expectations, but less so than laypeople, while List (2003) finds that the degree of market experience is correlated with the degree of rationality in decision making. Feng and Seasholes (2005) support this finding by reporting that increased sophistication and trading experience are strongly related to the elimination of biased decision making. In addition, Dhar and Zhu (2006) document a negative correlation among financial literacy, trading experience, and the disposition effect. Shapira and Venezia (2001) report that professionally managed accounts exhibit less biased decision making (in terms of the disposition effect) than independent individual investors. These findings all indicate that education and experience reduce behavioral biases that hurt performance, though they may not entirely eliminate them. Finally, Loewenstein (2003) confirms that emotions may have a key impact on decision making, and experience is related to the level of these emotions, such that Lo and Repin (2002) observe significant differences in emotional responses between experienced and less experienced foreign exchange and derivatives dealers.

Beyond these potential benefits resulting from advisor experience, the legal setting provides advised investors some guarantee that financial transactions will fit their characteristics and financial situations. Dutch and EU regulations (in particular the MiFID) require advisors to make recommendations that fit well within an elaborate client profile, whereas for execution-only services, this client profile is much more limited and transactions do not need to be checked against the client profile.

3.2.3. Self-Selection of Investors into Advice Taking

In the sample for this study, investors decide whether to hire an advisor. Therefore, differences in behavior and performance between the groups cannot solely reflect the input of the advisor as any difference that emerges is a combined result of investor heterogeniety and advisor influence. Resolving this issue would require running an experiment that assigns participants randomly to an advised or self-directed investor group.[7] Hung and Yoong (2010) similarly implement a hypothetical choice experiment and find that investors with lower financial literacy are more likely to take advice and enjoy better investment performance suggesting a positive effect of advice. Furthermore, they find that older, more wealthy people are more likely to use advisors, but are also significantly less financially literate. The notion that less sophicated investors are more likely to take advice is consistent with the outcomes of theoretical models, such as those proposed by Stoughton *et al.* (2011), who predict that underperforming active funds sell only through financial advisors to unsophisticated investors and Inderst and Ottaviani (2009), who assume that naive clients do not rationally anticipate advisors' conflicts of interest. Both models imply that advisors mainly service less sophisticated investors.

Therefore, if advised investors are less sophisticated than self-directed investors, assuming that portfolio performance is a function of sophistication in the absence of an advisor, a direct comparison of the two groups would underestimate the added value of financial advice. In addition, Bergstresser *et al.* (2009) report that clients of brokers are slightly more risk averse. Bluethgen *et al.* (2008) also find that customers of a German retail bank are older, wealthier, and more risk averse. In this case, risk aversion likely leads to less risky portfolios for investors who take advice and, thus, to lower returns.

3.2.4. Account Size

This study compares the results of relatively large portfolios (values exceeding €25,000 or €100,000) with the results of the whole sample since the impact of advisors on portfolios may depend on the portfolios' size. Large portfolios provide a larger profit potential for the bank giving advisors incentive to pay more attention to them. Large portfolios may also contain more complex securities that require more advisory efforts. For example, a large number of (especially large) advised portfolios hold structured products. Alternatively, since portfolio size is often used as a proxy for sophistication (Anderson, 2008), small

[7] Other, more advanced econometric methods also provide ways to deal with self-selection bias. For example, the panel structure of the data set supports fixed- or random-effects regressions. However, the fixed-effects estimator needs time-varying data, which are largely absent from the study data set as few investors switch between groups. The random-effects model requires the stringent assumption of no correlation between unobserved individual effects and explanatory variables, which seems highly unlikely. For example, investment skill would need to be uncorrelated with gender or wealth. Instrumental variable regressions demand variables that correlate well with the choice of hiring an advisor and not with returns. As is the case for many empirical studies, these variables are unavailable. Thus, I am not confident that these methodologies solve the potential self-selection bias in this case, so I use this more qualitative approach. Note, however, that the analysis of switchers in Section 3.5 aims to identify causal effects of advisory intervention.

portfolios may deviate more from normative recommendations, which may lead to a greater advisory impact even when less attention is paid to it. In Section 3.5, I formally test the advisory impact on small and large portfolios.

3.3. Data

3.3.1. The Sample

The primary database comes from a medium-sized, full service retail and business bank that offers an array of financial products. The bank, which advertises itself as a relationship bank, offers services throughout the Netherlands through a network of bank branches, though it has a stronger presence in some regions of the country than others. Customers typically have an account manager who communicates all the financial services the bank offers. For investment advice, clients visit the investment department, although non-clients may also visit this department by making an appointment themselves. Some clients receive advice after they switch from execution-only services. Execution-only and advised investors of the bank receive service from different departments within the bank. Investors with an advisory relationship cannot trade through the execution-only department, nor can investors who use execution-only services trade with the help of an advisor.

During our sample period, all customers were eligible for advice; that is, smaller investors could access advisory services as well.[8] Although most banks require that a minimum amount of money be invested before a client is eligible for advisory services, this was not the case for the bank in this research during the sample period. Note that assignment to a specific advisor is random. Both new and existing investment clients are directed to an advisor depending on availability at the time. Advisors in the sample are paid fixed wages only, so they have no direct personal financial incentive to generate commissions, but career and prestige considerations are likely to play a role.

For all investment clients in the sample, I obtained both position and transaction files for a 52-month period from April 2003-August 2007. I use only the accounts of private investors with unrestricted accounts excluding any portfolios owned by a business, linked to mortgage loans, or part of a company savings plan[9]. Therefore, the final sample consists of 16,053 investors. To compare the results with those from other empirical studies, I also report results based on common equity holdings, which involves a sample of more than 6,100 investors. Accounts opened or closed during the sample period are included for the months in which they were active. This procedure partly solves possible survivorship bias. The overall trade file contains the following data fields: 1) account identifier, 2) transaction date, 3) security identification code, 4) transaction type, 5) quantity traded, 6) trade price, 7) currency, and 8) commission paid. The file consists of 535,543 transactions, with a

[8] The fifth percentile of the portfolio value distribution of advised customers was approximately €600.

[9] I make this selection because business may contain professional investors. Portfolios that are linked to a mortgage or part of a company savings plan are not freely accessible.

combined market value of €1.6 billion. Thirty percent of all trades are option trades.[10] The position file consists of 2,434,326 investor-security-month positions, which I aggregated into 654,036 monthly individual portfolio statements. The position file also includes information about the type of the client (execution-only or advised), gender, zip code, and date of birth. The six-digit zip code data (representing, on average, 15 households) from Statistics Netherlands (Centraal Bureau voor de Statistiek, 2006) provide information about residential property values and incomes. Specifically we use the average official property value for tax purposes (the so called "WOZ waarde") and the gross household income within each six-digit zip code data area.

To obtain an impression about the representativeness of my sample, I compare my sample with the investment portfolios of 1.5 million Dutch households with security investments using data from the Dutch Central Bank (DNB, 2006) in Table 3.I. According to average portfolio size and composition, it seems likely that my sample reasonably represents the average investor in the Netherlands. A 2007 survey (DNB, 2008) suggests that the investment portfolios in my sample represent a significant proportion of financial wealth for most households and cannot be considered a "play account" (Goetzmann and Kumar, 2008).[11] In addition, I compare the portfolios in my sample with samples from other empirical studies of individual investor behavior in the U.S., Germany, and the Netherlands (Dorn and Huberman, 2005; Barber and Odean, 2008; Bauer, Cosemans, and Eichholtz, 2009). This comparison reports many similarities in terms of trading style, portfolio composition, and sociodemographics.

Table 3.I: Comparison Investment Portfolio of Average Dutch with Current Sample

This table compares the asset allocations and values of the aggregate portfolio of Dutch households with current sample as of 2006.

	DNB Data	Own Research Sample
Equity allocation	54%	52%
Common Equity	37%	30%
o.w. Dutch	*75%*	*81%*
Equity Mutual Funds	17%	22%
Fixed Income allocation	25%	36%
Common bonds	18%	18%
o.w. Dutch	*56%*	*87%*
Bond Mutual Funds	7%	18%
Other allocation	21%	12%
Balanced funds	4%	0%
Structured Products	6%	6%
Other	11%	6%
Average Portfolio Size	€ 70.000	€ 65.376

[10] Bauer *et al.* (2009) report that almost 50% of the trades in their sample are option trades. Their data come from a Dutch online broker.

[11] Respondents reported gross assets of €233,000 on average, 20% (€ 47,000) of which was invested in financial assets.

3.3.2. Measuring Investor Portfolio Returns

In contrast with most empirical studies regarding investor performance, I take a broader perspective to consider all portfolio holdings[12] including mutual funds, bonds, and derivatives, and explicitly account for both the size and the timing of deposits and withdrawals including intramonth trades. For comparison, I provide a separate analysis of returns on common equity positions for the sample.

To calculate portfolio and common equity returns, I use the modified version of the Dietz measure (Dietz, 1968):

$$R_{it}^{gross} = \frac{MV_{it} - MV_{it-1} - \sum NC_{it}^{gross}}{MV_{it-1} + \sum w_{it} NC_{it}^{gross}}, \tag{3 .1}$$

$$R_{it}^{net} = \frac{MV_{it} - MV_{it-1} - \sum NC_{it}^{gross} - COSTS}{MV_{it-1} + \sum w_{it} NC_{it}^{gross}}, \tag{3.2}$$

where R_{it}^{gross} (R_{it}^{net}) is the gross (net) monthly return of investor *i* in month *t*, MV_{it} is the end-of-month market value of the investment (or common equity only) portfolio that investors have at our sample bank excluding the cash balance, NC_{it}^{gross} is the net contribution (deposits minus withdrawals) in month *t* before transaction costs, and w_{it} is the weight attributed to this net contribution. This weight is determined by the timing of the contributions. The earlier in the month a contribution takes place, the greater is the weight. Specifically, each contribution is weighted by the fraction of remaining days in the month of the contribution.

$COSTS_{it}$ refer to both transaction costs and custodial fees (including 19% VAT). Since I use market values in the calculations, I underestimate the actual costs as some market values are observed on an after-cost basis, such as mutual fund market values that are observed after the deduction of various fees (e.g., management fees). For withdrawals that result from a dividend payment, dividend withholding taxes are added back.[13] Bond transactions are net of accrued coupon interest. For every month that a portfolio holds a fixed income security, the coupon (recalculated on a monthly basis) is included in the transaction file. Monthly turnover is calculated by dividing all purchases and sales by the beginning of the month portfolio value. These calculations provide a sample of 604,831 investor-month portfolio return observations and 217,129 common equity return

[12] I do note however, that the cash balance on the investment account is not known.
[13] In the Netherlands, private investors can neutralize these withholdings in their income tax filings.

observations. Any missing values indicate investors who invest for less than the whole sample period of 52 months or the elimination of extreme outliers.[14]

The gross and net monthly returns of the average advised and self-directed investors in every month, for use in the time-series regressions, are calculated as follows:

$$\overline{R}_{ADVt}^{gross} = \frac{1}{N_{ADVt}} \sum_{i=1}^{N_{ADV_t}} R_{it}^{gross}, \quad \overline{R}_{SDt}^{gross} = \frac{1}{N_{SDt}} \sum_{i=1}^{N_{SD_t}} R_{it}^{gross}, \qquad (3.3a)\ (3.3b)$$

$$\overline{R}_{ADVt}^{net} = \frac{1}{N_{ADVt}} \sum_{i=1}^{N_{ADV_t}} R_{it}^{net}, \quad \overline{R}_{SDt}^{net} = \frac{1}{N_{SDt}} \sum_{i=1}^{N_{SD_t}} R_{it}^{net}, \qquad (3.4a)\ (3.4b)$$

where N_t is the total number of investors at time *t* and the subscripts *ADV* and *SD* denote advised and self-directed investors, respectively. Thus, I have four time-series of equally weighted returns that serve as the basis for the time-series analysis in Section 3.4.2. Fama (1998) strongly advocates the use of aggregate calendar time portfolios especially so when cross sectional dependence is likely. Given that many empirical researchers in the field of individual investor behavior follow this advice, we also employ a calendar time approach to ensure comparability.

3.3.3. Control Variables

Several variables may influence returns. Thus, this research includes the following controls: 1) gender, 2) age, 3) turnover, and 4) wealth (three wealth proxies: portfolio size, residential value, and income, the latter two observed at the six-digit zip code level). Barber and Odean (2001) find that men trade 45% more than women causing them to underperform by almost 1% per year. Korniotis and Kumar (2011) confirm that older, more experienced investors exhibit greater investment knowledge, but they seem to have poorer investment skills, perhaps due to cognitive aging. Portfolio turnover also may hurt net returns (Barber and Odean, 2000) such that the most active traders outperform in gross terms, but underperform in net terms (Bauer *et al.*, 2009). Finally, with regard to wealth, portfolio size is a widely used proxy for investor sophistication. Anderson (2008) reports a positive association between portfolio value and trading performance, and Bauer *et al.* (2009) indicate that large portfolios outperform small portfolios. However, Barber and Odean (2000) find no significant differentials between the largest and smallest portfolios. Moreover, Dhar and Zhu (2006) report that income, age, trading experience, and portfolio size are all negatively correlated with the disposition effect, a bias that lowers returns (Odean, 1998).

[14] I winsorize the return distribution at 1% and 99%.

3.4. Analysis and Results

3.4.1. Univariate Results

Table 3.II presents a comparison of investor and portfolio characteristics of advised and self-directed investors. According to Panel A, of the more than 16,000 investors in the sample, approximately 70% are registered with the advisory department for at least one month during the sample period.[15] For portfolios with a value exceeding €100,000, the percentage increases to more than 90%. The advised group contains more women (27% vs. 24% for self-directed investors) and joint accounts (40% vs. 36%). The average advised investor is somewhat older (56 vs. 52 years) and the portfolio size is considerably larger than for the self-directed group (€70,000 vs. € 15,000).

Panel B of Table 3.II further indicates that advised investors perform much worse in terms of gross and net raw portfolio returns. The results also indicate (see Panel D) that advised investors invest a considerably smaller fraction of their wealth in equity, which may explain their lower portfolio returns given the favorable market conditions for equity during the sample period. For equity-only portfolios, the net return differences are much smaller and better for advised investors in the largest portfolios. Return volatilities for both the whole and the equity portfolios are considerably smaller for advised portfolios.

The average portfolio turnover is 4.7% per month (Panel C, Table 3.II), less than the 6% reported by Barber and Odean (2000) and much less than the 9% and 24% reported for option and equity traders, respectively, by Bauer *et al.* (2009). This result likely occurs because the other samples are from Internet brokerage firms, whereas my sample includes investors who use full service or telephone-based, execution-only brokerage services. Although advised investors execute almost twice as many trades (0.27 vs. 0.14 per month), they are less active in terms of turnover (4.4% vs. 5.5% per month). Since advised portfolios are generally better diversified, changes require more trades. Furthermore, there is great heterogeneity in trading activity: 45% of the investors never trade and the 1% of the most active investors turn their portfolio over approximately 1.5 times annually.[16]

Panel D of Table 3.II contains the asset allocations indicating large differences in the asset mixes of average advised and self-directed investors. For both groups, equity and bonds represent the main assets (approximately 85% of portfolio value), while advised investors have less risky portfolios. Their asset mix consists of less than 50% equity, whereas self-directed portfolios allocate almost 70% to this asset class.[17]

[15] This 70% represents the investors who were advised during the whole sample period as well as the investors that switched from or to receiving advice.
[16] These details do not appear in Table 3.II, but were derived from additional analyses of the underlying data.
[17] The whole portfolio of self-directed investors may not be observable given the average portfolio size of approximately €15,000, whereas the average portfolio size in the Netherlands is approximately €70,000 (see Table 3.I). Thus, these figures may be biased.

Table 3.II. Characteristics, Performance, Trades, and Portfolios (Related to Portfolio Size) of Individual Investors

This table presents descriptives of household and portfolio characteristics split across all households and households with beginning-of-the-month portfolio values exceeding €25,000 and €100,000. Advised is the percentage of households that receive advice at least once during the sample period. Woman is the percentage of accounts held by a woman only. Joint Account is the percentage of portfolios held by two people. Age is the age of the primary account holder. Account Value is the beginning of the month account value. Residential Value is the home value, while Income is the gross monthly household income, both of which are measured at the six-digit zip code level. Gross and Net Portfolio and Equity Returns (in %) are the cross-sectional averages of the time-series average returns of each individual investor calculated using the modified version of Dietz (1968). Portfolio and Equity Volatility are cross-sectional averages of standard deviations of the time-series of returns calculated according to individual portfolios with at least 24 return observations. Turnover is the sum of buys and sells divided by the beginning of the month account value. (Derivative) Trades are the average number of (derivative) buys and sells per month. Equity, Fixed Income, Real Estate, Structured, Mix, and Mutual Funds refer to fractions of the total account value of specific asset classes. Equity refers to both individual stock holdings ("direct holdings") and equity mutual funds ("fund holdings"), Fixed Income to individual bonds and bond funds, Real Estate to real estate funds, Structured to structured products, and Mix to mix funds. Derivative is the percentage of portfolios that held options at least once during the sample period. Common Equity Positions are the number of common equity positions in each portfolio.***, **, * denote significance at the 1 percent, 5 percent, and 10 percent levels, respectively.

	All Households				Household Portfolio at least € 25,000				Household Portfolio at least € 100,000			
	All	Advised (ADV)	Self Directed (SD)	Difference ADV-SD	All	Advised (ADV)	Self Directed (SD)	Difference ADV-SD	All	Advised (ADV)	Self Directed (SD)	Difference ADV-SD
Panel A: Characteristics:												
Advised (%)	70%				84%				93%			
Woman (%)	25,6%	26,7%	23,7%	3.0%***	25,1%	25,4%	25,1%	0,2%	25,1%	25,1%	23,7%	1,5%
Joint Account (%)	39,2%	40,0%	36,0%	4.0%***	43,0%	43,5%	38,8%	4.7%**	41,5%	42,0%	37,6%	4,4%
Age (years)	55,0	56,4	51,7	4.7***	61,7	61,6	62,0	-0,4	63,9	63,7	67,3	-3.59**
Account Value (€)	52.468	69.364	15.101	54.263***	148.431	163.575	65.559	98,016***	319.754	327.917	181.999	145,917***
Residential Value (€)	139.809	140.715	137.577	3,138***	154.879	155.790	149.128	6,662*	172.840	172.845	172.764	81
Income (€)	2.099	2.100	2.096	3	2.222	2.232	2.158	73**	2.383	2.382	2.402	-20
Panel B: Monthy raw return and risk												
Gross portfolio return (%)	0,70	0,62	0,89	-0.27***	0,70	0,67	0,89	-0.22***	0,75	0,74	0,87	-0,12
Net portfolio return (%)	0,62	0,56	0,80	-0.24***	0,64	0,61	0,84	-0.23***	0,69	0,68	0,83	-0.15*
Gross equity return (%)	1,78	1,79	1,75	0,05	1,66	1,66	1,68	-0,02	1,65	1,66	1,58	0,08
Net equity return (%)	1,45	1,43	1,49	-0,06	1,51	1,49	1,59	-0,10	1,57	1,58	1,55	0,03
Volatiltiy portfolio returns (%)	2,54	2,27	3,21	-0.94***	2,19	2,10	2,81	-0.72***	2,16	2,12	2,96	-0.84***
Volatiltiy equity returns (%)	5,10	4,92	5,38	-0.46***	4,33	4,27	4,67	-0.41***	3,92	3,88	4,39	-0.51***

Table 3.II. Characteristics, Performance, Trades, and Portfolios (Related to Portfolio Size) of Individual Investors (Continued)

	All Households				Household Portfolio at least € 25,000				Household Portfolio at least € 100,000			
	All	Advised (ADV)	Self Directed (SD)	Difference ADV-SD	All	Advised (ADV)	Self Directed (SD)	Difference ADV-SD	All	Advised (ADV)	Self Directed (SD)	Difference ADV-SD
Panel C: Monthly Trading Activity												
Turnover (%)	4,70	4,36	5,48	-1.12***	5,21	5,25	5,08	0.17	5,98	6,03	5,15	0.88
Trades (#)	0,23	0,27	0,14	0.13***	0,54	0,57	0,37	0.20***	0,99	1,02	0,66	0.36
Derivative trades (#)	0,07	0,08	0,04	0.04***	0,16	0,17	0,13	0.04	0,32	0,32	0,34	-0.02
Panel D: Portfolio Composition												
Equity (%)	54,9%	47,9%	68,3%	-20.4%***	47,3%	44,3%	60,1%	-15.8%***	49,7%	48,5%	61,1%	-12.6%***
Of which direct holdings (% of equity)	46,1%	37,5%	60,4%	-22.8%***	46,5%	43,2%	68,2%	-25.0***	48,3%	46,8%	80,4%	-33.6%***
Of which fund holdings (% of equity)	53,9%	62,5%	39,6%	22.8%***	53,5%	56,8%	31,8%	25.0***	51,7%	53,2%	19,6%	33.6%***
Fixed Income (%)	30,7%	36,1%	20,0%	16.1%***	38,9%	40,6%	32,5%	8.1%***	35,7%	36,5%	30,6%	5.8%*
Real Estate (%)	2,3%	3,0%	0,8%	2.2%***	5,3%	6,0%	2,0%	4.0%***	6,3%	6,4%	3,7%	2.7%**
Structured (%)	7,5%	8,5%	5,8%	2.7%***	6,1%	6,7%	2,7%	4.0%***	6,8%	7,2%	1,3%	5.9%***
Mix (%)	3,0%	3,4%	2,3%	1.2%***	2,2%	2,2%	2,1%	0,1%	1,1%	1,1%	1,7%	-0,7%
Mutual Funds (%)	61,0%	66,1%	48,5%	17.7%***	52,9%	54,5%	42,9%	11.6%***	43,9%	44,7%	29,1%	15.5%***
Derivative (% of portfolios)	4,9%	4,5%	6,0%	-1.5%***	9,0%	8,4%	11,9%	-3.5%**	12,8%	12,5%	14,8%	-2.2%
Structured products (% of portfolios)	23,1%	28,0%	12,3%	15.7%***	41,3%	45,3%	17,7%	27.6%***	60,1%	62,9%	21,5%	41.4%***
Common equity positions (#)	4,40	5,16	3,26	1.90***	6,83	7,12	5,65	1.47***	8,83	8,91	7,86	1,05
Portfolios (#)	16.053				5.120				1.867			

For larger portfolios (exceeding €100,000), the average equity allocation drops to almost 50% and the difference between advised and self-directed portfolios becomes smaller. The average number of common equity positions is 4.4, but it is higher for advised portfolios (5.3 vs. 3.3), although this difference is mainly due to the higher average portfolio size of advised investors.[18] Larger portfolios hold more common equity positions (almost nine for portfolios over €100,000). Well diversified portfolios may also be obtained by means of mutual funds. In advised portfolios, 66% of wealth is allocated to mutual funds, whereas self-directed investors allocate 48%. Similarly, fund allocation in equity exposure is 63% for advised investors, considerably more than that for self-directed investors (40%). Additionally, less advised investors own options (4.5% vs. 6%). Of the portfolios with average values greater than €100,000, almost 13% contain options. Although structured products are much less important than equity and fixed income in terms of value, the number of portfolios holding structured products is considerable (23%) and much more prevalent for advised portfolios (28%) than for self-directed portfolios (12%), especially for larger portfolios. This difference may be an indication that banks are pushing these products to exploit uninformed investors (Benet, Giannetti, and Pissaris, 2006; Henderson and Pearson, 2011).

3.4.2 Time-Series Analysis of Returns

To analyze risk-adjusted return differences, I calculate the alphas of a long-short portfolio, long on the aggregate equally weighted portfolio of advised investors and short on the aggregate equally weighted portfolio of self-directed investors. As Seasholes and Zhu (2010) note, forming portfolios creates a single time series that is free from cross-sectional correlation. In addition, since advisors may have an incentive to devote most of their attention to larger clients, it might be that the effect of advice is more pronounced for large clients. Therefore, I also create portfolios based on various account sizes.

The regression of the monthly common equity return differences uses a three-factor model developed by Fama and French (1993) to correct for different style tilts in the portfolios. I also regress monthly portfolio return differences using a six-factor model that, beyond the three Fama-French factors, features variations in portfolio characteristics (Bauer *et al.*, 2009). I use the following model to calculate differences in alphas for the overall investor portfolio:

$$R_{ADV_t}^{gross} - R_{SD_t}^{gross} = \alpha + \beta_1 (R_{mt} - R_{ft}) + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 BOND_t + \beta_5 CALL_t + \beta_6 PUT_t + \varepsilon_t, \tag{3.5}$$

And I estimate the alpha differences in the equity portfolio as follows:

$$R_{ADV_t}^{gross} - R_{SD_t}^{gross} = \alpha + \beta_1 (R_{mt} - R_{ft}) + \beta_2 SMB_t + \beta_3 HML_t + \varepsilon_t, \tag{3.6}$$

[18] For further analysis on this issue, see Table 3.VI.

In these models, R^{gross}_{ADVt} and R^{gross}_{SDt} are the average equally weighted gross returns for the advised and self-directed portfolio in month *t*, respectively, as calculated in Equations (3.3a), and (3.3b). We perform identical regressions using net returns as calculated in (3.4a), and (3.4b) (see Section 3.3.2). $R_{mt} - R_{ft}$ is the return on the MSCI Netherlands index in month *t* in excess of the three-month Euribor. SMB_t is the return on a zero investment factor mimicking the portfolio for size. HML_t is the return on a zero investment factor mimicking the portfolio for value and $BOND_t$ is the excess return on the Iboxx 10-year Dutch Government Index. These return series have been obtained from Datastream. As in Agarwal and Naik (2004), $CALL_t$ (PUT_t) is a return series, based on data obtained from NYSE-Euronext, generated by a buying two month at the money index call (put) option at the end of each month and selling it again at the end of the following month. The procedure repeats every month, generating a time-series of 52 monthly returns. To avoid multicollinearity problems, both $CALL_t$ and PUT_t factors are orthogonalized on the R_{mt} factor. The computation of standard errors follows the Newey-West (1987) correction and takes into account autocorrelation up to three lags.

The results in Panel A of Table 3.III indicate that, as expected from the average asset mix and the favorable stock market in the sample period, the average aggregated portfolio of advised investors underperforms the average self-directed portfolio by a significant margin in terms of raw returns. For the whole sample, the difference in gross returns is 0.25% per month (3% per year), similar to the findings in Table 3.II. For larger portfolios, this return difference is smaller, but still considerable. Moreover, the risk-adjusted return (alpha) differences indicate that although a negative sign dominates the various alphas, the hypothesis of no return differentials between advised and self-directed portfolios cannot be rejected. Panel B of Table 3.III reports that many of the risk exposures across the various specifications are quite similar, while advised investors expose themselves to less market risk over the entire portfolio, consistent with the lower equity exposure of this group. For both groups, the market betas are quite low[19], with values of approximately 0.8 for the equity portfolios. Investors in this sample apparently prefer low beta stocks. Indicative of this finding is that the two most widely held stocks, in terms of both value and number of portfolios, have market betas of 0.5 and 0.4, respectively, during the sample period.

[19] This finding cannot be derived from this table, but is based on additional analysis of the underlying data.

Table 3.III. Investment Performance of Advised vs. Self -Directed Investors

This table presents return differences (in %) and factor loadings of advised and self-directed portfolios. Panel A reports the raw and risk-adjusted gross and net returns differences of a portfolio that is long on the aggregate equally weighted advised portfolio and short on the aggregate equally weighted self-directed portfolio. Households are classified as advised (self-directed) if they were advised (self-directed) during the whole period of the sample of 52 months. Risk-adjusted monthly portfolio (equity) returns are calculated from a six-factor (three-factor) accounting for both the three Fama-French (1993) factors *(Market, SMB,* and *HML)* and three additional factors. *Bond* is the excess return on the Iboxx 10-year Dutch Government Index. *Call (Put)* is a return series generated by buying at two months at the money index call (put) option (see the section on methodology). Panel B provides the estimated factor loadings difference of these three (six) factors based on the portfolios of advised and self-directed investors. The results are expressed in percentages for all households and households with portfolio values exceeding €25,000 and €100,000. t-statistics which are based on standard errors that are computed in line with the Newey-West (1987) correction, taking into account autocorrelation up to three lags, are in parentheses. ***, **, * denote significance at the 1 percent, 5 percent, and 10 percent levels, respectively.

	Aggregate, equally weighted portfolios of:											
	All Households				Household Portfolio at least € 25,000				Household Portfolio at least € 100,000			
	Whole Portfolio		Equity only		Whole Portfolio		Equity only		Whole Portfolio		Equity only	
	Gross Returns	Net Returns	Gross Returns	Net Returns	Gross Returns	Net Returns	Gross Returns	Net Returns	Gross Returns	Net Returns	Gross Returns	Net Returns
	Panel A: Return Differences											
Raw return	-0.25	-0.23	0.01	0.02	-0.14	-0.15	-0.03	-0.1	-0.11	-0.12	-0.02	-0.09
	(-0.79)	(-0.72)	(0.02)	(0.04)	(-0.48)	(-0.49)	(-0.05)	(-0.17)	(-0.33)	(-0.38)	(-0.04)	(-0.16)
Alpha	-0.07	-0.05	-0.04	-0.03	-0.00	-0.01	-0.02	-0.07	0.04	0.03	-0.05	-0.11
	(-1.35)	(-0.99)	(-0.46)	(-0.32)	(-0.15)	(-0.30)	(-0.28)	(-0.86)	(0.65)	(0.39)	(-0.69)	(-1.11)
	Panel B: Factor Loadings											
Market	-0.12***	-0.11***	0.04*	0.03*	-0.09***	-0.09***	-0.01	-0.02	-0.10**	-0.10**	0.02	0.01
	(-7.23)	(-6.92)	(1.88)	(1.89)	(-4.57)	(-4.60)	(-0.42)	(-0.82)	(-2.45)	(-2.46)	(0.80)	(0.30)
SMB	-0.02	-0.02	-0.05	-0.05	-0.01	-0.01	-0.08***	-0.08***	0.02	0.01	-0.04*	-0.05*
	(-1.42)	(-1.37)	(-1.53)	(-1.51)	(-1.52)	(-1.51)	(-3.57)	(-3.33)	(0.75)	(0.64)	(-1.74)	(-1.77)
HML	-0.00	-0.00	-0.04	-0.04	0.03*	0.03*	-0.04***	-0.03**	0.09***	0.09***	0.00	0.01
	(-0.25)	(-0.23)	(-1.11)	(-1.09)	(1.86)	(1.87)	(-3.05)	(-2.25)	(3.08)	(3.11)	(0.08)	(0.33)
Bond	0.04	0.05			0.03	0.03			0.03	0.03		
	(1.33)	(1.37)			(0.95)	(1.00)			(0.38)	(0.41)		
Call	-0.00***	-0.00***			-0.00***	-0.00***			-0.00***	-0.00***		
	(-3.52)	(-3.55)			(-4.10)	(-4.31)			(-2.74)	(-2.83)		
Put	0.00	0.00			0.00	0.00			0.00	0.00		
	(1.42)	(1.41)			(0.71)	(0.68)			(0.04)	(0.02)		
R^2	70%	70%	15%	14%	65%	65%	34%	24%	40%	40%	8%	6%

3.4.3 Cross-Sectional Analysis of Returns

The analysis of risk- and style-adjusted performance indicates no differences between the advised and self-directed investor groups. The previous section treated advised and self-directed investors as a homogeneous group, but as Table 3.II reports, large cross-sectional differences between advised and self-directed investors exist in terms of investor characteristics and portfolio compositions, which are known determinants of investor performance (Section 3.3.3). Therefore, to be able to estimate the coefficient for advice taking, I need to control for these return determinants to avoid a potential omitted variables bias. Specifically, I applied the cross-sectional methodology developed by Fama and MacBeth (1973)[20], which Petersen (2009) indicates provides unbiased statistical inferences when cross-sectional correlation is present.[21] Specifically, the Fama and MacBeth (1973) procedure assumes $\mathrm{cov}(\varepsilon_{it}, \varepsilon_{it-1}) = 0$ and $\mathrm{cov}(\varepsilon_{it}, \varepsilon_{jt}) \neq 0$.

For each month, I ran the following cross-sectional regression for returns generated by the whole portfolio:

$$\begin{aligned} R_{it} &= \alpha_{0t} + \beta_{1t} Advice_{it} + \beta_{2t} Woman_{it} + \beta_{3t} Joint_{it} + \beta_{4t} Age_{it} + \beta_{5t} ln(Value)_{it} + \\ &\beta_{6t} ln(Turnover)_{it} + \beta_{7t} ln(Residential\,Value)_{it} + \beta_{8t} ln(Income)_{it} + \beta_{9t} Equity_{it} + \\ &\beta_{10t} FixedIncome_{it} + \beta_{11t} RealEstate_{it} + \beta_{12t} Structured_{it} + \beta_{13t} Mix_{it} + \beta_{14t} Derivative_{it} + \varepsilon_{it} \end{aligned} \quad , (3.7)$$

and the following regression on common equity returns:

$$\begin{aligned} R_{it} &= \alpha_{0t} + \beta_{1t} Advice_{it} + \beta_{2t} Woman_{it} + \beta_{3t} Joint_{it} + \beta_{4t} Age_{it} + \beta_{5t} ln(Value)_{it} + \\ &\beta_{6t} ln(Turnover)_{it} + \beta_{7t} ln(Residential\,Value)_{it} + \beta_{8t} ln(Income)_{it} + \varepsilon_{it} \end{aligned} \quad , \quad (3.8)$$

The Fama-MacBeth (1973) estimators reported in table 3.IV are calculated as time-series averages of the monthly cross-sectional parameter estimates, as follows:

$$\beta_{FM} = \sum_{t=1}^{T} \frac{\beta_t}{T} \quad (3.9)$$

while the estimated variance of the Fama-MacBeth estimate is calculated as

$$S^2(\beta_{FM}) = \frac{1}{T} \sum_{t=1}^{T} \frac{(\beta_t - \beta_{FM})^2}{T-1} \quad , \quad (3.10)$$

[20] Specifically, I employ the Stata routine "XTFMB" developed by D. Hoechle (version: 2.0.0, 2011).

[21] To test whether this technique is appropriate, I follow Petersen's (2009) advice and compare White standard errors with time-clustered or investor-clustered standard errors. Standard errors are indeed affected when I cluster by time, implying that cross-sectional dependence is present. For standard errors clustered by investor, they rise only fractionally and are well within the margins of Factors 3 and 4, which Petersen (2009) indicates as problematic. This implies that the Fama-MacBeth (1973) procedure is justified here.

As noted before, Petersen (2009) indicates that this procedure is only valid when an individual effect is absent in the data. As indicated in footnote 21, this assumption seems warranted.

In equations 3.6 and 3.7, R_{it} denotes the gross or net portfolio or equity return in excess of the three-month Euribor for investor *i* in month *t*. $Advice_{it}$ (the main variable of interest) is a dummy variable equal to one for investors with an advisor in the relevant month and zero otherwise. $Woman_{it}$ is a dummy variable equal to one if the portfolio is held by a woman and zero otherwise. $Joint_{it}$ is a dummy variable equal to one if the portfolio is held by two people (usually a married couple) and zero otherwise. Age_{it} is the age of the primary account holder in month *t*, while $Value_{it}$ is the beginning of the month portfolio market value in month *t* [or equity value of the portfolio for Equation (3.7)]. $Turnover_{it}$ is the sum of all purchases and sells in month *t* divided by the beginning of the month portfolio value (or, for Equation (3.7), the sum of all equity buys and sells divided by the beginning of the month equity portfolio value). $Residential\ Value_{it}$ and $Income_{it}$ are the average house value and average gross monthly household income, respectively, based on averages of the six-digit zip code of the area in which the investor lives.

Since the portfolios differ remarkably in terms of asset allocation, it is necessary to control for these differences. Therefore, I use the fractions of the total account value allocated to a specific asset class as a percentage of the total monthly portfolio as an additional control when estimating the cross-sectional regressions on the whole investor portfolio. $Equity_{it}$ refers to both individual stock holdings and equity mutual funds, $Fixed\ Income_{it}$ indicates individual bonds and bond funds, $Real\ Estate_{it}$ refers to real estate funds, $Stuctured_{it}$ is structured products, Mix_{it} involves balanced funds, and $Derivative_{it}$ is a dummy variable equal to one if the account holds derivatives (mainly options) in that month.

To assess the robustness of the results, I performed similar analyses for the first and second subperiods in the sample. Specifically, I ran regressions based on the first and second 26 months of the sample. Since the overall sample period can be characterized as a bull market, I also performed separate analyses for the months when equity markets showed negative returns[22], providing an indication as to whether the results hold in more adverse market periods. This approach seems appropriate considering the large fraction of inert investors who probably did not change their portfolio behavior dramatically, even during the recent economic crisis.

The most important finding from the regression results in Table 3.IV is that the coefficient for the *Advice* dummy, that is sometimes positive, but mostly negative, almost never differs statistically from zero at conventional confidence levels.

[22] I used the MSCI Netherlands index to determine when equity markets were in decline.

Table 3.IV. Cross-Sectional Differences Portfolio Performance

This table presents coefficient estimates on various Fama-MacBeth (1973) regressions on investor and portfolio characteristics. The left-hand side of the table uses portfolio returns (in %) as dependent variables, and the right-hand side refers to common equity returns (in %). Both gross (column 1 and 7) and net returns (all other columns) are used. The full sample covers all 52 months from April 2003-August 2007, and Sub 1 (2) refers to the first (second) 26 months of this period. Downward market refers to all months in which the MCSI-Netherlands had a negative excess return and >€25,000 to portfolios with beginning of the month account values greater than €25,000. The dependent variables are various investor and portfolio characteristics. *Advice* is a dummy variable equal to one if an advisor is used. *Woman* is a dummy equal to one if the account was held by a woman. *Joint Account* is a dummy variable equal to one if the account was held by two people. *Age* is the age of the primary account holder. *Value (ln)* is the logarithm of the beginning of the month account value. *Turnover (ln)* is the common logarithm of the sum of buys and sells divided by the beginning of the month account value. *Residential Value (ln)* is the home value and *Income (ln)* is the gross monthly household income, both of which are measured at the six-digit zip code level. *Equity, Fixed Income, Real Estate, Structured, and Mix* refer to fractions of specific asset classes of the total account value at the beginning of each month. *Equity* refers to both individual stock holdings and equity mutual funds, *Fixed Income* to individual bonds and bond funds, *Real Estate* to real estate funds, *Structured* to structured products, and Mix to balanced funds. *Derivative* is a dummy variable equal to one if the account held options or turbos. t-statistics are in parentheses. ***, **, * denote significance at the 1 percent, 5 percent, and 10 percent levels, respectively.

	Whole Portfolio						Equity only					
	Gross	Net					Gross	Net				
	Full	Full	Downward market	Sub 1	Sub 2	> €25,000	Full	Full	Downward market	Sub 1	Sub 2	> €25,000
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Advice	-0.07	-0.07	0.01	-0.03	-0.10	0.18	0.04	0.01	-0.00	0.13	-0.12	-0.03
	(-1.63)	(-1.58)	(0.11)	(-0.58)	(-1.51)	(1.19)	(0.63)	(0.13)	(-0.04)	(1.53)	(-1.42)	(-0.37)
Woman	-0.02	-0.01	0.02	-0.01	-0.01	0.01	-0.00	-0.01	0.06	0.05	-0.07	-0.07
	(-0.79)	(-0.65)	(0.71)	(-0.38)	(-0.57)	(0.25)	(-0.03)	(-0.16)	(0.57)	(0.32)	(-0.80)	(-0.77)
Joint Account	-0.00	0.00	0.01	-0.00	0.01	-0.07	0.04	0.04	-0.12**	0.06	0.01	0.00
	(-0.21)	(0.06)	(0.53)	(-0.21)	(0.37)	(-1.22)	(1.20)	(0.98)	(-2.36)	(0.94)	(0.35)	(0.10)
Age	0.00**	0.00*	-0.00	0.00	0.00*	0.00	0.00**	0.00**	0.01**	0.00	0.00**	0.00
	(2.26)	(1.90)	(-0.57)	(1.14)	(1.76)	(0.10)	(2.22)	(2.15)	(2.59)	(1.05)	(2.22)	(0.70)
Value (ln)	0.09*	0.12**	-0.01	0.16**	0.08	0.22	-0.09	0.02	-0.20	0.11	-0.06	-0.02
	(1.75)	(2.34)	(-0.12)	(2.52)	(0.98)	(1.22)	(-0.85)	(0.24)	(-1.22)	(0.63)	(-0.52)	(-0.30)
Turnover (ln)	0.26***	-0.13**	-0.20*	-0.19*	-0.07	-0.15**	0.38***	-0.31**	-0.42*	-0.38	-0.24**	-0.29**
	(3.98)	(-2.11)	(-1.88)	(-1.78)	(-1.14)	(-2.37)	(3.06)	(-2.47)	(-1.95)	(-1.65)	(-2.24)	(-2.38)
Residental value (ln)	0.09	0.09	0.02	0.17	0.02	-0.27	0.03	0.06	0.05	0.05	0.06	0.13
	(1.46)	(1.44)	(0.48)	(1.39)	(0.40)	(-0.84)	(0.35)	(0.64)	(0.49)	(0.34)	(0.71)	(1.12)
Income (ln)	-0.01	0.00	0.02	0.03	-0.03	-0.06	0.17	0.16	0.13	0.49	-0.17	-0.26
	(-0.28)	(0.00)	(0.35)	(0.37)	(-0.50)	(-0.93)	(0.73)	(0.71)	(0.74)	(1.14)	(-1.38)	(-1.47)

Table 3.IV. Cross-Sectional Differences Portfolio Performance (Continued)

	Whole Portfolio						Equity only					
	Gross	Net					Gross	Net				
	Full	Full	Downward market	Sub 1	Sub 2	> €25,000	Full	Full	Downward market	Sub 1	Sub 2	> €25,000
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Equity	0.75	0.95**	-1.49*	1.13*	0.77	0.95***						
	(1.67)	(2.08)	(-1.90)	(1.86)	(1.11)	(2.87)						
Fixed Income	-0.47	-0.24	0.29	0.19	-0.68	-0.35						
	(-1.08)	(-0.57)	(0.36)	(0.38)	(-1.00)	(-1.06)						
Real Estate	-0.01	0.23	0.12	0.90	-0.44	0.11						
	(-0.03)	(0.48)	(0.15)	(1.26)	(-0.67)	(0.27)						
Structured	0.01	0.22	-0.83	0.21	0.23	0.10						
	(0.03)	(0.55)	(-1.15)	(0.42)	(0.36)	(0.38)						
Mix	-0.18	0.01	-0.57	0.36	-0.35	-0.19						
	(-0.44)	(0.02)	(-0.80)	(0.73)	(-0.52)	(-0.41)						
Derivative	0.19*	0.15	-0.32**	0.01	0.29**	0.17						
	(1.90)	(1.55)	(-2.24)	(0.07)	(2.13)	(1.47)						
Intercept	-0.06	-0.44	-0.22	-1.09*	0.21	-0.01	1.13	0.61	-1.80	-0.80	2.02**	2.11**
	(-0.12)	(-0.88)	(-0.26)	(-1.84)	(0.26)	(-0.02)	(1.09)	(0.60)	(-1.54)	(-0.44)	(2.20)	(2.33)
R^2	24.8%	24.6%	23.3%	22.7%	26.6%	29.9%	3.2%	3.2%	2.7%	4.0%	2.3%	5.3%
NxT	573,592	573,592	180,586	277,975	295,617	208,705	200,581	200,581	62,674	100,732	99,849	66,905

Some coefficients do approach significance though, such as the whole portfolio returns during the entire sample period (Columns 1 and 2, negative by 7 basis points) and the equity returns in the first half of the sample period (Column 10, positive by 13 basis points). Overall, however, this analysis does not reveal any clear or robust pattern of out or underperformance. As such, the advised investors do not seem to be performing any better or worse than self-directed individual investors.

Furthermore, in contrast with Barber and Odean's (2001) finding, women do not outperform men and trading activity has a positive impact on gross portfolio and equity returns (Bauer *et al.*, 2009). Apparently, trades are motivated by some informational advantage. However, taking trading costs into consideration makes this advantage disappear. Turnover significantly influences net returns adversely, in line with Barber and Odean (2000).

Of the asset allocation variables, two coefficients are particularly noteworthy. First, equity exposure almost always contributes significantly to returns [e.g., positive for the whole sample period (Columns 1 and 2) and negative in adverse market conditions (Column 3)]. Additionally, derivatives add to the returns for the entire sample period (Column 1), but hurt returns when equity markets fall (Column 3). This finding is intuitive. Most of the derivative traders in the sample buy call options, but this is contradictory to Bauer *et al.* (2009), who indicate that options traders lose the most in bull markets.

3.4.4 Cross-Sectional Analysis of Risk

Retail portfolios tend to be under diversified opposing the insights from portfolio theory. Goetzmann and Kumar (2008) indicate that most individual investors hold few stocks in their portfolios. And, they often select stocks with similar volatilities, thereby exposing themselves to more avoidable risk (Dorn and Huberman, 2010). Table 3.I already reported that risk in advised portfolios is lower than that in self-directed portfolios. In this section, a more rigorous analysis of this finding provides insight into the association between advisors and both total and idiosyncratic risk.

Total risk refers to the standard deviation of net monthly portfolio returns for investors with at least 24 monthly returns observations and has been calculated as follows:

$$\sigma_i = \sqrt{\frac{\left(R_{it}^{net} - \overline{R_i^{net}}\right)^2}{n_i - 1}} \quad if\, n_i \geq 24, \tag{3.11}$$

The calculation of idiosyncratic risk relies on the regressions on the returns in a three-factor (equity portfolio) and six-factor (whole portfolio) model. I do not apply these models on the average portfolio, as previously, but instead use the time-series of returns for each individual portfolio, as follows:

$$R_{it}^{net} = \alpha_i + \beta_{i1}(R_{mt} - R_{ft}) + \beta_{i2}SMB_t + \beta_{i3}HML_t + \beta_{i4}BOND_t + \beta_{i5}CALL_t + \beta_{i6}PUT_t + \varepsilon_{it}, \quad (3.12)$$

$$R_{it}^{net} = \alpha_i + \beta_{i1}(R_{mt} - R_{ft}) + \beta_{i2}SMB_t + \beta_{i3}HML_t + \varepsilon_{it}, \quad (3.13)$$

Please refer to section 3.4.2 for an explanation of the factors used in these models. The idiosyncratic risk measures for each individual portfolio is calculated as the standard deviation of the return residuals (ε_{it}) from regressions 3.12 and 3.13.

Table 3.V presents the results. Panel A provides the comparison of the averages between the two groups. Advised portfolios are associated with lower total and diversifiable risk for both the total and equity-only portfolios. For the total risk measure, this finding should not be surprising. Advised portfolios have less equity in their total portfolio and more equity positions in their equity portfolio, both of which reduce volatility. The lower idiosyncratic risk for advised portfolios means better diversification, but it is necessary to take differences in investor characteristics into consideration as well. I apply a single cross-sectional regression of the various risk measures to the time-series averages of the same investor characteristics discussed in Section IIIC. Panel B of Table 3.V indicates that for the whole portfolio, *Advice* is associated with lower total and lower idiosyncratic risk when controlling for observed investor heterogeneity. Residual volatility is 0.53 percentage points lower for advised portfolios, which is considerable, noting the average standard deviation of monthly return residuals of approximately 2%.[23] The equity-only portfolio reveals no significant differences between the two groups for the sample of all households, but those with values exceeding €25,000 are associated with less risk.[24] These findings imply that although advisors are not associated with higher returns, they may guide investors in their asset allocation decisions to lower avoidable risk.

3.4.5 Cross-Sectional Analysis of Asset Allocation

The findings in the previous section indicate that advice is associated with less risk. Since nonsystematic risk is a function of diversification, which in turn is a function of the number of securities and their return correlations, it is worthwhile to examine the diversification and asset allocation decisions of the investors in the sample more closely. Many studies indicate widespread under diversification in retail portfolios, but they are limited as they consider only common equity, even though many households use mutual funds as an effective and easy way to diversify. Polkovnichenko (2005) reports that many households simultaneously invest in well diversified portfolios of mutual funds and undiversified portfolios of individual stock. Goetzmann and Kumar (2008) report that this under diversification is a function of investor sophistication and related to behavioral biases.

[23] Obtained from additional analysis of the underlying data set.
[24] Given that return observations are cross-sectionally dependent (see n. 21) t-statistics in Table 3.V may be somewhat inflated. Therefore, especially when t-statistics are small, inference is less certain.

Table 3.V. Cross-Sectional Differences in Risk

This table presents averages (Panel A) and coefficient estimates (Panel B) of risk on various cross-sectional differences between investors. Risk is measured as the standard deviation of the net portfolio and equity returns ("Total risk") and the standard deviation of residuals obtained from regressing each individual net portfolio and equity return time series on the three- and six-factor models 3.12 and 3.13 ("Idiosyncratic Risk"). The left-hand side of the table uses all portfolios, while the right-hand side refers to portfolios with values greater than €25,000. In Columns 1, 2, 5, and 6, the dependent variable is the risk of the whole portfolio. The other columns refer to common equity risk. Risk is only calculated when portfolios have at least 24 return observations. The dependent variables are various investor characteristics. *Advice* is a dummy variable equal to one if an investor is used. *Woman* is a dummy equal to one if the account was held by a woman. *Joint Account* is a dummy variable equal to one if the account was held by two people. *Age* is the age of the primary account holder. *Value (ln)* is the logarithm of the beginning of the month account value. *Turnover (ln)* is the common logarithm of the sum of buys and sells divided by the beginning of the month account value. *Residential Value (ln)* is the home value and *Income (ln)* is the gross monthly household income, both of which are measured at the six-digit zip code level. Robust t-statistics are in parentheses. ***, **, * denote significance at the 1 percent, 5 percent, and 10 percent levels, respectively.

	All Households				Household Portfolio at least € 25,000			
	Whole Portfolio		Equity Only		Whole Portfolio		Equity Only	
	Total risk	Ideo-syncratic risk	Total risk	Ideo-syncratic risk	Total risk	Ideo-syncratic risk	Total risk	Ideo-syncratic risk
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Averages								
Advised	2.27%	1.59%	4.84%	3.55%	2.10%	1.37%	4.24%	2.87%
Self-Directed	3.21%	2.31%	5.29%	4.08%	2.81%	1.94%	4.66%	3.33%
Difference	-0.94%***	-0.72%***	-0.45%***	-0.53***	-0.72***	-0.57***	-0.43***	-0.46***
Panel B: Regressions								
Advice	-0.73***	-0.53***	0.01	-0.02	-0.74***	-0.53***	-0.26***	-0.29***
	(-21.18)	(-19.71)	(0.14)	(-0.42)	(-10.06)	(-10.21)	(-3.26)	(-3.32)
Woman	-0.19***	-0.12***	-0.06	-0.05	-0.19***	-0.08**	-0.06	0.08
	(-5.57)	(-4.81)	(-0.98)	(-0.88)	(-3.68)	(-2.38)	(-0.79)	(0.88)
Joint Account	0.03	0.00	-0.08	-0.17***	-0.14***	-0.09***	-0.02	-0.07
	(0.95)	(0.16)	(-1.64)	(-3.53)	(-2.80)	(-2.89)	(-0.28)	(-0.90)
Age	-0.00***	0.00**	0.01***	0.01***	-0.00**	0.00	0.00	0.01***
	(-2.73)	(2.24)	(4.41)	(5.10)	(-2.06)	(1.09)	(0.68)	(2.66)
Value (ln)	-0.61***	-0.55***	-1.09***	-1.19***	-0.36***	-0.42***	-0.86***	-0.94***
	(-25.41)	(-29.67)	(-26.82)	(-32.57)	(-6.51)	(-10.92)	(-11.73)	(-11.60)
Turnover (ln)	3.11***	2.08***	1.98***	1.84***	2.43***	1.62***	1.29***	1.49***
	(24.31)	(21.23)	(12.44)	(11.61)	(15.79)	(13.70)	(6.63)	(7.23)
Residental value (ln)	0.52***	0.29***	0.27*	0.27*	0.38***	0.12	0.02	0.05
	(5.51)	(3.95)	(1.81)	(1.82)	(2.90)	(1.41)	(0.12)	(0.25)
Income (ln)	0.09	-0.02	-0.24	-0.13	0.03	0.04	-0.31	-0.16
	(0.64)	(-0.16)	(-1.08)	(-0.59)	(0.16)	(0.29)	(-1.09)	(-0.49)
Intercept	4.12***	3.71***	9.10***	7.91***	3.65***	3.37***	9.43***	7.54***
	(10.82)	(12.60)	(15.69)	(13.68)	(6.58)	(9.22)	(11.75)	(8.51)
R^2	21.5%	21.9%	25.7%	31.1%	16.6%	18.0%	17.0%	17.0%
N	9,728	9,728	3,293	3,293	3,372	3,372	1,055	1,055

If advice introduces more sophistication into a portfolio, better diversification should emerge in advised portfolios. Specifically, I use specification 3.14, based on pooled OLS using investor clustered standard errors and time dummies.

$$W_{it} = \alpha_{0t} + \beta_{1t}Advice_{it} + \beta_{2t}Woman_{it} + \beta_{3t}Joint_{it} + \beta_{4t}Age_{it} + \beta_{5t}ln(Value)_{it} + \beta_{6t}ln(Turnover)_{it} + \beta_{7t}ln(Residential\,Value)_{it} + \beta_{8t}ln(Income)_{it} + \varepsilon_{it} \quad , \tag{3.14}$$

In this specification W_{it} is the fraction of the portfolio that investor i allocated to a specific asset class at the beginning of month t. Specifically, this analysis uses the fraction of equity, the fraction of mutual funds (in both the whole and the equity-only portfolios), the allocation to index funds, and the allocation to domestic equity. W_{it} may also refer to the number of different asset classes, and the number of common stocks. In addition, I investigate whether advisors tend to push customers into mutual funds managed by their own banks, by using the relative allocation to own bank funds. Although banks sell their own products, advisors may recommend other mutual funds as well. Therefore, the fraction of own bank funds may be an indication of the use of mutual funds for the benefit of the bank rather than the investor. Table 3.VI contains the results.[25]

The advised portfolios are associated with better diversification for almost all proxies (Panel A): more mutual funds, more index funds, less domestic equity, more asset classes, and more common equity positions. In Panel B, controlling for investor characteristics, the results largely remain the same in sign and magnitude. Advised portfolios are associated with a 21% higher allocation to mutual funds and a 26% increase in the mutual fund portion within the equity allocation. Mutual funds provide investors with an easy way to diversify, but advisors may also be tempted to push mutual funds that provide maximal benefits to themselves, perhaps through kickback fees (Stoughton *et al.*, 2011). The data cannot confirm the latter interpretation, but in advised portfolios, a large fraction of the mutual fund holdings is allocated to funds managed by the bank that provided the data. However, this trend is even more evident among self-directed portfolios (Columns 4 and 5, Table 3.VI). Therefore, these mutual funds seem to provide both the advisor and its client with benefits, even though better alternatives may be available to the client (e.g., index funds, which are almost absent in the allocation, Column 6). Home bias is much less pronounced in advised portfolios, largely driven by the higher allocation to mutual funds with typical a greater international exposure. Advised portfolios are also associated with a higher number of asset classes. The number of common equity positions is marginally lower for advised portfolios, but not significantly so. For portfolios higher than €25,000 and €100,000, the results are generally quite similar in sign and magnitude. Overall, it seems safe to conclude that advised portfolios achieve better diversification which largely drive the lower idiosyncratic risk in Table 3.V.

[25] A similar analysis, as described in n. 21, indicates that both serial correlation and cross-correlation are present and that serial correlation has the greatest impact on standard errors. Therefore, I follow Petersen's (2009) advice and report results based on pooled ordinary least squares estimates with standard errors clustered by investor and the inclusion of time dummies in all specifications.

Table 3.VI. Cross-Sectional Differences in Asset Allocation

This table presents averages (Panel A) and pooled ordinary least squares estimates (Panels B, C, and D) of various asset allocation decisions on cross-sectional differences between investors. The dependent variables are calculated (at the beginning of each month) as follows: Column 1: the value of all equity (including equity mutual funds) holdings divided by the portfolio value; Column 2: the value of all mutual funds divided by the total portfolio value; Column 3: the value of all equity mutual funds divided by the value of all equity holdings; Column 4: the value of the equity funds managed by the "own" bank divided by the value of all equity mutual funds; Column 5: the same as Column 4, but for the bond funds of the bank,; Column 6: the value of index equity funds divided by the value of all equity funds; Column 7: the value of the equity holdings listed in the Netherlands by the value of all equity; Column 8: the number of asset classes (defined as equity, bonds, real estate, derivatives, and structured products); and Column 9: the number of common equity positions. *Advice* is a dummy variable equal to one if an investor is advised. *Woman* is a dummy variable equal to one if the account was held by a woman. *Joint Account* is a dummy variable equal to one if the account was held by two people. *Age* is the age of the primary account holder. *Value (ln)* is the logarithm of the beginning of the month account value. *Turnover (ln)* is the logarithm of the sum of buys and sells divided by the beginning of the month account value. *Residential Value (ln)* is the home value and *Income (ln)* is the gross monthly household income. The last two control variables are determined at the six-digit zip code level. Panels C and D present, for larger portfolios, only the coefficients on the advice dummy and not the controls. All specifications include time dummies. t-statistics (based on investor clustered standard errors) are in parentheses. ***, **, * denote significance at the 1 percent, 5 percent, and 10 percent levels, respectively.

	Equity Allocation as fraction of Total Portfolio	Mutual Fund Allocation as fraction of Total Portfolio	Equity Mutual Fund Allocation as fraction of Total Equity Allocation	Own Bank Equity Fund Allocation in fraction of All Equity Funds	Own Bank Bond Fund Allocation in fraction of All Bond Funds	Equity Index Fund Allocation as fraction of All Equity Funds	Home Bias: Dutch Equity Allocation in fraction of All Equity	Number of Asset Classes	Number of Individual Common Equity Positions
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
				Panel A: Averages					
Advised	0.48	0.66	0.62	0.58	0.81	0.01	0.35	1.54	5.25
Self Directed	0.68	0.48	0.40	0.74	0.91	0.00	0.56	1.16	3.16
Difference	-0.20***	0.18***	0.23***	-0.16***	-0.10***	0.00**	-0.21***	0.38***	2.09***
				Panel B: All Households					
Advice	-0.16***	0.21***	0.26***	-0.02	-0.03***	0.00***	-0.24***	0.14***	0.15
	(-19.89)	(22.97)	(25.06)	(-1.21)	(-2.72)	(2.79)	(-23.80)	(14.32)	(1.52)
Woman	-0.06***	0.07***	0.07***	-0.02	-0.02	-0.00	-0.06***	-0.04***	-0.77***
	(-6.12)	(7.11)	(5.56)	(-1.23)	(-1.45)	(-1.06)	(-4.90)	(-3.06)	(-5.02)
Joint Account	0.01	-0.01	-0.00	-0.02	0.01	0.00	0.01	0.01	-0.07
	(1.11)	(-1.47)	(-0.29)	(-1.44)	(0.65)	(0.22)	(0.84)	(0.51)	(-0.49)
Age	-0.00***	0.00	-0.00***	0.00***	0.00***	-0.00	0.00***	-0.00***	-0.01***
	(-16.48)	(1.39)	(-6.60)	(7.67)	(4.76)	(-1.41)	(5.82)	(-10.85)	(-4.38)
Value (ln)	-0.09***	-0.06***	-0.04***	-0.25***	-0.12***	0.00***	0.05***	0.54***	2.61***
	(-18.99)	(-10.39)	(-5.73)	(-31.26)	(-14.53)	(3.10)	(7.67)	(58.04)	(30.14)
Turnover (ln)	0.05***	-0.13***	-0.11***	-0.11***	-0.04***	0.00***	0.09***	0.16***	0.50***
	(13.70)	(-34.19)	(-26.75)	(-20.22)	(-8.92)	(3.07)	(22.41)	(19.04)	(5.84)

Table 3.VI. Cross-Sectional Differences in Asset Allocation (Continued)

Residental value (ln)	0.21***	-0.19***	-0.12***	-0.20***	-0.12***	0.00	0.08***	0.02	0.52
	(8.30)	(-6.81)	(-3.60)	(-5.82)	(-4.22)	(1.05)	(2.66)	(0.53)	(1.25)
Income (ln)	0.12***	-0.08**	-0.01	-0.15***	-0.11**	0.02	0.01	0.20***	0.87
	(3.23)	(-2.01)	(-0.26)	(-2.94)	(-2.35)	(1.45)	(0.15)	(3.33)	(1.47)
Intercept	0.42***	1.41***	0.99***	2.52***	1.91***	-0.08**	0.03	-1.28***	-10.40***
	(4.23)	(13.25)	(7.98)	(18.59)	(14.92)	(-2.22)	(0.27)	(-7.85)	(-6.55)
R^2	14.6%	8.4%	9.7%	24.5%	8.6%	0.8%	8.8%	32.0%	28.3%
Panel C: Household Portfolio at least €25,000									
Advice	-0.20***	0.18***	0.28***	-0.12***	-0.05**	0.01**	-0.26***	0.34***	-0.56**
	(-11.32)	(9.33)	(13.01)	(-3.89)	(-2.15)	(2.15)	(-12.15)	(10.28)	(-1.96)
R^2	8.3%	11.4%	9.8%	22.8%	12.6%	1.1%	8.4%	25.4%	22.1%
Panel D: Household Portfolio at least €100,000									
Advice	-0.19***	0.18***	0.34***	-0.04	-0.03	0.00	-0.32***	0.83***	0.02
	(-4.36)	(4.23)	(7.86)	(-0.60)	(-0.51)	(0.23)	(-7.42)	(10.30)	(0.03)
R^2	3.8%	6.9%	12.0%	13.3%	12.5%	1.2%	10.9%	15.0%	17.9%

3.4.6 Timing Returns

No evidence thus far suggests better characteristics or risk-adjusted returns for advised portfolios. However, the added value of advisors might appear in the form of changes to asset allocations that enable investors to benefit from future market movements, rather than stock selection.

To assess whether advised portfolios exhibit better timing ability in their asset allocation decisions, I calculate the returns of various portfolios using passive index returns (R_t), similar to Bergstresser *et al.* (2009), as follows:

$$R_t = \sum_{i=1}^{I} \sum_{j=1}^{5} \left[R_{jt} \times W_{jit} \times \frac{Value_{it}}{\sum_{i=1}^{I} Value_{it}} \right], \qquad R_t = \sum_{i=1}^{I} \sum_{j=1}^{5} \left[R_{jt} \times W_{jit} \times \frac{1}{I} \right], \qquad (3.15)\ (3.16)$$

in which R_{jt} is the return of a return index of asset class j (defined below) at month t, W_{jit} is the relative allocation to asset class j of investor i, $Value_{it}$ is the beginning of the month portfolio value of investor i.

I create these portfolio returns using both changing allocation weights based on actual asset allocation weights at the beginning of each month ("Monthly Rebalancing"), and also based on actual allocations in the first month an investor becomes active ("Fixed Allocation Weights"; W_{jit} contains then only cross sectional variation). These asset allocation weights are calculated on both a value-weighted (as in specification 3.15) and an equal-weighted (as in specification 3.16) basis. Asset class j refers to the following five asset classes, where I specify the specific total return index that has been used between brackets: 1) domestic equity [*MSCI Netherlands*], 2) foreign equity [*MSCI World*], 3) domestic bonds [*IBOXX 10 year Dutch Government Index*], 4) foreign bonds [*City Group World Government Non Euro Bond Index 10 year*], and 5) real estate [*AEX Real Estate Index*]. These asset classes represent 87% and 89% of advised and self-directed portfolios, respectively. Other asset classes, such as structured products and balanced funds, cannot be tied unambiguously to an index and, therefore, are not included.

Consistent with the previous results, the findings in Table 3.VII indicate that excess returns of advised investors are considerably lower due to lower equity exposure in favorable equity market conditions. The risk-adjusted returns, based on Sharpe ratios, again reveal few differences between the two groups. In addition, when I compare the returns of the fixed asset allocation with the monthly rebalancing strategy, timing seems to add marginally to the value-weighted return of both groups. However, because volatilities also tend to rise, Sharpe ratios are practically unaffected. Overall, this evidence suggests that tactical asset allocation does not add to the risk-adjusted return for both groups.[26]

Table 3.VII. Comparison of Timing Returns

This table compares timing skills of advised and self-directed investors. Average actual allocation weights in April 2003 ("Fixed Allocation Weights") and average actual allocation weights at the beginning of each month ("Monthly Rebalancing") are applied to passive index returns. Both value and equally weighted allocation weights are used. ADV refers to advised portfolios, while SD refers to self-directed portfolios. The following asset classes are taken into consideration: 1) domestic equity, 2) foreign equity, 3) domestic bonds, 4) foreign bonds, and 5) real estate. Excess return refers to the return above the three-month Euribor.

	Fixed Allocation Weights				Monthly Rebalancing			
	Value weighted		Equally weighted		Value weighted		Equally weighted	
	ADV	SD	ADV	SD	ADV	SD	ADV	SD
Mean excess return per month	0.84%	0.98%	0.90%	1.11%	0.88%	1.04%	0.88%	1.12%
Standard deviation of monthly excess return	1.47%	1.73%	1.56%	1.96%	1.55%	1.88%	1.55%	2.00%
Sharpe ratio	0.57	0.57	0.58	0.56	0.57	0.55	0.57	0.56

3.5. Self-Directed Investors Who Switched to Advice

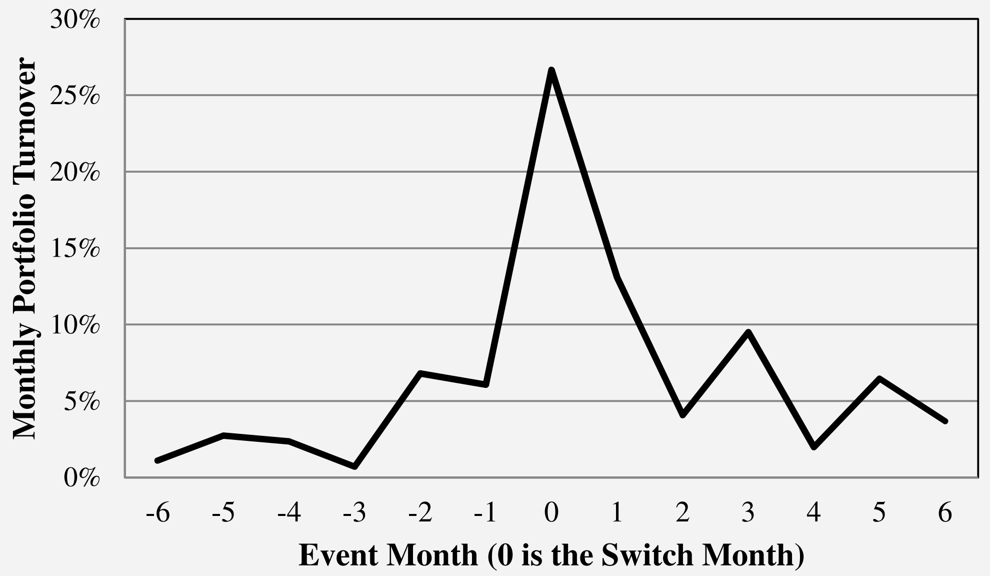
Thus far, the analysis has compared two groups of investors, those who received investment advice and those who did not. In Section 3.2.3., I emphasized that any differences between these two groups are the combined result of both investor heterogeneity and advisory intervention. In this section, I formally test whether advisors influence portfolio decision making. To this end, I use the group of 228 investors in the data set who switched from being self-directed to being advised (hereinafter, I refer to these investors as switchers). The first investors switched in June 2003 and the last in July 2007. Thus, the sample period is 48 months.

To influence portfolio outcomes, an advisor must propose changes to a portfolio. Therefore, I first analyze portfolio turnover around the date of switch. Figure 3.I depicts the average portfolio turnover of switchers during the 12-month event window surrounding the switch month. As this graph illustrates, significant changes occur in the month of and just after the switch. Cumulative mean portfolio turnover in Month 0-3 is

[26] I confirm this conclusion by performing another analysis on the basis of flows (the results are available upon request). This analysis reveals that the aggregate monthly equity buy-sell imbalance (calculated as in Barber and Odean, 2008) is not correlated with leading equity markets returns, implying no forecasting skills. However, aggregate monthly equity buy-sell imbalance is positively, though moderately, correlated with lagged stock market returns for both groups of investors (but more so for self-directed investors), implying some return chasing.

more than 50%. The majority of this turnover is caused by reallocation within the existing portfolio.[27] Investors also bring in more capital: One month after switching, the average portfolio size of switchers increased by approximately €7,000 more than the matched control group.

Figure 3.I: Portfolio Turnover around Switch Month



I then analyze the changes that occur in the portfolio after the switch to an advisor. I compare the same portfolio allocations of switchers analyzed in Table 3.VI just prior to and after the switch. Following Barber and Odean (2002), who analyze individual portfolio behavior before and after going online, I employ a matched-pair research design. That is, I match each of the 228 switchers to a self-directed investor who does not switch. This matching occurs in the month preceding the switch by means of a propensity score. The propensity score is the probability of switching and is calculated by regressing a switch dummy (one for switchers and zero otherwise) on several key investor (gender, age, residential value, and income) and portfolio (portfolio value and equity allocation) variables. I use the propensity score of the non-switching self-directed investor who is closest to the propensity score of the switcher in the month preceding the switch as the

[27] Approximately 40 percentage points of the 50% turnover is based on reallocation. Since I calculate turnover as the sum of buys and sells in a particular month divided by the beginning of the month portfolio value, on average, 20% of the value of a portfolio is reallocated within three months after the switch.

matched control.[28] Table 3.VIII, comparing switchers with their matched controls, indicates the effectiveness of this matching.

Table 3.VIII. Descriptives of Investors Who Switched to Advice

This table presents descriptive statistics for 228 investors who switched from being self-directed to being advised ("switchers") and a control group of 228 self-directed investors who did not switch ("matched controls"). This control group was selected according to the nearest-neighbor propensity score in the month preceding the switch. *Woman* is the percentage of accounts held by a woman only. *Joint Account* is the percentage of portfolios held by two people. *Age* is the age of the primary account holder. *Account value* is the beginning of the month account value. *Residential Value* is the home value and *Income* is the gross monthly household income, both of which are measured at the six-digit zip code level. *Equity Allocation* refers to the percentage of total account value invested in equity.

	Switchers	Matched Controls
Investors (#)	228	228
Woman (%)	25.0%	21.5%
Joint Account (%)	46.1%	36.4%
Age (years)	57.2	57.3
Account Value (€)	64,433	55,217
Residential Value (* €1.000)	132.9	135.7
Income (€)	2,077.9	2,021.3
Equity allocation (%)	51.8%	50.2%

The main analysis is on the changes in differences in asset allocation between switchers and their matched controls from the pre-switch month (t = –1) to the post-switch month (*t* = 1 and *t* = 3). Table 3.IX presents the results. For insight into the question whether advisors have more influence on large investors because they put more effort into large portfolios than on small investors who make more investment mistakes, I also split the sample into groups of larger and smaller investors according to the median portfolio value in the pre-switch month.

As Table 3.IX illustrates, large asset allocation changes occur for switchers. In line with the results in Table 3.VII, advisors tend to recommend lower equity exposure, more mutual funds, less own bank equity funds, less domestic equity, and more asset classes. As an example of the changes that occur because of advisory intervention, Table 3.IX (Column 3 of Panel A) reports that in the pre-switch month, switchers allocate 5.2% less to mutual funds within their equity exposure than their matched peers. Two months later (at *t* = 1), the difference changes by 5.7%, implying that switchers now have 0.5% higher exposure to equity mutual funds. Another two months later (at *t* = 3), the difference

[28] I use the nearest-neighbor algorithm by employing the Stata module psmatch2 from Leuven and Sianesi (2003).

Table 3.IX. Differences in Asset Allocation Before and After Taking Advice

This table presents asset allocation differences between 228 investors who switched from being self-directed to being advised ("Switchers" or "SW") and a control group of 228 self-directed investors who did not switch ("Matched Controls" or "MC") before and after the switch. This control group was selected according to the nearest-neighbor propensity score in the month before the switch. Portfolio compositions are compared with the pre-switch month (t = –1) for various months after the switch (t = 1 and t = 3). In Panel A, the results for all investors are presented, while in Panel B (C), the sample is restricted to investors with below- (above-) median portfolio value in the pre-switch month. The following portfolio allocations are presented: Column 1: the value of all equity (including equity mutual funds) holdings divided by the portfolio value; Column 2: the value of all mutual funds divided by the total portfolio value; Column 3: the value of all equity mutual funds divided by the value of all equity holdings; Column 4: the value of the equity funds managed by the "own" bank divided by the value of all equity mutual funds; Column 5: the same as Column 4, but for the bond funds of the bank; Column 6: the value of index equity funds divided by the value of all equity funds; Column 7: the value of the equity holdings listed in the Netherlands by the value of all equity; Column 8: the number of asset classes (defined as equity, bonds, real estate, derivatives, and structured products); and Column 9: the number of common equity positions. Significance of changes in differences between switchers and matched controls is based on a paired sample t-statistic (two-sided). ***, **, * denote significance at the 1 percent, 5 percent, and 10 percent levels, respectively.

	Equity allocation as % of total portfolio	Mutual fund allocation as % of total portfolio	Equity mutual fund allocation as % of total equity allocation	Own bank equity fund allocation in % of all equity funds	Own bank bond fund allocation in % of all bond funds	Equity index fund allocation as % of all equity funds	Home bias: Dutch equity allocation in % of all equity	Number of asset classes	Number of individual common equity positions
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: All Switchers									
Switchers (pre switch: t=-1)	51.8%	58.5%	50.7%	77.5%	90.8%	0.0%	48.1%	1.46	5.05
Matched Controls (pre switch: t=-1)	50.2%	62.8%	55.9%	81.1%	91.6%	0.0%	43.6%	1.26	4.96
SW-MC (pre switch: t=-1)	1.7%	-4.3%	-5.2%	-3.6%	-0.7%	0.0%	4.5%	0.20	0.09
Change in SW-MC (t=1 - t=-1)	-2.1%**	3.8%**	5.7%**	-5.4%**	2.6%	0.0%	-6.2%***	0.10***	0.00
Change in SW-MC (t=3 - t=-1)	-2.8%**	6.0%***	8.9%***	-5.0%**	3.8%*	0.0%	-9.4%***	0.19***	-0.13
Panel B: Small Switchers									
Switchers (pre switch: t=-1)	60.3%	60.5%	58.8%	91.6%	98.9%	0.0%	40.8%	1.12	3.14
Matched Controls (pre switch: t=-1)	57.8%	63.7%	61.2%	90.7%	92.0%	0.0%	38.5%	1.15	3.93
SW-MC (pre switch: t=-1)	2.6%	-3.2%	-2.5%	1.0%	6.9%	0.0%	2.3%	-0.03	-0.79
Change in SW-MC (t=1 - t=-1)	-3.2%*	3.7%*	4.9%	-6.2%*	0.0%	0.0%	-5.5%*	0.09**	0.38
Change in SW-MC (t=3 - t=-1)	-5.5%***	5.3%**	7.5%**	-5.4%*	0.0%	0.0%	-8.1%***	0.13**	0.40
Panel C: Large Switchers									
Switchers (pre switch: t=-1)	43.5%	56.5%	40.1%	53.6%	85.0%	0.0%	57.6%	1.79	6.90
Matched Controls (pre switch: t=-1)	42.7%	61.9%	48.9%	65.0%	91.3%	0.0%	50.2%	1.37	5.97
SW-MC (pre switch: t=-1)	0.8%	-5.4%	-8.8%	-11.4%	-6.3%	0.0%	7.3%	0.42	0.93
Change in SW-MC (t=1 - t=-1)	-0.9%	3.9%*	6.8%**	-4.0%	4.5%	0.0%	-7.1%**	0.12**	-0.35
Change in SW-MC (t=3 - t=-1)	0.2%	6.6%**	10.8%***	-4.4%	6.6%*	0.0%	- 10.9%***	0.25***	-0.56*

changes by 8.9%, implying a 3.7% higher equity fund allocation. In general, switchers' asset allocations change in the direction of the allocations of all advised investors reported in Table 3.VI. These results demonstrate that in line with Bluethgen et al.'s (2008) findings, advisors have a significant influence on investors' asset allocations and direct their clients to better diversified portfolios. Panels B and C of Table 3.IX report the results for smaller and larger investors. For small portfolios, advisors recommend less risky portfolios because of their negative impact on equity exposure (Panel B, Column 1). Larger portfolios already contain considerably less equity. Thus, advisors have no need to make further changes. For the other asset allocation decisions, the largest changes occur in the large portfolios (see Panel C, Columns 2, 3, 5, 7, 8, and 9). Although advisors tend to reduce small portfolios' exposure to own bank equity funds (Panel B, Column 4), they increase large portfolios' exposure to the own bank bond funds (Panel C, Column 5). In general, the allocation to own bank funds remains large.

In the final step, I analyze whether the observed changes in portfolio composition due to advisory intervention have any measurable impact on risk and return. I employ the same methodology as that of Barber and Odean (2002) and compare the returns earned by investors who already switched with those who had not yet switched during the same months. Since the first investors switched in June 2003 and the last in July 2007, I calculate a return series for 48 months. I regress the monthly return differences on the same factors as those in Models 4 and 5.[29] Table 3.X presents the results of this analysis. Gross and net monthly portfolio returns are 27 and 25 basis points lower for the investors who already switched. Differences in alphas are also negative, but much smaller and not significant reinforcing the conclusion that advisors do not enhance or reduce risk-adjusted returns. The factor loadings of Columns 1 and 2 in Table 3.X indicate a significant decrease in the exposure to the market factor of 0.15 after investors switched to advice. This finding is consistent with the notion that advisors lower the equity exposure in a portfolio and increase the fixed income allocation. Within the equity-only portfolio, no significant changes in factor loading are observed from pre- to post-advice seeking behavior (see Columns 3 and 4 of Table 3.X).

3.6. Conclusion

This paper provides detailed insights into the differences between advised and self-directed investors and their portfolios and provides evidence of the added value of financial advice. Although I find significant differences in the characteristics of advised and self-directed investors, these differences are quite small in general. Differences in portfolio composition are more noteworthy. Advised portfolios contain significantly less equity and more fixed income securities in line with previous findings that retail investors who seek advice are typically more risk averse.

[29] This is a return series from a long portfolio in which switchers already switched and a short portfolio in which switchers did not yet switch.

Table 3.X: Performance of Investors Who Switched to Advice vs. Investors Who Did Not Yet Switch to Advice (But Do So Before August 2007)

This table presents raw and risk-adjusted net returns (Panel A) and factor loadings (Panel B) of the aggregate equally weighted portfolios of (previously) self-directed investors who already switched to advice and the aggregate equally weighted portfolios of self-directed investors who did not yet switch to advice, but did so before August 2007. The first investors (of 228) switched in June 2003 and the last investors switched in July 2007, providing a time series of 48 months. Risk-adjusted monthly portfolio (equity) returns (in %) are calculated from a six-factor (three-factor) model accounting for both the three Fama-French (1993) factors (*Market, SMB, and HML*) and the three additional factors for portfolio returns. *Bond* is the excess return on the Iboxx 10-year Dutch Government Index. *Call (Put)* is a return series generated by buying at two months at the money index call (put) option (see the section on methodology). Standard errors are computed in line with the Newey-West (1987) correction taking into account autocorrelation up to three lags. The results are expressed in percentages. t-statistics are in parentheses. ***, **, * denote significance at the 1 percent, 5 percent, and 10 percent levels, respectively.

	Whole Portfolio return			Equity only return		
	Investors Not Yet Advised (NYA)	Investors Already Advised (AA)	Difference (AA-NYA)	Investors Not Yet Advised (NYA)	Investors Already Advised (AA)	Difference (AA-NYA)
	(1)	(2)	(3)	(4)	(5)	(6)
			Panel A: Returns			
Raw return	0.72	0.47	-0.25	1.20	1.09	-0,12
			(-0.83)			(-0.18)
Alpha	0.08	0.03	-0.05	-0.06	-0.18	-0.14
	(0.51)	(0.81)	(-0.37)	(-0.21)	(-0.68)	(-0.62)
			Panel B: Factor Loadings			
Market	0.38***	0.23***	-0.15***	0.79***	0.80***	0.01
	(13.21)	(5.97)	(-6.00)	(7.01)	(7.17)	(0.24)
SMB	0.11***	0.08*	-0.02	0.29***	0.28***	-0.01
	(5.60)	(1.98)	(-0.62)	(5.32)	(5.53)	(-0.22)
HML	0.01	-0.03	-0.04	0.05	0.03	-0.02
	(0.15)	(-0.45)	(-0.88)	(0.56)	(0.39)	(-0.29)
Bond	0.14***	0.27***	0.13			
	(2.74)	(2.81)	(1.42)			
Call	0.01***	0.01***	0.00			
	(4.18)	(2.98)	(0.46)			
Put	-0.00**	-0.01**	-0.00			
	(-2.57)	(-2.58)	(-1.55)			

Analyses of aggregate style-adjusted returns, cross-sectional assessments of returns, and returns based on timing skills indicate that the two groups perform similarly. Also, comparing portfolio returns before and after advice seeking indicates no return effects of advisory intervention. Although, generally, professionals are associated with better portfolio performance than retail investors, it is possible that conflicts of interest eliminate that benefit. The large fraction of advised investors holding structured products may be an indication that this is indeed the case.

In terms of diversification, advised portfolios perform much better than self-directed portfolios, thus reducing avoidable risk. Advised portfolios are associated with more mutual funds, less domestic equity, and more asset classes. Additional analyses on investors who switch to advice taking confirm that advisors positively affect diversification. Therefore, the reduction of idiosyncratic risk observed in advised portfolios can (at least in part) be attributed to advisory intervention.

It is widely known that retail investors make suboptimal portfolio decisions. Although advisors are sometimes subject to similarly biased decision making or have incentives to exacerbate their clients' biases, this paper confirms that advisors do add positive value. They improve portfolio diversification.

Chapter 4

Performance of Advised vs. Self-Directed Investors Controlling for Self-Selection[1]

4.1. Introduction

Most retail investors rely on financial advisors to improve their portfolio investment decisions,[2] such that financial planning and advice represent big business, worth $44 billion in U.S. revenues alone and employing more than 240,000 people (Ibisworld, 2011[3]). Understanding the role and impact of financial advisors thus is of utmost importance, yet little empirical research addresses this topic. Moreover, existing research offers rather negative assessments of the relevance of financial advisors. Some authors find *potential* positive effects (e.g., List, 2003; Feng and Seasholes, 2005; Bhattacharya *et al.*, 2012; Kramer, 2012), but a long list of research indicates that financial advisors do more harm than good (e.g., Hackethal, Haliassos, and Jappelli, 2012; Bergstresser, Chalmers, and Tufano, 2009; Zhao, 2003). In theoretical work, Stoughton, Wu, and Zechner (2010) and Inderst and Ottavianni (2009) show that opaque commission structures, in combination with naïve customers, produce biased, bad advice. The negative impacts of advisors may thus arise due to biased advice, caused by fee structures that lead to moral hazard.

In addition, we argue that the overly negative picture of advisors reflects the failure of most existing studies to control for the endogeneity of the decision to use financial advisors. In this case, self-selection bias is likely, because investors choose to take advice or not. These selection concerns can seriously bias estimates of the impact of an advisor, and ignoring selection problems probably leads to underestimates of the true impact of advisors, because their advice tends to be solicited primarily by less sophisticated investors. Two recent experimental studies provide us with some guidance on this issue.

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[1] This chapter has been co-authored with Robert Lensink. The joint paper has been submitted for publication under a different title, notably: "The Impact of Financial Advisors on the Stock Portfolios of Retail Investors".

[2] In the Netherlands—our research domain—approximately 51% of households with an investment portfolio rely on financial advice (Millward Brown, 2010); in the United States, ICI (2010) reports that 81% of mutual fund–owning households rely on a financial advisor. Bluethgen *et al.* (2008) also find that roughly 80% of individual investors in Germany rely on financial advice for investment decisions, and Hung *et al.* (2008) discover that 75% of investors participating in a U.S. survey consulted a financial advisor before conducting stock market or mutual fund transactions.

[3] http://www.ibisworld.com/industry/default.aspx?indid=1316

Bhattacharya *et al.* (2012) offered 8,200 execution-only investors the option to receive free and unbiased advice in a financial advice choice experiment, and showed that investors that followed the advice improved their portfolio efficiency. Also in a laboratory choice experiment, Hung and Yoong (2010) find that participants who choose to follow the investment advice improved their investment performance.

Randomized experiments have the obvious advantage to control for unobserved heterogeniety. Unobserved heterogeneity in individual investment behavior is well-established in finance literature. Barnea, Cronqvist, and Siegel (2010) even document the impact of a genetic factor. Therefore, ignoring differences among individual investors creates inference problems. The sample selection bias associated with the endogenous choice to use an advisor could go either way: Hackethal, Haliassos, and Jappelli (2012) argue that more sophisticated investors exhibit greater advice-seeking propensity, but most models instead imply that advisors mainly provide services to less sophisticated investors. Stoughton, Wu, and Zechner (2010) assert that financial advisors sell underperforming active funds to unsophisticated investors, and Inderst and Ottaviani (2010) assume that naïve customers do not rationally anticipate conflicts of interest for their advisors. In the choice experiment of Hung and Yoong (2010) less sophisticated participants were more likely to take advice. Similarly, with a survey, Van Rooij, Kool, and Prast (2007) reveal that respondents who considered themselves more financially literate prefered more autonomy in their pension decisions.

As this short review indicates, advice taking is a choice variable, so advice is not random. Yet no existing studies into the impact of financial advisors rigorously control for selection biases. To provide new evidence on the potential added value of financial advisors, we examine whether they provide tangible benefits to customers in terms of risk, returns, costs, and diversification while controlling for selection bias. We deliberately focus on common equity holdings, which is convenient given that it greatly reduces moral hazard behavior inherrent in mutual fund advice. It is important to note that we are not interested in determining whether financial advisors are capable of beating the market; rather, we aim to compare equity returns for individual investors when they do or do not hire advisors.

In addition, we base our analysis on a unique, rich data set from a Dutch retail bank that allows all investors, even very small ones, to use advisors. The activities of this retail bank concentrate in the northern Netherlands and focus on small traders. Therefore, the pool of clients, whether they use advisors or not, shares a similar backgroud. However, selection bias is still possible. The data set features more than 190,000 monthly equity returns for approximately 5,500 Dutch common stock investors. Because the bank pays advisors a fixed wage, there is no direct financial incentive related to commissions, and the fee structure does not incentivize advisors to work only with the most profitable investors. Moreover, the bank uses random assignments to specific advisors. Both new and existing investment clients work with whichever advisor is available at the moment the client asks for advice or makes an appointment. Thus, most investors in our sample likely have dealt with various financial advisors over time, and this setting eliminates the possibility that more skilled or experienced investors select the best advisors and/or that advisors select the best investors.

The remaining selection bias therefore is a result of an investor's binary choice to use an advisor. Finally, to control for this endogenous choice, we use a Hausman-Taylor panel estimator, which can identify time-invariant variables (e.g., binary choice to use an advisor[4]), even if some variables correlate with a time-invariant individual effect.

In our empirical analyses, we first examine the impact of advisors, with the assumption that selection problems do not exist. For these analyses, we rely on ordinary least squares (OLS) regressions and find advisors do not add value or have only a minor effect. Next, we attempt to control for possible endogeneity problems by estimating the same models with the Hausman-Taylor estimator. In contrast with the OLS estimates, we find that using an advisor benefits individual investors. The impact of advisors on equity returns is significantly positive for the average private investor. Advisors reduce risk not as a result of naïve diversification (increasing the number of stocks) but likely as a result of sophisticated diversification. As an example Dorn and Huberman (2010) find a lower degree of volatility specialization in more sophisticated portfolios. In addition we find that advisors increase the share of domestic stock. These findings, as well as higher returns, receive support from evidence in other studies that indicate benefits of holding concentrated portfolios (Ivkovic, Sialm, and Weisbenner, 2008) and local portfolios (Coval and Moskowitz, 2011; Ivkovic and Weisbenner, 2005). Moreover, our study reveals that advisors increase costs, though in an amount less than the increase in gross gains, so investors increase their net equity returns. Overall, our study provides a rather positive picture of the potential impact of advisors.

In the next section, we provide a more detailed overview of related studies. Section 4.3 contains the data and summary statistics; it also explains in detail how the advisory process functions for the clients in our sample. In Section 4.4 we present our results and describe our methodology for assessing the impact of advisors on portfolio returns. Finally, we conclude in Section 4.5.

[4] For common equity investors, the number of switchers between execution–only and advice is very small. Therefore, unlike section 3.5 of the previous chapter, we focus on the large majority of investors that do not switch, eliminating the possibility of using a fixed-effects estimator.

4.2. Overview of Related Research

4.2.1 Possible Links Between Financial Advice and Individual Portfolio Performance

Despite the debate about whether advisors provide clients with tangible benefits, a well-established finding is that advisors have an incentive to missell. Zhao (2003) reports that when there is a conflict of interest, financial advisors—who ultimately serve as the decision makers for investments in load funds—guide customers to funds with higher loads. Vast theoretical literature cites conflicting interests as the main deterrent to unbiased advice. Inderst and Ottaviani (2009) find that they arise because financial advisors perform two tasks: prospecting for customers and advising on the suitability of products. Loonen (2006) also highlights different financial concerns of financial advisors, including (1) generating commissions for their financial institutions, (2) generating performance-based bonuses, and (3) enhancing the performance of investors' portfolios. Stoughton, Wu, and Zechner (2010) model intermediaries as distinct agents between investors and money managers; in their model, financial advisors facilitate the entry of small investors into the market by economizing on information costs. However, when investors are unsophisticated, kickbacks to financial advisors support aggressive marketing and negatively affect the portfolio performance of mutual funds. Their model further predicts that underperforming funds get sold only to unsophisticated investors through indirect channels—a result confirmed empirically by Bergstresser, Chalmers, and Tufano (2009). A similar conclusion emerges from Inderst and Ottaviani's (2010) model: When customers are naïve about the true conflict of interest, firms exploit their incorrect perceptions. In Krausz and Paroush's (2002) model, conflicts of interest and information asymmetry induce advisors to exploit clients, so some exploitation occurs when investors pay for both financial advice and investment execution as a joint product and the cost of switching is nonnegligible. When different assets earn different commissions, advisors also might be tempted to choose higher commission products, regardless of their suitability for the client. Ottaviani (2000) derives similar conclusions from a model in which the advisor faces a trade-off between providing good advice, which leads to returning clients and good publicity, versus maximizing commissions and offering preferential treatment to product providers.

In addition, financial advisors may be more biased than clients or, in facing agency conflicts, have an incentive to exacerbate clients' biases. Shapira and Venezia (2001) find more trading activity in professionally managed accounts, which they propose is an outcome of greater overconfidence among the managed group. Glaser, Weber, and Langer (2010) document that though all participants are overconfident to some extent, financial professionals tend to be more overconfident than laypeople, and Kaustia and Perttula (2011) confirm overconfidence among financial advisors. Kaustia, Laukkanen, and Puttonen (2009) find strong framing effects among financial advisors too, whereas Mullainathan *et al.* (2010) analyze whether advisors debias clients. Although advisors tend to match portfolios to client characteristics, they fail to debias customers and in some cases even exacerbate client biases.

Such agency problems often give rise to biased advice that hurts the investor, but potentially, advisors can add value by providing greater financial sophistication, based on their investment experience, financial education, and investment knowledge. Kaustia, Alho, and Puttonen (2008) find that financial expertise significantly attenuates anchoring in financial decision making, and List (2003) shows that the degree of market experience correlates positively with the degree of rationality in decision making. Feng and Seasholes (2005) support this finding with evidence that increased sophistication and trading experience relate strongly to the elimination of biased decision making. Shapira and Venezia (2001) further report that professionally managed accounts exhibit less biased decision making than do independent individual investors. Dhar and Zhu (2006) also document a negative relationship among financial literacy, trading experience, and the disposition effect. Therefore, education and experience—characteristics that should be associated with a financial advisor—should reduce behavioral biases that hurt performance, even if they do not completely eliminate them.

4.2.2. Portfolio Performance of Individual and Professional Investors

Most prior studies of individual investor portfolio performance exclude investors who use financial advice or investigate only the behavior of online investors. The average individual investor in these studies performs poorly (e.g., Odean, 1999; Barber and Odean, 2000; Barber *et al.*, 2008; Bauer, Cosemans, and Eichholtz, 2009). Yet we still find great heterogeneity in the results; some groups of investors perform well. Ivkovic, Sialm, and Weisbenner (2008) show that skilled individual investors earn abnormal returns by concentrating their portfolios in stocks about which they have favorable information. Ivkovic and Weisbenner (2005) also indicate that individual investors can exploit informational advantages about local holdings, though Seasholes and Zhu (2010) challenge their claim. Coval, Hirschleifer, and Shumway (2005) instead document that some individual investors are persistently better than others.

These empirical studies ignore the large proportion of investors who use financial advice. Some recent empirical studies explicity investigate the role and impact of financial advisors on retail portfolios. Bergstresser, Chalmers, and Tufano (2009) investigate the value of brokers for helping clients select mutual funds: They compare the performance of directly and indirectly (i.e., funds sold through an advisor) sold funds, and they find lower risk-adjusted gross returns for broker-sold mutual funds than for directly sold funds. Thus they conclude that advisors deliver benefits that customers do not observe or that conflicts of interest prevent advisors from giving optimal advice. Yet they do not investigate the portfolios of the investors directly.[5] Hackethal, Haliassos, and Jappelli (2012) study German retail investors who receive advice from independent or bank financial advisors. The advised clients tend to be older, women, wealthier, and more experienced; furthermore, independent advisors are associated with lower returns but also lower portfolio variance, whereas bank advisors are associated with both lower returns and higher risk. Both advisors produce high turnover and a lower share of single stocks, indicating better diversification. Their main results thus rely on associations, though they attempt to solve the endogeneity issue. As we noted in the introduction, the (nonrandom) financial advice choice experiment of Bhattacharya *et al.*'s (2012) included 8,200 execution-only investors, who had the option to receive free and unbiased advice. Clients who choose to participate received portfolio recommendations derived from a portfolio optimizer (Markowitz, 1952a), and those who rejected the offer acted as a control group. Only 385 (5%) investors accepted the offer, and 157 (2%) at least partly followed the recommendations. In line with Hackethal, Haliassos, and Jappelli (2012), clients that accepted the advice were older, wealthier, and more sophisticated, and those who followed the recommedations improved their portfolio risk–return trade-off. That is, if the advice is unbiased, it has the potential to benefit investors. Kramer (2012) investigates a sample of 16,000 Dutch advised and self-directed investors and finds that the characteristics and portfolios of the two groups differ remarkebly. Although he finds no portfolio perfomance differences, advisors seem to add value through better diversifcation and lower ideosyncratic risk. A sample of investors that switch from execution-only to advice confirms these findings.

Other studies compare the performance of professionals and retail investors more generally. Professionals (who have difficulty outperforming the market[6]) perform better than individual investors. Grinblatt and Keloharju (2000) find that professional institutions significantly outperform less sophisiticated investors, such as domestic households; Shapira and Venezia (2001) confirm this claim by comparing independent and professionally managed investors in Israel and finding better performance among the latter. Barber *et al.* (2009) also document underperformance by the aggregate portfolio of Taiwanese individual investors, even when institutional investors gain in their trading. Thus, though retail and professional investors both tend to exhibit mediocre investment performance, in principle, advisors could improve the performance of individual investors.

[5] There may be an alternative explanation for their results: Broker-sold funds reveal a different universe than directly sold funds, so it is not clear whether the advisor performs poorly or if the problem lies with the supplier. A fund supplier might offer only underperforming funds to advisors' distribution channel, as predicted by Stoughton, Wu, and Zechner (2010). Bergstresser, Chalmers, and Tufano (2009) show that the asset-weighted performance of funds sold by brokers is not as poor as equally weighted performance. That is, the asset-weighted returns indicate the quality of decisions, whereas the equally weighted returns represent available choice options. This finding implies that brokers provide customers with a valuable service, given choice options they have.

[6] Jensen (1967) was one of the first to show that mutual funds cannot outperform buy-and-hold strategies on average. More recent studies indicate that money managers have difficulty outperforming passive indexes (e.g., Busse, Goyal, and Wahal, 2010; Fama and French, 2010). Bergstresser, Chalmers, and Tufano (2009) indicate that equity funds in general, whether directly or broker sold, exhibit negative alphas.

As this literature survey shows, research on financial advisors is expansive and growing. Not all existing papers mention the potential for self-selection bias, but it seems surprising that no study explicitly and rigorously controls for possible endogeneity problems, even though advisor choice clearly is endogenous. Failing to account for possible selection problems can bias results considerably. The three studies most closely related to our study do not control for selection explicitly but attempt to estimate the likely impact of selection on their results. That is, Bergstresser, Chalmers, and Tufano (2009) indicate that advised investors are less educated and more risk averse; Bhattacharya *et al.* (2012) acknowledge that their study is not based on a random assignment, though they argue that their basic empirical methodology (difference-in-difference) can ameliorate that shortcoming; and Hackethal, Haliassos, and Jappelli (2012, p.14) suspect "that portfolio performance actually induced the choice of the advisor" and attempt to estimate an instrumental variables model as a robustness check. They note that "finding suitable instruments in our context is not easy" (Hackethal, Haliassos, and Jappelli, 2012, p.14) and admit they cannot test the quality of their instrument.

4.3. Data, the Advisory Process, and Descriptive Statistics

For our analysis, we draw on the complete history of common stock portfolio holdings and transaction data for a sample of customers from a medium-sized, full-service retail and business bank that offers an array of financial products. The bank, which advertises itself as a relationship bank, offers services throughout the Netherlands through a network of bank branches, though it has a particularly strong presence in the northern part of the country. The bank offers both advisory and execution-only investment services. Customers typically have an account manager who communicates all the financial services the bank offers. Although the bank is accessible to all people, the typical investment client (both advised and execution only) is a man or couple, older than 50 years of age, with middle-class income and wealth.

The data span a 52-month period, from April 2003 to August 2007. We only use accounts of private investors with unrestricted accounts and exclude those owned by a business, portfolios linked to mortgage loans, or portfolios that represent part of a company savings plan, given that in these portfolios investors and their advisors may be restricted in making changes. Because we want to abstract from possible incentive conflicts that are inherent to mutual fund advice[7], we deliberately consider only advisory impacts on common stock recommendations. The focus on common equity will also facilitate analyses given the large difference in asset allocations between advised and self-directed portfolios. This procedure, of course, reduces our sample size considerately. Whereas in chapter 3 our analysis was based on observations from 16,053 investors, in this chapter our sample is

[7] In the Netherlands new legislation has recently been adopted that aims at solving this conflict of interest. Therefore, it becomes more relevant to focus on the impact of advisors abstracting from incentive conflicts.

restricted to the 5,661 common equity investors with a total of 193,418 monthly equity return observations.

For most investors in our sample, equity is the most important asset class (on average, 82% of portfolio value, with almost 60% in individual equity positions). We also gather information about the type of client (execution-only or advised), gender, zip code, and age. On a six-digit zip code level,[8] we gain information about income and residential value. A comparison of some key characteristics in our data set with retail investor data sets in the Netherlands (Bauer, Cosemans, and Eichholtz, 2009), Germany (Bhattacharya *et al.*, 2012); Dorn and Huberman, 2010), and the United States (Ivkovic and Weisbenner, 2005) reveal that our data offer a high degree of external validity.

Execution-only and advised investors represent different departments, so investors with advisory relationships cannot trade through the execution-only department, and investors who use execution-only services cannot rely on the help of an advisor. The investors choose between an advisory relationship or execution-only services. For our sample period, all customers were eligible for advice, which is unusual, in that most banks require a minimum investment to be eligible for advisory services. Thus our data set is unique. After the sample period, the bank stopped offering advisory services to clients whose portfolios were worth less than €100,000; therefore, we restrict our sample to the period before 2008.

Advisors receive a fixed wage only, so there is no direct personal financial incentive to generate commissions. Furthermore, clients' assignments to advisors is random. Both new and existing investment clients work with advisors based on availability. The advisory relationship always starts with an initial intake meeting, in which an advisor assesses the investor's investment goals, preferences, knowledge, and experience. From this first meeting, they develop a risk profile, which constitutes the main input for the recommended strategic asset allocation. This asset allocation advice is predetermined by the bank, and the individual advisor has no real impact. After the initial meeting, some advice is given in face-to-face meetings, but most recommendations occur over the telephone. We cannot discern whether granted advice is followed by the investors; Bhattacharya *et al.* (2012) report that less than 50% of investors that choose to receive advice actually follow it. However, the investors in their sample initially opted for an execution-only investment service, then considered whether to receive advice from an automatic portfolio optimizer. Their sample appears likely to behave quite differently than the investors in our sample, who deliberately opted to receive advice. In discussions with the bank management, we also learned that most calls initiated by the advisor contain explicit advice, as the very reason for the call, whereas calls initiated by investors rarely prompt any portfolio changes.

[8] In the Netherlands, 6,940,000 households represent 436,000 six-digit zip codes; these variables offer average values for an average of 16 households each.

Advisors offer concrete stock recommendations and have great latitude about which stocks to recommend. In our sample period, advisors received research on financial markets and individual firms from an external research agency. They could use this research in their recommendations as they pleased. Advisors also could recommend stocks based simply on their own preferences, as long as they would document this in the client file.

Because we include accounts that were opened or closed during the sample period for only the months in which they were active, making survivorship bias less of a concern, although attrition bias may still exist. We calculate individual investor performance using a modified Dietz (1968) measure, which accounts for both the size and the timing of deposits and withdrawals. We report gross and net (market adjusted) returns, but we focus on the latter in our regression specifications; to calculate net returns, we deduct transaction and custodian fees. Net returns are calculated as:

$$R_{it}^{net} = \frac{MV_{it} - MV_{it-1} - \sum NC_{it}^{gross} - COSTS}{MV_{it-1} + \sum w_{it} NC_{it}^{gross}}, \tag{4.1}$$

where R_{it}^{net} is the net monthly return of investor i in month t, MV_{it} is the end-of-month market value of the portfolio, NC_{it}^{net} is the net contribution (deposits minus withdrawals) in month t, and w_{it} is the weight attributed to each contribution, determined by the timing of contributions[9]. When a contribution takes place earlier in the month, its weight is higher. Finally, $COSTS_{it}$ are transaction costs and custodial fees, recalculated monthly.

Table 4.I contains the summary statistics for the portfolio returns and investor and portfolio characteristics. Individual investors in our sample underperform the market by a small margin in gross terms, but they underperform in net terms by 20 basis points per month. Advised investors perform better than self-directed investors in both raw and market-adjusted gross and net terms, but the differences are modest. The average volatility of net returns is 5.45%, considerably higher than the volatility of the Dutch stock market (3.51%), which may reflect the average portfolio holding of only 4.4 stocks. Advised portfolios exhibit significantly less volatility and idiosyncratic risk, likely due to the higher number of stocks in their portfolios (5.2 versus 3.3 for self-directed portfolios). Advised portfolios also are associated with a lower market beta, though this difference is statistically insignificant. Most portfolios are joint accounts (44%), and 21% are held by women. Advised accounts are more common among joint account holders and women. The average age of the primary account holder is 57 years, but advised investors are

[9] This weight has been calculated as the absolute difference between the day the cash flow occurred and the number of calendar days in the month divided by the number of calendar days in the month.

Table 4.I: Summary Statistics of Individual Investors and Portfolio Characteristics

The sample consists of 5,661 individual investors that hold common equity positions at least once during the sample period of 52 months. Gross (Net) excess monthly portfolio return is the return in excess of 3 months Euribor. *Gross (Net) Market adjusted return* is the gross (net) monthly return minus the return on the MCSI-Netherlands Index. *Return Volatility* is the standard deviation of the monthly net returns. *Market beta* is the loading on the market factor obtained from using the Fama and French 3 factor model on each individual investor's time series of portfolio returns. *Return residual* is the idiosyncratic component of the factor model described above. *Woman* is the percentage of account held by a woman only. *Joint Accounts* is the percentage of portfolios held by 2 persons, mostly a man and a woman. *Age* is the age of the primary account holder. *Income* is the average gross monthly income in the 6 digit zip code of the investor. *Residential Value* is the average house price in the 6 digit zip code of the investor. *Active months* is the average amount of months that an investor holds a portfolio in our dataset. *Account value* is the beginning of the month account value of common equity. *Common equity positions* is de average number of stocks in each portfolio. *Turnover* is the sum of buys and sells of common equity divided by the beginning of the month account value of common equity.

	All	Advised	Self-Directed	Difference	p-value
Panel A: Monthly Returns					
Gross Monthly Return (%)	1.63	1.65	1.59	0.06	0.01
Net Monthly Return (%)	1.48	1.51	1.43	0.08	0.00
Gross Market Adjusted return (%)	-0.04	-0.03	-0.07	0.04	0.05
Net Market Adjusted return (%)	-0.20	-0.18	-0.23	0.06	0.01
Observations (#)	193,418	121,413	72,005		
Panel B: Risk					
Return Volatility (%)	5.45	5.34	5.74	-0.40	0.00
Market Beta	0.72	0.69	0.78	-0.09	0.61
Return Residual (%)	2.88	2.72	3.13	-0.42	0.00
Panel C: Investor Characteristics					
Investors (#)	5,661	3,648	2,013		
Woman (%)	21%	23%	18%	5%	0.00
Joint accounts (%)	44%	44%	45%	-1%	0.00
Age (years)	56.50	58.68	52.86	5.82	0.00
Income (2006) (€)	2,205	2,251	2,131	119	0.00
Residential Value (2006) (€)	151,104	157,130	141,212	15,918	0.00
Active months	44,97	45,45	44,15	1,29	0.00
Panel D: Portfolio Characteristics					
Common equity value (€)	44,866	62,534	15,075	47,459	0.00
Domestic equity (%)	92.7%	93.0%	92.3%	0.63%	0.29
Common equity positions (#)	4.44	5.21	3.29	1.92	0.00
Equity Turnover (%)	4.96	5.27	4.39	0.88	0.01
Equity Trades per month (#)	0.56	0.74	0.23	0.51	0.00

marginally older. Advised investors also seem wealthier in their gross monthly income, residential value, and portfolio value. The average size of advised stock portfolios is €57,000, almost four times greater than the size of self-directed portfolios. Common stock, the focus of our study, constitutes the largest asset class; almost 60% of the average portfolio consists of common stock, and the rest represents a combination of common bonds, equity and bond mutual funds, and structured products. Trading activity, with an average monthly turnover of almost 5%, appears broadly in line with activity documented in other studies.[10] Advised portfolios reveal significantly higher turnover than self-directed portfolios and execute more trades. Among our observations, 60% come from advised investors who are active for an average of 45 months during the sample period, whereas 40% represent the benchmark group of execution-only investors.

4.4. Empirical Results

To estimate the impact of an advisor on the returns of individual investor portfolios, we applied a general model:

$$Y_{it} = \alpha + A_i\beta_1 + X_{it}\beta_2 + \varepsilon_{it} , \qquad (4.2)$$

where Y_{it} is the net return on the portfolio of investor i in month t, α is a constant term, and A_i is a dummy variable that takes the value of 1 if the investors receive investment advice and 0 otherwise.

In addition, X_{it} represents a set of control variables known to influence returns. Bauer, Cosemans, and Eichholtz (2009) indicate that turnover, gender, age, income, and account size are significant determinants, and Barber and Odean (2000, 2001), suggest that portfolio turnover hurts net returns and that men trade 45% more than women. Because of the trading costs they incur, men underperform women by almost 1% per year. Bauer, Cosemans, and Eichholtz (2009) also report that the most active traders outperform in gross terms but underperform in net terms. Wealth often serves as a proxy for investor sophistication: Anderson (2008) finds a positive relation between portfolio value and trading performance, and Bauer, Cosemans, and Eichholtz (2009) indicate that large portfolios outperform small portfolios. Yet Barber and Odean (2000) find no significant risk-adjusted return differentials between the largest and smallest portfolios. We use three variables related to wealth: portfolio value, residential value, and income (the latter two measured at the six-digit zip code level). Age also should relate to investor experience. Bauer, Cosemans, and Eichholtz (2009) report a negative impact of age on performance, and Korniotis and Kumar (2011) show that older, more experienced investors exhibit greater investment knowledge, though they appear to have poor investment skills, perhaps due to cognitive aging, and suffer 3–5% lower annual returns.

[10] Barber and Odean (2000) report an average of 6%, and Hackethal, Haliassos, and Jappelli (2012) report an average of almost 5%.

Our sample might suffer from cross-sectional dependence too. Investors may make similar decisions at the same time and hold the same securities in their portfolios. Petersen (2009) shows that ignoring cross-sectional dependence leads to biased standard errors and overly small confidence errors. When time effects are fixed, such that they have the same impact on all investors, time dummies can completely remove correlations between observations in the same period. We therefore include time dummies in all our estimations.

In Table 4.II, we present the results based on ordinary least squares (OLS); the first two columns show that the difference in raw and risk-adjusted performance between advised and self-directed investors is indistinguishable from 0. Many of the other relationships between advice and portfolio behavior are also insignificant or small. Based on these estimates, without controlling for selection effects that arise because investors make the choice of whether to hire an advisor, the advisory impact seems rather limited.

4.4.1. Controlling for Self-Selection

We investigate the effect of an advisor on the outcome of investment decisions. If we assume no unobserved individual heterogeneity, we could estimate our model with OLS, as in Table 4.II. However, returns likely are affected by unmeasurable attributes, such as investment skills, financial literacy, or risk aversion, so an OLS model, which suffers from an omitted variable bias, is inappropriate. To allow for unobserved individual heterogeneity, we can use fixed and random estimators. The random effects model assumes that all unobserved factors that affect returns are distributed randomly across cross-sectional units. It also assumes that unobserved, time-invariant individual effects are uncorrelated with all other regressors in the model. In our specification, this effect implies that unobservable variables such as skill, literacy, and risk aversion do not relate to the choice of advice, which seems highly unlikely. For every specification, we formally test differences in the coefficients from fixed effects and random effects regressions, using a Hausman test. The random effects estimator is rejected in all our specifications. The fixed effects estimator allows for correlation between unobserved individual effects and regressors. Because it also eliminates time-invariant elements, it cannot identify time-invariant variables. However, our main variable of interest, the advice dummy, is time invariant, so identifying the impact of the advisor with a fixed effects model is impossible.

Finally, the Hausman-Taylor approach (Hausman and Taylor, 1981) preserves the advantages of both a fixed effect estimator (i.e., correlation between individual effects and regressors) and the random effects estimator (i.e., identifying the effect of time-invariant regressors). Because of this the Hausman-Taylor approach is referred to as a hybrid model (Cameron and Trivedi, 2005). It does not require external instruments, which solves the problem of finding suitable instruments. Because all the variables are instrumented in the fixed effects approach, including those that are exogenous, the Hausman-Taylor approach may be more efficient than a fixed effects model. However, it requires us to distinguish

Table 4.II: Financial Advice and Return, Risk, Trades, Cost and Diversification, OLS estimates

This table presents coefficient estimates of financial advice on retail investor portfolio return, risk, Trading, Costs, Number of Equity positions and the share of domestic stock using pooled OLS. *Return* is the net monthly equity portfolio returns of each individual portfolio, *Risk-adjusted return* is the individual portfolio market beta's adjusted return, *Risk* is the monthly absolute net return residual that has been calculated using the 3 factor Fama and French (1993) model for each individual portfolio. *Trades* is the number of monthly equity trades in each individual portfolio. *Cost* is the difference between the gross and net monthly portfolio return, *Number of equity positions* which is the number of individual common stock positions in each individual investor portfolio at the beginning of each month and *Share domestic stock* which is the percentage of portfolio value allocated to domestics common stock position at the beginning of each month. Independent variables are *Advice* which is a dummy variable equal to 1 is an investor is advised, *Age* which is the age of the primary account holder, *Woman* which is a dummy equal to 1 if the account was held by a woman, *Joint Account* which is a dummy variable equal to 1 if the account was held by 2 persons, mostly a man and a woman, *Value* which is the logarithm of the beginning of the month account value of common equity positions, *Turnover* which is the logarithm of the sum of buys and sells of common equity positions divided by the beginning of the month account value of common equity positions, *Income* which is the logarithm of the average gross monthly income in the 6 digit zip code of the investor, *Residential Value* which is the logarithm of the average house price in the 6 digit zip code of the investor, *Experience* which is the number of months that each investor holds a portfolio during the sample period. In each regression time dummies for each of the 52 months in the sample are used. Portfolios with equity values of below € 250 are excluded. Nonparametric bootstrapped standard errors (in parentheses) are presented below the corresponding parameters (250 replications). ***, **, * denote significance at the 1 percent, 5 percent, and 10 percent levels, respectively.

	Log returns	Log risk-adjusted returns	Risk	Trades	Costs	No. Equity positions	Share domestic stock
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Advice	0.000	-0.000	-0.072***	0.003	0.000***	0.348***	0.001
	(0.393)	(0.604)	(0.000)	(0.340)	(0.000)	(0.000)	(0.518)
Age	0.000**	0.000**	0.006***	-0.002***	0.000***	-0.029***	0.000***
	(0.042)	(0.020)	(0.000)	(0.000)	(0.001)	(0.000)	(0.006)
Woman	-0.000*	-0.000	-0.063***	-0.100***	0.000***	-0.609***	-0.005***
	(0.088)	(0.186)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Joint Account	0.000*	0.000	-0.151***	-0.052***	0.000***	0.261***	0.003**
	(0.084)	(0.237)	(0.000)	(0.000)	(0.003)	(0.000)	(0.011)
Value	0.001***	0.000***	-0.952***	0.227***	-0.001***	4.308***	-0.001
	(0.000)	(0.009)	(0.000)	(0.000)	(0.000)	(0.000)	(0.209)

Table 4.II: Financial Advice and Return, Risk, Trades, Cost and Diversification, OLS estimates (Continued)

Turnover	-0.004***	-0.004***	0.646***		0.007***	0.545***	-0.014***
	(0.000)	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)
Income	0.000	0.001	-0.017	-0.018	0.000	0.590***	-0.023***
	(0.775)	(0.515)	(0.788)	(0.383)	(0.388)	(0.000)	(0.000)
Residential Value	0.000	0.000	0.173***	0.030	-0.000***	0.153*	-0.071***
	(0.522)	(0.640)	(0.000)	(0.101)	(0.003)	(0.050)	(0.000)
Experience	0.000***	-0.000	-0.005***	-0.008***	-0.000***	0.025***	0.002***
	(0.000)	(0.484)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	-0.038***	-0.019***	7.618***	-0.234***	0.008***	-15.795***	1.084***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	154,397	143,941	143,941	154,397	154,397	154,353	154,353
R-Squared	31.3%	9.5%	12.5%	3.7%	23.3%	43.0%	2.3%

between exogenous and endogenous variables, which in practice is not obvious, though Hausman and Taylor (1981) suggest economic intuition can indicate which variables to treat as endogenous.

The technique has been advocated by Angrist and Krueger (2001) and McPherson and Trumbull (2008), and is used in various economic settings, usually to assess the impact of some time-invariant variable or policy intervention assigned in a non-random fashion. Hausman and Taylor (1981) apply it to a classical example of estimating the effect of education on wages. Greenwood, McDowell, and Zahniser (1999) assess the influence of social programs on immigration; Garcia, Molinaab, and Navarroc (2010) consider the effects of education on spouse satisfaction; Egger and Pfaffermayr (2004) investigate the effects of distance between countries on investment trades; Dixit and Pal (2010) study the impact of group incentives on firm performance; Serlenga and Shin (2007) use the method for gravity models in international trade; and Contoyannis and Rice (2001) employ it to determine the impact of health on wages in the United Kingdom.

4.4.2 Hausman-Taylor Estimation

The Hausman-Taylor specification assumes that any set of explanatory variables contains time-varying and time-invariant variables. A subset of both types of variables would be exogenous and assumed to be uncorrelated with the unobserved time-invariant individual effect, though some of both types of variables may correlate with the time-invariant individual effect. In line with the random effects, and fixed effects approaches, the Hausman-Taylor model assumes strict exogeneity (so the individual effect nor the regressors correlate with ε_{it}, the individual time-varying disturbance term). The model can be specified as follows:

$$Y_{it} = v + X_{1it}\beta_1 + X_{2it}\beta_2 + M_{1i}\gamma_1 + M_{2i}\gamma_2 + \mu_i + \varepsilon_{it}, \tag{4.3}$$

where Y_{it} denotes the net returns of private investor i in period t; v is a constant term; the vectors X and M capture sets of observed time-varying and time-invariant control variables, respectively, that affect the outcome variable; μ_i represents the individual fixed effect; and ε_{it} refers to the time-varying individual error. The subscript 1 denotes variables that are assumed to be uncorrelated with μ_i (and ε_{it}), whereas the subscript 2 refers to those that are assumed to be correlated with μ_i (but still uncorrelated with ε_{it}). Our main variable of interest is advice, which equals 1 if private investor i uses an advisor in period t, and 0 otherwise. Because advice is entirely time invariant and likely endogenous, we include it in M_{2i} We provide an overview of all included variables in Table 4.III. We assume all wealth-related variables are endogenous. Therefore, in addition to advice, portfolio value, residential value, and household income appear in our list of endogenous variables. Also experience is treated as endogenous. Unobservable variables such as ability, financial literacy, investment skill, or motivation likely drive these variables, in that they influence the portfolio performance measures that serve as our dependent variables. In other finance settings, wealth is also considered endogenous; for example, Becker (2006) argues that wealth may be endogenous for assessing CEO compensation, because highly skilled CEOs should have accumulated more wealth. Similarly, Hurst and Lusardi (2004) state that the traits that render some households more likely to accumulate wealth make them more likely to behave particularly in other settings too. All other variables (*Women*, *Joint*, *Age*, *Turnover*) are assumed to be exogenous. Antonakis *et al.* (2010) indicate that stable individual differences may serve as good instruments. For the first three of the variables that we defined exogenous, this poses no problem. We also assume that *Turnover* is exogenous, given that it may serve as a proxy for overconfidence, while overconfidence in turn may be considered a stable personality trait.

Table 4.III: List of Variables

This tables provides an overview of the variables used in various HT-regressions. For each variable is indicated whether it is time variant or time invariant (TV or TI), and whether we treat the variable as endogenous (End) or exogenous (Ex). The last column (HT) refers explicitly to the Hausman-Taylor notation of model 4.3.

Variable	**Description**	**TV or TI**	**Ex or End**	**HT**
Advice	Dummy variable that is 1 if the accountholder is advised by advisor from the bank, zero otherwise	TI	End	M_2
Woman	Dummy variable that is 1 if the account is held by a woman only	TI	Ex	M_1
Joint Account	Dummy variable that is 1 if the account is held by 2 person, mostly a man and women together	TI	Ex	M_1
Age	Age of primary account holder in years	TV	Ex	X_1
Income	Logarithm of gross monthly income in Euro's at 6 digit zip code level in 2006	TV	End	X_2
Residential Value	Logarithm of residential value in Euro's in 2006 at 6 digit zip code level	TV	End	X_2
Account Value	Logarithm of value of all common equity positions at the beginning of each month	TV	End	X_2
Turnover	Logarithm of the absolute sum of all buys and sells divided by the beginning of the month account value	TV	Ex	X_1
Experience	Number of months that investor hold a portfolio during our sample period	TV	End	X_2

In the Hausman-Taylor approach, all dependent and independent variables are transformed as in a random effects estimation, and all the variables are instrumented. In line with the fixed effects model, both time-varying exogenous and endogenous variables are instrumented by a within-variable transformation, whereas the time-invariant endogenous variables use the individual averages of the exogenous time-variant variables. The time-invariant exogenous variables are instruments themselves.

For all our estimations, we first report the Breusch-Pagan test to check whether panel techniques are more appropriate than OLS. For all our specifications we reject the null hypothesis of this test, which implies that investor-specific effects are present. Then we apply the Hausman test to determine if a fixed or random effects estimation is preferable. In all cases, the fixed effects estimator is preferred, but as indicated before, time invariant variables cannot be identified when using the fixed effect estimator. This directs us to the Hausman-Taylor technique.

Given that in a Hausman-Taylor estimation the sampling distribution may be hard to derive, we calculate standard errors using the conventional nonparametric panel bootstrap with 250 replications. This bootstrapping allows estimating standard errors which are robust to possible heteroskedasticity that may arise as a result of multiple observations for each individual. As noted before the inclusion of time dummies in all our estimations removes the bias as a result of possible cross sectional dependence (Petersen, 2009). To confirm the quality of our instruments, we report the F-statistic for the first-stage regression with advice taking, and the Hansen-J statistic of overidentifying restrictions.

4.4.3. Impact of Advisors on Portfolio Returns: Empirical Results

In Table 4.IV, we present the performance results of our Hausman-Taylor specification, including the small, significant, positive impact of advice on portfolio performance. Advised portfolios are associated with lower market risk (see Table 4.I), so this advisory impact is slightly stronger when we consider risk-adjusted performance (column 2). This result contradicts findings by Hackethal, Haliassos, and Jappelli (2012) and Bergstresser, Chalmers, and Tufano (2009), but it aligns with the experimental findings of Battacharya *et al.*'s (2011) and Hung and Yoong (2010). We focus on common equity, for which unbiased advice is more likely, as was true for Battacharya *et al.* (2011), whereas the inclusion of mutual fund advice increases the likelihood of bias in the other studies. Mutual fund inflows relate positively to front-end loads, so advisors may put their own interests before those of clients. For common equity though, advisors have much less incentive to direct clients to securities that benefit only advisors, though conflicts of interest remain possible. Because income from stock advice primarily depends on trade commissions, advisors might encourage churn in portfolios, as we address subsequently. Fecht, Hackethal and Karabulut (2010) also find that banks relocate underperforming stocks from proprietary portfolios into retail clients' portfolios. The bank of our sample

Table 4.IV: The Influence of Financial Advice on risk and Return, Hausman Taylor Estimates

This table presents coefficient estimates on retail investor portfolio return and risk using the Hausman-Taylor technique. Dependent variables are (1) *Return* which is the net monthly equity portfolio returns of each individual portfolio, (2) *Risk-adjusted return* which is the individual portfolio beta's adjusted return only calculated for investors with more than 24 return observations) and (3) *Risk* which is the monthly absolute net return residual that has been calculated using the 3 factor Fama and French (1993) model for each individual portfolio. *Advice* is a dummy variable equal to 1 is an investor is advised. *Age* is the age of the primary account holder. *Woman* is a dummy equal to 1 if the account was held by a woman. *Joint Account* is a dummy variable equal to 1 if the account was held by 2 persons, mostly a man and a woman. *Value* is the logarithm of the beginning of the month account value of common equity positions. *Turnover* is the logarithm of the sum of buys and sells of common equity positions divided by the beginning of the month account value of common equity positions. *Income* is the logarithm of the average gross monthly income in the 6 digit zip code of the investor. *Residential Value* is the logarithm of the average house price in the 6 digit zip code of the investor. *Experience* is the number of months that each investor holds a portfolio during the sample period. In each regression time dummies for each of the 52 months in the sample are used. Portfolios with equity values of below € 250 are excluded. Nonparametric bootstrapped standard errors (in parentheses) are presented below the corresponding parameters (based on 250 replications). ***, **, * denote significance at the 1 percent, 5 percent, and 10 percent levels, respectively

	Log returns	**Log risk-adjusted returns**	**Risk**
	(1)	**(2)**	**(3)**
Advice	0.022***	0.029***	-1.488***
	(0.000)	(0.008)	(0.000)
Age	0.000**	-0.000	0.017***
	(0.028)	(0.879)	(0.000)
Woman	-0.002***	-0.003**	0.026
	(0.000)	(0.036)	(0.643)
Joint Account	-0.001	-0.000	-0.192***
	(0.147)	(0.717)	(0.000)
Value	-0.009***	-0.008***	-1.220***
	(0.000)	(0.000)	(0.000)
Turnover	-0.004***	-0.004***	0.597***
	(0.000)	(0.000)	(0.000)
Income	-0.007	-0.007	-0.039
	(0.144)	(0.213)	(0.895)
Residential Value	0.006*	0.005	0.020
	(0.094)	(0.143)	(0.929)
Experience	0.000***	-0.000	0.001
	(0.000)	(0.748)	(0.729)
Constant	-0.002	0.015	9.113***
	(0.855)	(0.340)	(0.000)
Observations	154,397	143,941	143,941
Breusch-Pagan LM test statistic, p-value	0.00	0.00	0.00
FE vs RE, p-value	0.00	0.00	0.00
F-statistic first stage regression	19.58	14.10	14.10
Hansen J Statistic, p-value	0.50	0.47	0.28

does not trade with its own money however, so this possible relocation is absent in our data.

The negative coefficient for *Turnover* indicates that trading activity has a negative effect on returns; Barber and Odean (2000) similarly report that active traders underperform passive traders in net terms, because of their large trading costs. The small but negative coefficients for *Woman* and *Joint Account* contrast with Barber and Odean's (2001) findings though. It appears that their finding that women's performance is superior mainly reflects the lower turnover in portfolios held by women, for which we explicitly control.

Portfolio size (*Value*) relates negatively to returns, but other wealth proxies have a positive (residential value) or insignificant (income) effect. The negative relation between portfolio size and returns contrasts with findings by Bauer, Cosemans, and Eichholtz (2009) but might be explained by Ivkovic, Sialm, and Weisbenner (2008), who report lower returns for better diversified portfolios. In our sample, larger portfolios tend to be better diversified.

Our methodology controls for selection bias due to unobserved characteristics that do not change over time. Moreover, assignments to specific advisors are random. Yet we cannot entirely rule out the possibility that our results are partly biased by selection on time-varying unobservable variables, such as investment experience. It has a positive impact on portfolio returns and increases over time. By including the number of months the investor is active in our sample period, we try to proxy for experience; the effect is insignificantly positive and quite small.

All F-statistics of the first-stage regressions for *Advice* are greater than 10, so the instruments appears relevant and reasonably explanatory for the advice dummy. In addition, the high *p*-values on the Hansen-J statistics indicate the instruments are valid for all our specifications.

4.4.4. Impact of Advisors on Risk

The impact of advisors on portfolio returns is small but positive for the average investor. To assess the value of financial advisors, we consider their impact on the risk exhibited by clients' portfolios. Contrary to lessons from portfolio theory, individual investors generally diversify poorly; as Barber and Odean (2000) document, a typical investor holds only four stocks (similar to the 4.4 stocks we report in Table 4.I). Finance textbooks routinely illustrate the positive effect of adding more stocks to a portfolio: It reduces nonsystematic risk (e.g., Berk and DeMarzo, 2010). Sophisticated investors follow these lessons, as Goetzman and Kumar (2008) show, but most investors still suffer significant idiosyncratic risk because they choose imperfectly correlated stocks. These findings reflect recent evidence noted by Dorn and Huberman (2010) that individual investors expose themselves to idiosyncratic risk due to volatility specialization. Because diversification is a basic lesson, we expect financial advisors, in principle, to increase portfolio diversification.

Bluethgen *et al.* (2008) and Kramer (2012) also confirm better portfolio diversification among advised investors, though mainly as a result of adding mutual funds to retail portfolios.

To assess the impact of advisors on risk, similarly as in Cheng (2008), we obtain residuals from a Fama-French three-factor model, which we apply to all time series of net monthly portfolio returns for each individual investor with at least 24 monthly return observations in our sample. Second, we use the absolute value of the residuals[11] of the regressions in the first step and regress it on the same predictors as in our previous models. Specifically, we estimate:

$$R_{it} = \alpha_i + \beta_{1i}\left(R_{mt} - R_{ft}\right) + \beta_{2i} SMB_t + \beta_{3i} HML_t + \varepsilon_{it} \tag{4.4}$$

where R_{it} is the return on the portfolio of investor i in month t; $R_{mt} - R_{ft}$ is the excess return on the MSCI Netherlands index in month t; R_{ft} is a proxy for the risk-free rate, for which we use the three-month Euribor; SMB_t is the return on a zero-investment factor that mimics portfolio size; and HML_t is the return on a zero-investment factor that mimics portfolio value. Both SMB_t and HML_t have been calculated using Dutch stock market data given that the majority of stocks in our sample are Dutch. We take the residuals from this model and use the absolute value as a proxy for the variability of the investor's portfolio return.

The OLS results for the second step in Table 4.II indicate, similar to our previous return regressions, a small relationship with advisory intervention. Advised portfolios appear associated with less risk, but a selection bias may drive these results. We cannot infer the *impact* of advice from these regressions, so we turn again to the Hausman-Taylor methodology (see Column 3, Table 4.IV). For portfolio volatility, we find a much larger negative impact of advisory intervention. Apparently advisors improve diversification, as we discuss subsequently. Therefore, we assert that financial advisors provide the necessary investment knowledge and experience to increase diversification. The average value of the monthly return residuals of 2.9% in Table 4.I suggests the impact of advice is considerable.

The controls we use exhibit the expected signs. Portfolio value has a large negative impact on idiosyncratic risk, in line with Dorn and Huberman's (2010) reports of a negative relation between the Herfindahl-Hirschmann index[12] and wealth. Diversification in portfolios of individual securities is less expensive when portfolios grow larger, considering the fixed costs associated with adding each new security. Turnover relates positively to diversifiable risk. Turnover is often considered a proxy for overconfidence, which drives excessive risk-taking. Barber and Odean (2000) report lower risk aversion for

[11] This procedure maintains the panel structure of the data.
[12] This index is calculated as the sum of the squared weights of the assets in a portfolio and therefore serves as a proxy for the amount of diversification.

active traders. Finally, in line with previous findings, we note that joint accounts are associated with lower avoidable risk, but the coefficient for women is insignificant.

4.4.5. Impact of Advisors on Trading Activity and Costs

In Table 4.V we report the Hausman-Taylor estimates of activity and cost measures. *Trades* is the number of common equity transactions in each month; *Cost* is the difference between the gross and net return of each individual investor in each month, such that it captures the effect of transaction costs and custodial fees. The coefficient for *Advice* reveals some interesting patterns. In contrast with the results in Table 4.II, we find that advisors lower the number of trades (Table 4.V, columns 1 and 2). Apparently, they reduce the number of trades investors execute, which conflicts with the commonly held belief that advisors induce churn to generate more commissions. Women and joint accounts engage in less trading activity, consistent with Barber and Odean's (2001) findings that single men trade most. Increased portfolio value is associated with more trades, though these relationships appear nonmonotonic, according to the sign changes when we add a squared variable for value. By adding a squared term for age, we overidentify the model and can test for the quality of our instruments. When we include them, the impact of advice on trading diminishes, though the effect is still considerable. The Hansen-J statistics indicate no correlation between our instruments and the error term. In line with Dorn and Huberman (2005), our estimates show that respondents with more experience trade significantly less.

Although trading declines in advised portfolios, advisors have a positive impact on costs (Table 4.V, column 3). When advisors execute trades, investors pay more in commissions compared with execution-only services. Consistent with our expectations, increased portfolio value lowers costs, and higher turnover increases costs. Experience lowers cost, though the effect is small.

4.4.6. Impact of Advisors on Diversification

Better diversification lowers unnecessary risk in portfolios. As Table 4.IV already revealed, advisors lower idiosyncratic risk, whether by increasing the number of securities in a portfolio or selecting securities with low correlations. Dorn and Huberman (2010) show that retail investors typically specialize in volatility, in that they select securities with similar volatilities rather than low correlations. To assess the diversification skill of advisors, we use two measures: the advisory impact on the number of individual shares in each portfolio and the effect on home bias. Although home bias is widespread (French and Poterba, 1991), debate continues about whether it actually harms investors. Normative finance theory indicates diversification benefits from investing abroad, but others argue

Table 4.V: The Influence of Advice on Trading Activity and Costs, Hausman-Taylor Estimates

This table presents coefficient estimates on retail investor portfolio return and risk using the Hausman-Taylor technique. Dependent variables are (1) *Trades,* which is the number of montly equity trades in each individual portfolio and (2) *Cost* which is the difference between the gross and net monthly portfolio return. *Advice* is a dummy variable equal to 1 is an investor is advised. *Age* is the age of the primary account holder. *Woman* is a dummy equal to 1 if the account was held by a woman. *Joint Account* is a dummy variable equal to 1 if the account was held by 2 persons, mostly a man and a woman. *Value* is the logarithm of the beginning of the month account value of common equity positions. *Turnover* is the logarithm of the sum of buys and sells of common equity positions divided by the beginning of the month account value of common equity positions. *Income* is the logarithm of the average gross monthly income in the 6 digit zip code of the investor. *Residential Value* is the logarithm of the average house price in the 6 digit zip code of the investor. *Experience* is the number of months that each investor holds a portfolio during the sample period. In each regression time dummies for each of the 52 months in the sample are used. Portfolios with equity values of below € 250 are excluded. Nonparametric bootstrapped standard errors (in parentheses) are presented below the corresponding parameters (250 replications). ***, **, * denote significance at the 1 percent, 5 percent, and 10 percent levels, respectively.

	Trades	Trades	Cost
	(1)	(2)	(3)
Advice	-0.400***	-0.264*	0.002***
	(0.003)	(0.068)	(0.000)
Age	-0.001	0.002	0.000
	(0.497)	(0.620)	(0.185)
Age Squared		-0.000	
		(0.283)	
Woman	-0.075***	-0.084***	-0.000
	(0.001)	(0.001)	(0.669)
Joint Account	-0.047**	-0.028	0.000
	(0.031)	(0.196)	(0.519)
Value	0.325***	-1.617***	-0.003***
	(0.000)	(0.001)	(0.000)
Value Squared		0.249***	
		(0.000)	
Turnover			0.008***
			(0.000)
Income	0.142	0.155	0.000
	(0.150)	(0.113)	(0.750)
Residential Value	-0.080	-0.120*	-0.000
	(0.248)	(0.089)	(0.725)
Experience	-0.010***	-0.009***	-0.000***
	(0.000)	(0.000)	(0.000)
Constant	-0.678**	2.876***	0.010***
	(0.015)	(0.003)	(0.000)
Observations	154,397	154,397	154,397
Breusch-Pagan LM test statistic, p-value	0.00	0.00	0.00
FE vs. RE, p-value	0.00	0.00	0.00
F-statistic first stage regression	22.65	16.97	19.58
Hansen J Statistic, p-value		0.999	0.037

that home bias (or local bias within a country) may be driven by informational advantages (Ivkovic and Weisbenner, 2005); Coval and Moskowitz, 2001). We calculate home bias by dividing the initial monthly common stock portfolio value invested in Dutch stocks by the total initial monthly value in common equity. Our findings in Table 4.VI (column 1) reveal that though the coefficient of *Advice* on the number of equity position is positive, it is far from significant. With our assumption that lower sophistication drives advisor choice, we could predict a positive sign of advisory intervention on the number of equity positions. Given the large negative effect of idiosyncratic risk reported in table 4.IV, we must conclude that advisors use more sophisticated diversification rather than just increasing the number of stocks. This is in line with the recent finding of Dorn and Huberman (2010) that sophistication drives lower volatility specialization. In addition, recent evidence suggests a positive effect of holding concentrated portfolios (Ivkovic, Sialm, and Weisbenner, 2008), implying that just increasing the number of stock in a portfolio may not be beneficial at all in terms of returns.

We also note from Table 4.VI (column 2) that advisors increase exposure to domestic equity, which seems intuitively to conflict with our previous finding that advisors lower idiosyncratic risk. It might be explained by findings from Kramer (2012) and Hackethal, Haliassos, and Jappelli (2012), who indicate a positive effect of advisors on mutual fund holdings. Most mutual funds distributed in the Netherlands have a strong international focus, so advisors could focus on domestic stocks for their domestic portfolio and diversify internationally through mutual funds. This finding also supports prior results (Ivkovic and Weisbenner, 2005; Coval and Moskowitz, 2001) that indicate investors benefit from local holdings due to the informational advantages. Our finding that advisors focus more on domestic equity and achieve higher returns is consistent with this view.

4.5. Conclusion

We estimate the causal impact of an advisor on the portfolio returns of an individual investor. We use a unique database of approximately 195,000 monthly equity returns for more than 5,500 Dutch investors, who are either advised or self-directed. Because our variable of interest is likely endogenous, due to self-selection, and does not change over time, we employ the instrumental variable approach developed by Hausman and Taylor (1981).

We find, irrespective of the exact model specification, a small positive effect of advisors on portfolio returns for average individual investors. In addition, we show that advice lowers idiosyncratic risk which is the result of sophisticated diversification. There is a significant positive impact of advisory intervention on the home-country bias, but it does no harm in terms of risk and return, consistent with the view that retail and professional investors have an informational advantage when selecting domestic stocks.

Table 4.VI: The Influence of Advice on Diversification, Hausman-Taylor Estimates

This table presents coefficient estimates on retail investor portfolio return and risk using the Hausman-Taylor technique. Dependent variables are (*1) Number of equity positions* which is the number of individual common stock positions in each individual investor portfolio at the beginning of each month and (2) *Share domestic stock* which is the percentage of portfolio value allocated to domestics common stock position at the beginning of each month. *Advice* is a dummy variable equal to 1 is an investor is advised. *Age* is the age of the primary account holder. *Woman* is a dummy equal to 1 if the account was held by a woman. *Joint Account* is a dummy variable equal to 1 if the account was held by 2 persons, mostly a man and a woman. *Value* is the logarithm of the beginning of the month account value of common equity positions. *Turnover* is the logarithm of the sum of buys and sells of common equity positions divided by the beginning of the month account value of common equity positions. *Income* is the logarithm of the average gross monthly income in the 6 digit zip code of the investor. *Residential Value* is the logarithm of the average house price in the 6 digit zip code of the investor. *Experience* is the number of months that each investor holds a portfolio during the sample period. In each regression time dummies for each of the 52 months in the sample are used. Portfolios with equity values of below € 250 are excluded. Nonparametric bootstrapped standard errors (in parentheses) are presented below the corresponding parameters (250 replications). ***, **, * denote significance at the 1 percent, 5 percent, and 10 percent levels, respectively.

	No. Equity positions	Share domestic stock
	(1)	(2)
Advice	0.082	0.162***
	(0.906)	(0.004)
Age	-0.028***	-0.001***
	(0.000)	(0.002)
Woman	-0.573***	-0.011
	(0.000)	(0.292)
Joint Account	0.231*	0.010
	(0.087)	(0.145)
Value	4.428***	0.025**
	(0.000)	(0.013)
Turnover	-0.065***	0.001
	(0.000)	(0.374)
Income	-0.030	0.004
	(0.943)	(0.831)
Residential Value	0.554	-0.016
	(0.114)	(0.243)
Experience	0.025***	0.002***
	(0.000)	(0.000)
Constant	-14.926***	0.732***
	(0.000)	(0.000)
Observations	154,353	154,353
Breusch-Pagan LM test statistic, p-value	0.00	0.00
FE vs. RE, p-value	0.00	0.00
F-statistic first stage regression	19.58	19.58
Hansen J Statistic, p-value	0.99	0.32

These results contrast with recent findings that incorporate mutual fund advice. Inherent to mutual fund advice is the moral hazard problem in an advisor–advisee relationship. Mutual funds typically have opaque fee structures that may benefit advisors, not their customers. However, our findings are supported by evidence based on unbiased advice. Thus, when considering common stock advice only, incentive conflicts may be less pronounced, and advisors add value. Although we lack an empirical test, our findings glean support from research that indicates a positive effect of experience and financial knowledge on less biased decision making.

We also show that advisors affect trading activity. The number of trades declines as a result of advisory intervention. Advisors do not engage in churning behavior driven by conflicts of interest, perhaps because financial market regulations explicitly forbid churning.

In summary, our results show that advisors improve the portfolio decision making of retail investors when conflicts of interest are minimal and endogeneity is controlled for. Current attempts by policy makers in many countries to replace the current incentive structure, based on product fees, with a more transparent fee model in which investors pay for advice directly, will likely benefit retail investors.

Chapter 5

Financial Literacy, Cognitive Ability, and Financial Advice Seeking

5.1. Introduction

The relationship among financial literacy, cognitive abilities, and the propensity to seek expert financial advice is important, in that financial advice offers a potential mechanism to correct for inferior financial decision making resulting from a lack of financial literacy or poor cognitive abilities. Various studies also indicate just how widespread financial illiteracy and low cognitive abilities are. Using data from the U.S. Household and Retirement Survey (HRS), Lusardi and Mitchell (2007a) find that only one-third of households can answer three basic economic principle questions correctly. Van Rooij *et al.* (2011a) report similar results among Dutch households, and Christellis *et al.* (2010) show that many Europeans score poorly on various indicators of cognitive ability. Lack of financial literacy can adversely affect the quality of financial decision making[3], as a result of which one accumulates less wealth (Lusardi and Mitchell, 2007c). In addition, growing evidence indicates that cognitive ability is an important predictor of financial outcomes[4].

Various remedies attempt to correct for the negative effects of financial illiteracy or poor cognitive ability and improve financial decision making. Collins (2010) proposes financial advice as one component of a broader financial capacity building system. Sensible defaults have proven powerful as well; Thaler and Bernarzi (2004) indicate that default participation in a retirement savings plan has positive effects on retirement savings. Financial education may improve financial decision making, though empirical findings on its effects are ambiguous (Lusardi and Mitchell, 2007a).

Another option is the use of financial advice to correct for the impact of poor financial literacy or cognitive abilities. The financial advice and planning industry is substantial (IBIS, 2011), and a large fraction of retail investors rely on financial advice. In the United States, 81% of the households investing in mutual funds, outside a retirement plan, rely on a financial advisor (ICI, 2007), and 75% of them consult financial advisors before

[3] See, for example Lusardi and Mitchell, 2007b; Van Rooij *et al.*, 2011a and 2011b; Guiso and Japelli, 2009; Bayer *et al.*, 2009; Cole and Shastry, 2009; Lusardi and Tufano, 2009.

[4] See, for example Agarwal and Mazumder, 2010; Grinblatt *et al.*, 2011a; Cole and Shastry, 2009; Grinblatt *et al.*, 2012; Korniotis and Kumar, 2012.

conducting stock market or mutual fund transactions (Hung and Yoong, 2010). Bluethgen *et al.* (2008) indicate that roughly 80% of individual investors in Germany turn to financial advice for their investment decisions, and in the Netherlands, 51% of households with an investment portfolio rely on financial advice[5] (Millward Brown, 2010). However, whether financial expert intervention benefits investors remains up for debate (Bergstesser *et al.*, 2009; Hackethal *et al.*, 2012; Karabulut, 2011, Kramer, 2012), despite some consensus that it can improve retail investor portfolio decisions if conflicts of interest are minimized (Bhattacharya *et al.*, 2012 Hung and Yuoong, 2010; Kramer and Lensink, 2012).

If financial assistance is to mitigate limited financial literacy or cognitive abilities, it is necessary first to establish that those with lower literacy and/or cognitive abilities are more inclined to turn to financial experts. This link is not obvious. Instead, more literate or cognitively able investors might use financial advice more if they are less overconfident (Kruger and Dunning, 1999), have higher time-related opportunity costs (Hackethal *et al.*, 2011b), see advice as a complementary source of information (Calcagno and Monticone, 2011), induce advisors to provide better advice (Bucher-Koenen and Koenen, 2011), or are less impatient (Fredrick, 2005). They might avoid advice though if they perceive potential conflicts of interest (Hackethal *et al.*, 2012), see no need for assistance because of their information processing and learning capabilities and stronger social networks (Korniotis and Kumar, 2012), or are less risk averse (Frederick, 2005). Therefore, this study attempts to answer the empirical question of whether increased financial literacy and higher cognitive ability increase or lower the propensity to seek advice.

We use portfolio and survey data from a randomly selected, representative sample of Dutch retail and merchant bank customers and base our main analysis on the 467 investors that participated in a survey (conducted in October 2011). With this approach, we find no significant relationship among *measured* financial literacy, cognitive ability, and financial advice seeking, even when we control for potential reverse causality between financial literacy and advice. Advice is not a sufficient remedy for bad financial decision making that results from low financial literacy. However, we find a strong negative association between *perceived* financial literacy and the choice to ask for help, even when we control for actual knowledge, in line with the competence hypothesis (Heath and Tversky, 1991). This hypothesis posits that people are more willing to act on their own judgments when they perceive themselves as more competent. Investing without the help of a financial advisor is a typical example of relying on one's own judgment. Furthermore, we provide evidence of other factors related to advice-seeking behavior, such as the negative association of risk tolerance and positive links to age, wealth, and trust in advisors. Although less educated people exhibit a lower tendency to ask for expert help, regret aversion does not appear to play a role (cf. Shefrin, 2002).

[5] It is not entirely clear why this percentage is considerably lower; perhaps it results from the Netherlands having one of the highest Internet access rates in the world, or from the way advice is defined in various studies.

In addition to these main findings, we note differences in perceptions about financial advisors between advised and self-directed investors, as well as in their main choice motivations. The most important rationale for investors who opt for advisory services is their belief in the higher level of investment knowledge of the advisor. This outcome is consistent with our main finding that the degree of perceived literacy drives advice seeking. The primary reason investors choose execution-only services is their perception of control.

In the next section, we provide an overview of related literature before introducing the data set and methods applied in Section 5.3. Then in Section 5.4, we report the results of our empirical analysis. We conclude in Section 5.5.

5.2. Literature Review

Abundant evidence indicates that investors make suboptimal investment decisions[6] and underperform (Barber *et al.*, 2009; Bauer *et al.*, 2009). A major cause of biased financial decision making is a limited degree of financial literacy and/or a low level of cognitive ability. Bernheim (1998) cites the importance of financial literacy for household decision making; Bernheim *et al.* (2001) link better financial education to improved savings behavior. Bayer *et al.* (2009) and Cole and Shastry (2009) find that the less financial literate save less. Lusardi and Tufano (2009) also show that these less literate investors have more debt, and Gerardi *et al.* (2010) confirm their higher mortgage delinquency rates. Campbell (2006) finds less knowledgeable forgo refinancing possibilities when this is financially wise to do. Van Rooij *et al.* (2011b) and Lusardi and Mitchell (2007b) find that less financially literate plan less for retirement. As a result of which financially illiterate may accumulate less wealth (Lusardi and Mitchell, 2007a).

Other researchers specifically relate financial literacy to investment decisions. Dhar and Zhu (2006) document a negative relationship between financial literacy and the disposition effect. Van Rooij *et al.* (2011a) indicate that less financially literate people are less likely to participate in the stock market. Both Guiso and Japelli (2009) and Calvet *et al.* (2009) find that less literate investors diversify their portfolios insufficiently. Hung *et al.*'s (2009b) measure of financial literacy can predict inappropriate behaviors, such as a lack of retirement planning, holding zero equity, and being too aggressive or too conservative.

[6] Studies indicate, for example, that individual investors trade excessively (Barber and Odean, 2000; Dorn and Huberman, 2005; Odean, 1999); hold underdiversified portfolios (Goetzman and Kumar, 2008); are subject to the disposition effect (Grinblatt and Keloharju, 2001; Odean, 1998); concentrate their portfolios in domestic (French and Poterba, 1999), local (Huberman, 2001; Seasholes and Zhu, 2010,), or own company (Bernarzi, 2001) stock; select stocks on the basis of their volatility similarity (Dorn and Huberman, 2010); apply naïve diversification strategies (Bernartzi and Thaler, 2001); and buy stock because it catches their attention (Barber and Odean 2008) or because of the affective response it induces (Statman *et al.*, 2008). However, it is not clear whether deviations from normative theories always lead to inferior outcomes (Coval and Moskowitz, 2001; Ivkovic *et al.*, 2008; Ivkovic and Weisbenner, 2005), and substantial heterogeneity appears in both behavior and performance (Coval *et al.*, 2005).

Cognitive ability, which implies an ability to acquire and process information, also might drive suboptimal financial behavior. People with higher cognitive abilities likely develop better social networks, information-gathering capabilities, information interpretations, learning ability, and analytical and numerical abilities (Korniotis and Kumar, 2012). Agarwal and Mazumder (2010) find that low cognition relates to mistakes in credit card or home loan decisions. Grinblatt *et al.* (2011a) provide compelling evidence of a strong and sizable relation between IQ and stock market participation, a finding supported by both Cole and Shastry (2009) and Christelis *et al.* (2010). Benjamin *et al.* (2006) also show that intelligence influences the holding of financial assets more generally.

For participants in financial markets, a positive relationship arises between their cognitive abilities and the quality of their portfolio decisions. According to Grinblatt *et al.* (2011b), people with low IQs maintain portfolios with fewer stocks and are less likely to include a mutual fund; they also bear more idiosyncratic risk and achieve lower Sharpe ratios. Using the same data, Grinblatt *et al.* (2012) report that high IQ investors show significantly better portfolio performance, because they are less sensitive to the disposition effect, pick better stocks, have better market timing, pay lower trading costs and mutual fund fees, and are less likely to herd. Their trades also are informative about future price movements. Korniotis and Kumar (2012) reveal that portfolio distortions like concentration, excessive trading and holding local stocks must be conditioned on cognitive abilities. Departures from normative theories lead only to inferior outcomes for lower cognitive individuals, while high cognitive investors benefit, apparently because their actions are driven by informational advantages. Müller and Weber (2010) provide evidence of a positive impact of financial literacy on the likelihood of investing in low cost mutual funds but only weak evidence of superior fund selection.

Assuming a detrimental impact of low financial literacy and low cognitive abilities on portfolio decisions, we need to determine whether these investors try to overcome their limitations by asking for help in their investment decision making—even though the question of whether advisors improve portfolio decisions remains uncertain[7]. For advisors to aid less financially literate or cognitively able investors, there seemingly should be a negative relationship between financial literacy and cognitive abilities and advice-seeking

[7] Bergstresser *et al.* (2009) show that mutual funds sold though the broker channel tend to underperform directly sold funds, in line with Zhao's (2003) finding that financial advisors guide customers to funds with higher fees. Even when advisors match portfolios to client characteristics, they fail to debias customers and, in some cases, even exacerbate those client biases (Mullainathan *et al.*, 2010). Hackethal *et al.* (2012) indicate that advisors are associated with lower returns and higher turnover but also with better diversification. Such improved diversification is confirmed by Kramer (2012), though he cannot confirm lower returns in advised portfolios. Shapira and Venezia (2001) find more trading activity in professionally managed accounts but also a lower degree of disposition effect. According to Von Gaudekker (2011), losses from insufficient diversification are greatest for overconfident investors who combine poor financial skills with reliance on their own financial judgments. In a financial advice choice experiment, many investors rejected the offer to receive advice, whereas those who follow the advice actually improved their portfolio risk–return trade off (Bhattacharya *et al.*, 2012). This finding is in line with Hung and Yoong's (2010) assertion that only solicited advice helps improve portfolio outcomes.

propensity. Although, this relationship has, to our knowledge, not been studied as extensively as we do, some studies provide some indicative evidence. Hackethal *et al.* (2011) find that investors who rely more on financial advice perceive themselves as less knowledgeable, and in Hung and Yoong's (2010) choice experiment, less sophisticated people were more likely to take advice. Similarly, in a survey, respondents who considered themselves more financially literate preferred more autonomy in their pension decisions (Van Rooij *et al.*, 2007). Guiso and Japelli (2006) also find that investors who spend more time acquiring financial information (who should be more financially literate) delegate their financial decisions less. Although Georgarakos and Inderst (2011) suggest that advice matters most for households with low financial capability, they acknowledge that the finding holds only when households trust the advice. People with less cognitive ability are more risk averse (Dohmen *et al.*, 2010; Frederick, 2005) and may be more willing to ask for help, because investing on their own seems more risky. Overall, advised investors are indeed more risk averse (Bluethgen *et al.*, 2008).

Less financially literate (lower cognitive ability) investors may, in addition, be less aware of potential conflicts of interest and therefore less hesitant to consult an advisor. Theoretical models even suggest that advisors mainly provide services to less sophisticated investors: Stoughton *et al.* (2011) assert that financial advisors sell underperforming active funds only to unsophisticated investors, and Inderst and Ottaviani (2009) assume that naive customers do not anticipate advisors' conflict of interest. Hackethal *et al.* (2011) confirm that investors who rely more on financial advice perceive less conflict of interests, which may be explained by Ottaviani's (2000) model, in which advisors shift their moral hazard behavior according to the sophistication of their clients, such that more sophisticated investors receive better advice. Yet Collins (2010) warns against overstating the conflict of interest between advisors and their clients, because advisors care about reputation effects.

The negative relationship for advice-seeking propensity and financial literacy and cognitive abilities is not ambiguous, though. Calcagno and Monticone (2011) and Collins (2010) consider that financial literacy and financial advice complements rather than substitutes. Advisors may reveal information only to more knowledgeable investors, who anticipate such benefits and seek advice more often. Bucher-Koenen and Koenen (2011) reveal that more literate investors make more use of advisors because they can induce advisors to provide better advice. More sophisticated investors might have higher advice-seeking propensities because of their higher opportunity costs of time too (Hackethal *et al.*, 2011). Van Rooij *et al.* (2011a) find that people who are less financially literate rely more on informal sources of financial advice, such as friends and family, whereas more literate investors opt more for professional financial advice. According to Hackethal *et al.* (2012), wealthier investors, who tend to be more sophisticated, are more often matched with advisors than poorer investors. The finding that less literate people rely less on advice also resonates with psychological literature, which indicates that less knowledgeable people lack the ability to recognize their illiteracy, leading them to overestimate their ability and not seek advice (Kruger and Dunning, 1999). Finally, people with less cognitive abilities are less patient (Dohmen *et al.*, 2010; Frederick, 2005), so they may avoid expert help and opt for execution-only trades instead to lower the barrier to making and executing portfolio decisions.

In summary, the exact relationship among financial literacy, cognitive abilities, and the propensity to seek professional financial advice is still unclear. Arguments exist for both positive and negative relationships. To clarify the issue, we ask whether proxies for financial literacy and cognitive ability can predict advice-seeking behavior and derive answers from survey data obtained from a group of retail investors at a Dutch retail bank that offers both execution-only and advisory investment services.

5.3. Data and Methods

5.3.1. The Sample

We used two main data sources. First, we obtained detailed information about a randomly selected sample of retail investors from a Dutch, medium-sized, retail and merchant bank that provided information about each client's financial assets, debt, portfolio composition, and type of investment service chosen (execution only, investment advice, or delegated portfolio management). Second, we surveyed these same randomly selected investors with an e-mailed questionnaire, sent in October 2011 and then repeated after two weeks for investors who had not responded. If investors had no e-mail address listed, we sent them an invitation to participate through postal mail,[8] sent on the same day as the e-mail invitation but without any reminder. Of the 4,586 randomly selected investors, 251 could not be reached due to e-mail bounces. We received completed surveys from 467 investors, for a net response rate of 10.8%.

The bank that provided the data is a medium-sized retail and merchant bank operating throughout the Netherlands. The bank advertises itself as a relationship bank; many services are sold through account managers, private bankers, or retail advisors. Its services and products include checking accounts, savings, mortgages, insurance, business loans, investments, private equity, leasing, and pensions. Because we obtained data from just one retail bank, we took great caution to ensure that our sample of respondents was both internally and externally valid. We compared the respondents with nonrespondents and other similar data sets on various key variables in Table 5.I. Although some differences arose in the investor and portfolio characteristics between respondents and nonrespondents and between our sample and other databases, our overall impression suggests that sample selection bias is not a concern.

[8] For both e-mail and postal invitations, participants answered the questions in a web-based environment. Stanton and Rogelberg (2001) warn that web-based surveys may suffer from the so-called digital divide, in that some groups have much less Internet access. The Netherlands has one of the highest Internet access rates in the world, so it is unlikely to be a problem.

Table 5.I. Sample Validity

This table compares respondents and non-respondents in our sample to check for internal validity and compares our sample with other samples to check for external validity. DNB Data refers to data from the Dutch Central Bank.

	Our sample			Other samples	
	Full sample	Respondents	Non-Respondents	Bhattacharya et al., 2011 (Germany)	DNB Data, as of 31 June 2012 (The Netherlands)
Age	54.2	58.4	53.7	49.2	
Male (%)	73.1	79.0	72.4	81.8	
Liquid Assets (€)	66,170	95,675	66,142		
Debt (€)	-69,020	-87,476	-66,792		
Portfolio Value (€)	59,709	79,970	57,263	68,208	64,672
Equity (%)	70.8	69.7	71.0	731.0	53.77
Bond (%)	10.1	16.8	9.3	61.0	33.9
Cash (%)	19.0	13.5	19.7		
Mutual Funds (%)	46.9	47.8	46.8	30.0	51.3
Options (% of portfolios)	2.8	4.7	2.5		
N	4,335	467	3,868	8,195	1,200,000
Response (%)		10.77%			

[1]based on subsample that chose for advice

5.3.2. Defining Advice

Help for investment portfolio decisions can take various forms. Investors may rely on the advice of professional (financial) advisors or delegate their portfolio decisions to a portfolio manager. We use the group of investors who opt for execution-only as our benchmark; they use no financial advice or delegated portfolio management services. All others, who opt for some sort of financial expert assistance, constitute the financial advice-seeking group.

Our partner bank organizes its investment services as follows: All investors may open execution-only accounts after establishing the legally required limited client profile. Clients with at least €20,000 in financial assets available for investments can opt for execution-only services or delegate their portfolio decisions. Investors with financial assets of at least €100,000 may choose to have their own personal investment advisor or delegation, as well as execution-only. Considering our focus on drivers of help-seeking behavior in investment decisions, we limit our sample to investors with €20,000 available, who may act on their own or ask for help through portfolio management or financial advice. As a robustness check we estimated the restricted samples of investors who may only choose between execution-only or delegation (portfolio values of €20,000–€100,000) and investors who may also choose between financial advice or execution-only (portfolio values above €100,000).

Some execution-only investors in our sample also received advice from professional financial advisors external to the focal bank. When respondents indicated their connection to an investment portfolio at another bank, we added them to the advised group, rather than the execution-only group.

5.3.3. Measuring Financial Literacy

Most studies of financial literacy use three basic questions about inflation, compounding, and risk from the U.S. Health and Retirement Survey (HRS; Lusardi and Mitchell, 2007a, 2007b, 2008; Van Rooij *et al.*, 2011a). However, because our sample consists of investors, rather than general households, these three questions may be too easy for the respondents and may not enable us to distinguish between more and less literate investors. Therefore, we use more advanced literacy questions (Lusardi and Mitchell, 2007b; Van Rooij *et al.*, 2011a), specifically, eight of the eleven advanced questions from the DNB Household Survey (excluding three questions that require very similar knowledge). The eight survey questions have been well validated (Hung *et al.*, 2009b) as having good internal consistency and test–retest reliability. Thus, the questions in our survey relate to important elements of adequate investment decision making: the differences between saving accounts, stocks, and bonds; the function of the stock market; the relationship between interest rates and bond prices; how diversification works; and the use of mutual funds. Figure 5.1 provides an overview of the questions in our survey.

Instead of measuring literacy so directly, some authors rely on self-assessed financial literacy measures, because perceived literacy may have predictive value of its own (Hung *et al.*, 2009b). People may not be able to assess their actual financial knowledge and may base their decisions on how much they think they know. If they think they know more than they actually do, people exhibit a tendency toward overconfidence. Hung *et al.* (2009b) find that self-assessed literacy better predicts financial behaviors than measured financial literacy, and Parker *et al.* (2011) indicate specifically that confidence in one's own knowledge predicts financial behaviors, apart from actual knowledge. In providing evidence that self-perceived competence relates to both trading behavior and the home bias, Graham *et al.* (2009) relate their findings to the competence hypothesis (Heath and Tversky, 1991). That is, people rely more on their own judgment if they consider themselves more competent. Yet measured and perceived financial literacy are generally (moderately) positively correlated (Hung *et al.*, 2009b), and both have some predictive power for estimating stock market participation (Van Rooij *et al.*, 2011a). Because self-assessed literacy may be more related to actual behavior than our measure of financial literacy, we also asked about perceived literacy to test our predictions. Specifically, we measure perceived financial literacy using the question in Figure 5.2.

Figure 5.1. Measured Financial Literacy Questions

(All questions also included a "don't know" option).

1) Which of the following statements describes the main function of the stock market?
    - The stock market helps to predict stock earnings
    - The stock market results in an increase in the price of stocks
    - The stock market brings people who want to buy stocks together with those who want to sell stocks
    - None of the above.
2) Which of the following statements is correct?
    - Once one invests in a mutual fund, one cannot withdraw the money in the first year
    - Mutual funds can invest in several assets, for example invest in both stocks and bonds
    - Mutual funds pay a guaranteed rate of return which depends on their past performance
    - None of the above.
3) If the interest rate falls, what should happen to bond prices?
    - Rise
    - Fall
    - Stay the same
    - None of the above.
4) True or false? Buying a company stock usually provides a safer return than a stock mutual fund.
    - True
    - False.
5) True or false? Stocks are normally riskier than bonds.
    - True
    - False.
6) Considering a long time period (for example 10 or 20 years), which asset normally gives the highest return?
    - Savings accounts
    - Bonds
    - Stocks.
7) Normally, which asset displays the highest fluctuations over time?
    - Savings accounts
    - Bonds
    - Stocks.
8) When an investor spreads his money among different assets, does the risk of losing money:
    - Increase
    - Decrease
    - Stay the same.

Figure 5.2: Perceived Literacy Question

Financial knowledge varies from person to person. How would you assess your own financial knowledge?

Very Low						Very High	Don't Know
○	○	○	○	○	○	○	○

5.3.4. Reversed Causality

In estimating the relationship between advice seeking and financial literacy, we must consider the possibility that measured financial literacy is endogenous, because the choice of asking for expert help may influence the level of financial literacy. The sign of this relationship is not clear a priori. Both advised and self-directed investors may increase their literacy from interacting with financial markets; the effect even may be greater for self-directed investors, who deal with financial markets directly, find information themselves, and decide on their own which investments to pursue. Alternatively, advised investors may learn from their interactions with their financial advisor, who teaches them about risk, return, and diversification. In the group of help-seeking investors, we also anticipate that the learning mechanism through expert advice is probably stronger for investors who hold advised rather than managed portfolios.

To address causality directions, we included another question in the survey about the amount of education respondents received on economics before they entered the job market, which should be before they started to invest. Economic education thus should correlate positively with current financial literacy but be unrelated to having a financial advisor (e.g. Cole and Shastry, 2009; Lusardi and Mitchell, 2007b; Van Rooij *et al.*, 2011b). Specifically, with a seven-point scale ranging from “very little” to “very much,” respondents indicated: “How much of your formal education was devoted to economics?” We then created two dummies: one for respondents who indicated some economic education (score of 3–5) and one for respondents who indicated a lot of economic education (score of 6–7). Those with little economic education (score of 1–2) constitute the benchmark group.

5.3.5. Measuring Cognitive Ability

Cognitive ability may relate to various cognitive domains, such as mathematical (numerical) and verbal skills and memory functioning (Christellis *et al.*, 2010). Education and income can serve as proxies for cognitive abilities, though most studies attempt to measure them directly. The Wonderlic Personality Test, need for cognition scale, Scholastic Achievement Test, and American College Test are common in the United States for example. Such tests consist of many items and require considerable time to complete, and thus, for our survey methodology, they are not feasible. Frederick (2005) instead proposes a three-question cognitive reflection test (CRT). For applied researchers interested in allocating people to cognitive groups, the CRT is attractive because it demands a limited amount of time and correlates sufficiently with the scores on other IQ tests. It ranked as the best or second-best predictor across four decision-making domains in a comparison with four other tests (Fredrick, 2005). The CRT asks the three questions in Figure 5.3.

The noninvestment nature of these questions deviates considerably from the rest of the survey and may make respondents suspicious. Therefore, we framed the questions as a contest, in which participants could win one of two €50 prizes. A moderate proportion of 93 respondents (20%) opted not to participate in the contest, so our sample size drops to 374 when we include cognitive ability in our analysis. Both advised and self-directed investors participated equally. However, the nonparticipants might have obtained lower cognitive ability scores than participants; these nonparticipants scored significantly lower on measured financial literacy (t-value = -2.45, $p = 0.02$), and financial literacy correlates positively with cognitive ability ($\rho = 0.29$, $p = 0.00$).

Figure 5.3. Cognitive Ability Questions

(1) A bat and a ball cost $1.10 in total. The bat costs $1.00 more than the ball. How much does the ball cost? _____ cents.

(2) If it takes 5 machines 5 minutes to make 5 widgets, how long would it take 100 machines to make 100 widgets? _____ minutes.

(3) In a lake, there is a patch of lily pads. Every day, the patch doubles in size. If it takes 48 days for the patch to cover the entire lake, how long would it take for the patch to cover half of the lake? _____ days.

5.3.6. Control Variables

Guiso and Japelli (2006) indicate that men are less willing to delegate their portfolio decisions, which may relate to their higher level of overconfidence in financial matters (Barber and Odean, 2000) or their generally higher degree of financial literacy. Both Hackethal *et al.* (2012) and Bluethgen *et al.* (2008) find that men seek advice less often; they also indicate that age, account volume, self-employment, and investment experience relate positively to advice seeking. Although Bhattacharya *et al.* (2012) find a positive relationship between male gender and advice seeking, they confirm the positive relations with age and portfolio value. Older investors may opt for financial advice to compensate for their cognitive aging (Korniotis and Kumar, 2011). Elmerick *et al.* (2002) find that the likelihood of using a financial planner relates positively to educational achievement, income, and wealth and negatively to self-employment or being a married man. Self-employed people may be accustomed to making decisions independently; high income and high wealth investors likely have higher opportunity costs of time, which induces them to ask for assistance. Hung and Yoong (2010) find being married increases the propensity to seek advice. Therefore, we include the following socio-economic variables as controls in our multivariate analysis: gender, age, education, occupation, household composition, income, portfolio value, and investment experience.

5.4. Results

5.4.1. Degree of Financial Literacy, Cognitive Ability, and Advice Seeking

In Table 5.II we provide an overview of responses to the eight literacy questions (see also Figure 5.1). Although some of the questions may be considered difficult, the investors in our sample did remarkably well. The proportions of advised and self-directed investors that answered seven or eight of the eight questions correctly (Panel B, Table 5.II) were 47% and 43%, respectively, considerably higher than in similar studies. Only 11% of respondents answered no, one, or two questions correctly. The questions answered correctly by the largest majority (approximately 85%) were those on asset volatility and diversification (questions 7 and 8). The two most difficult questions refer to the determinants of bond prices and assets returns (questions 3 and 6). These results are similar to van Rooij *et al.*'s (2011a), though the respondents in our sample score much better.

The higher degree of financial literacy among our respondents, compared with other studies, likely is due to our sample selection process. We drew our sample from a group of households that already participate in financial markets; most other studies use samples from households in general. It seems reasonable that those who participate in financial markets are more financially literate than those who do not, such that the average literacy in our sample should be higher.

Table 5.II. Financial Literacy Score

This tables reports the percentages of 320 advised (ADV) and 147 self-directed (SD) investors providing correct, incorrect and "don't know" answers to 8 literacy questions. Panel B reports the distributions of the number of correct answers for both advised and self-directed investors. ***, **, * denote significance at the 1 percent, 5 percent, and 10 percent levels, respectively

Panel A: Percentages of total number of respondents per group

	% Correct			% Incorrect			% Don't know		
	ADV	SD	ADV-SD	ADV	SD	ADV-SD	ADV	SD	ADV-SD
1. Which statement describes the main function of the stock market?	73.0	71.0	2.0	9.0	17.0	-8.0**	18.0	12.0	6.0*
2. Which statement about mutual funds is correct?	68.0	65.0	3.0	12.0	18.0	-6.0*	20.0	17.0	3.0
3. What should happen to bond prices if interest rates fall?	46.0	52.0	-6.0	30.0	27.0	3.0	24.0	22.0	2.0
4. Buying a company stock usually provides a safer return than a stock mutual fund that invests worldwide?	73.0	71.0	2.0	5.0	7.0	-2.0	22.0	22.0	0.0
5. Stocks are normally safer than bonds, true or false	79.0	78.0	1.0	4.0	5.0	-1.0	18.0	16.0	2.0
6. Considering a long time period, which asset normally gives the highest return?	58.0	59.0	-1.0	27.0	27.0	0.0	15.0	15.0	0.0
7. Normally, which asset displays the highest fluctuations over time?	85.0	85.0	0.0	6.0	4.0	2.0	9.0	11.0	-2.0
8. What happens to the risk of losing money when an investor spreads money among different assets?	84.0	83.0	1.0	10.0	10.0	0.0	6.0	7.0	-1.0
N	320	147		320	147		320	147	

Panel B: Number of correct answers, percentages of respondents that are advised or self-directed

	ADV	SD	ADV-SD
None Correct	3.8	3.4	0.3
1 Correct	3.8	2.7	1.0
2 Correct	5.0	2.0	3.0
3 Correct	7.2	8.8	-1.7
4 Correct	5.3	8.2	-2.9
5 Correct	10.9	15.0	-4.0
6 Correct	16.9	17.0	-0.1
7 Correct	24.7	22.4	2.2
All Correct	22.5	20.4	2.1
Mean # correct	5.65	5.63	0.02
N	320	147	

A significantly greater proportion of self-directed investors answer some questions (1 and 2) incorrectly, compared with advised investors, though the proportion of self-directed investors who answer "don't know" is generally lower. Another notable pattern (Panel B, Table 5.II) is the slight U-shaped relationship between financial advice seeking and the number of correct answers: Advised investors are overrepresented in the groups that answer only a few (zero, one, or two) and that answer the most (seven or eight) questions correctly. The self-directed group is overrepresented in the middle category (three–five questions answers correctly): 32% of the self-directed investors are in this middle category, as opposed to only 23% of the advised group, and the difference is significant at the 5% level (t-statistic = 1.95). This finding may offer a preliminary indication that advisors cater to both the least and the most literate, serving as a substitute for the least and a complement for the most literate. We address this issue in more detail in the multivariate analysis in Section 5.4.4.

To obtain a score on financial literacy for each respondent, we perform a factor analysis similar to van Rooij *et al.* (2011a). We also use information contained in the difference between incorrect answers and "don't know" answers. Lusardi and Mitchell (2007b) show that those who answer "don't know" are different from other respondents: They are less likely to plan and succeed in a planning effort, even compared with those who give an incorrect answer. We therefore constructed two dummies for each of the questions. The first dummy indicates whether the question was answered correctly, and the second refers to "don't know" responses. From a factor analysis of these 16 dummies, we retained one key factor underlying the level of financial literacy. The Kaiser-Meyer-Olkin test of sampling adequacy (Kaiser, 1970) returned a value of 0.823, which indicates that factor analysis was appropriate. In addition, in Appendix 5.A we provide the factor loadings for our 16 variables. The use of a single factor to indicate literacy also was confirmed by a scree plot, which displays a point of inflexion after one factor (Field, 2005). We use the Bartlett (1937) method to determine factor scores for each respondent in our sample, which indicate their measured financial literacy. This variable ranged from -3.25 to 0.84.

Table 5.III provides the results of the cognitive test. Of the three questions, the bat and ball problem is by far the most difficult, and only about 35% of respondents gave the correct answer. The machines and lake problems were answered correctly by approximately 50% and 62%, respectively. No clear differences arose between advised and self-directed investors; questions 1 and 2 were answered correctly slightly more often by advised investors, but self-directed investors scored a little better on problem 3.

In Panel B of Table 5.III, we provide an overview of the distribution of correct answers; it is remarkably well spread out over the four categories. On average, the respondents provided 1.48 correct answers, more than the average of 1.24 reported by Frederick (2005). Although no significant difference in the mean score between advised and self-directed investors became apparent, we observed a slight U-shape, similar to that in the distribution of literacy questions. Advised investors were overrepresented in the low (zero correct) and high (three correct) cognitive groups; self-directed investors were overrepresented in the middle (one or two correct).

Table 5.III. Cognitive Ability Score

This tables reports the proportion of advised (ADV) and self-directed (SD) investors providing correct, incorrect and "don't know" answers to 3 cognitive ability questions. Panel B reports the distribution of the number of correct answers for both advised and self-directed investors. ***, **, * denote significance at the 1 percent, 5 percent, and 10 percent levels, respectively.

Panel A: Percentages of total number of respondents

	% correct			% Incorrect			% Don't know		
	ADV	SD	ADV-SD	ADV	SD	ADV-SD	ADV	SD	ADV-SD
1. Bat and ball problem	37.7	33.3	4.4	59.1	65.0	-5.8	3.1	1.7	3.1
2. Machines problem	50.6	48.7	1.9	46.3	48.7	-2.4	3.1	2.6	3.1
3. Lake problem	61.1	63.2	-2.2	33.9	29.9	3.9	5.1	6.8	5.1

Panel B: Number of correct answers, percentages of respondents that are advised or self-directed.

	ADV	SD	ADV-SD
None Correct	22.6	20.6	2.0
1 Correct	21.8	23.4	-1.6
2 Correct	30.5	35.5	-5.0
3 Correct	25.1	20.6	4.5
Mean # correct	1.49	1.45	0.04

Table 5.IV contains the overview of perceived financial literacy. Many respondents opted for the middle category, yet some interesting patterns still emerge. First, the mean perceived literacy score for advised investors was 3.95, significantly less than the 4.39 score by self-directed investors (t-statistic = -2.94). Second, the proportion of advised investors nearly monotonically decreased in perceived financial literacy. In the "very little" category, 80% of respondents sought advice, but only 43% of them did so in the "very much" category. When confronting perceived literacy to actual literacy, we observe that the mean perceived literacy score increases when moving up the actual financial literacy scores. The difference in the perceived literacy score between the highest and the lowest financial literacy quartile is 1.73 (t-statistic = 9.19). For cognitive ability scores a similar pattern is visible: investors with higher cognitive ability scores, rate their own financial literacy significantly higher that the low cognitive able.

In Table 5.V we detail the correlation between our key dependent and independent variables. The correlation between advice seeking and perceived literacy was significantly negative (rho = -0.14, p = 0.00). There were significant positive correlations between perceived literacy and measured financial literacy (rho = 0.44, p = 0.00); perceived literacy and cognitive ability (rho = 0.22, p = 0.00); and measured financial literacy and cognitive ability (rho = 0.29, p = 0.00), which should come as no surprise. Hung *et al.* (2009b)

Table 5.IV. Perceived Financial Literacy

This table reports the proportion of advised (ADV) and self-directed (SD) investors indicating their perceived financial literacy by answering the following question: "Financial literacy differs from person to person. How much financial knowledge do you possess?" on a 7-point scale ranging from "very little" to "very much". Differences are between the extreme ratings.

	Sample		Investor		Financial Literacy Quartiles[1]				Cognitive Ability Score			
	N	%	ADV	SD	1st	2nd	3rd	4th	0	1	2	3
1 "very little"	30	6.4	80.0	20.0	63.3	16.7	20.0	0.0	52.2	17.4	17.4	13.0
2	44	9.4	75.0	25.0	45.5	25.0	18.2	11.4	38.2	17.6	32.4	11.8
3	67	14.3	76.1	23.9	38.8	26.9	19.4	14.9	32.0	16.0	36.0	16.0
4	125	26.8	67.2	32.8	20.8	32.8	31.2	15.2	24.3	23.3	31.1	21.4
5	104	22.3	72.1	27.9	12.5	24.0	29.8	33.7	21.7	26.5	30.1	21.7
6	69	14.8	58.0	42.0	8.7	17.4	42.0	31.9	12.5	19.6	32.1	35.7
7 "very much"	14	3.0	42.9	57.1	0.0	14.3	28.6	57.1	21.4	21.4	21.4	35.7
Don't Know	14	3.0	50.0	50.0	50.0	21.4	7.1	21.4	27.3	36.4	18.2	18.2
Mean Score	4.09		3.95	4.39	3.11	4.00	4.42	4.84	3.61	4.27	4.16	4.60
Difference (t-stat.)			-0.44 (-2.94)			-1.73 (-9.19)				-0.99 (-4.40)		

[1] this refers to measured financial literacy

indicate that cognitive ability supports financial literacy and that though people think they know more than they actually do, actual and perceived knowledge are positively, moderately correlated. Our data support these claims.

Table 5.V. Correlation Coefficient Matrix

This table presents correlation coefficients between key variables. Numbers above the diagonal are the sample sizes from which the correlation coefficients have been calculated. ***, **, * denote significance at the 1 percent, 5 percent, and 10 percent levels, respectively.

	Advised	Measured Financial Literacy	Perceived Financial Literacy	Cognitive Ability
Advised		467	453	346
Measured Financial Literacy	-0.01		453	346
Perceived Financial Literacy	-0.14***	0.44***		338
Cognitive Ability	0.01	0.29***	0.22***	

To validate our individual financial literacy and cognitive ability scores, we contrasted the three measures with investor characteristics (Table 5.VI). The chi-square of advice seeking related to our literacy and cognitive ability measures was significant only for perceived financial literacy. In addition, the results in Table 5.VI indicate patterns in the distribution of socio-economic variables. Specifically, educational achievement was significantly associated with the propensity to seek advice; those with the least education were least inclined to seek expert help. Investors in low education groups also scored significantly lower on both financial literacy and cognitive ability tests, so this finding may indicate that those who might benefit the most from advice use it the least. Other significant differences included gender (women used expert help more often than men) and age (investors older than 60 years used advice more often than younger investors). Household income revealed no significant relation with advice seeking, nor did investment experience. Portfolios of advised investors on average were twice as large as those of self-directed investors. Within these portfolios, advised investors allocated considerably more to mutual funds (57%) than self-directed investors did (28%). In addition, advised portfolios contained options much less frequently (3.8% vs. 6.8% for self-directed portfolios).

The findings in Table 5.VI also confirm previous results regarding the relationship of socio-economic variables with financial literacy and cognitive ability. Literacy (measured and perceived) was positively associated with educational achievement, such that 57% (8%) of investors with little education ranked in the first (fourth) literacy quartile, and investors with college degrees were overrepresented in the third and fourth literacy quartiles (62%). A similar pattern emerged for cognitive ability groups. Among the least educated, 30% solved two or three problems correctly, a percentage which rose to 66% for those with more education.

Gender correlated strongly with (measured and perceived) literacy and cognitive ability; men scored significantly higher on all three variables. Of the female (male) respondents, more than 46% (19%) fell into the lowest financial literacy quartile, 29% (13%) were in the lowest perceived literacy group, and 34% (19%) represented the lowest cognitive ability class. Although the chi-square of age in relation to literacy and ability was insignificant, we observed some consistency with previous studies that report hump-shaped patterns in the relationship between cognitive abilities and age (Dohmen *et al.*, 2010, Korniotis and Kumar, 2011). Investors between 30 and 59 years of age were overrepresented in the higher literacy and ability groups; those 60 years and older scored lower. Similar to many other studies, income was significantly and positively associated with measured (perceived) financial literacy and cognitive ability: 56% (32%) of the households with the lowest earnings ranked in the lowest literacy group, and only 5% (7%) in the highest quartile. The corresponding numbers for the highest earning households were 11% (6%) and 29% (39%), respectively. We observed a similar pattern in the cognitive ability groups.

Finally, regarding the relationships of investment-related data, literacy, and cognitive ability, we again uncovered some interesting patterns. First, experienced investors (more than five years of investment experience) scored significantly higher on (measured and perceived) financial literacy, which may indicate that literacy can be improved through interactions with financial markets, or else that more literate investors survive in the market longer. For the cognitive ability groups, we found no relation with experience. Portfolio size was considerably higher for more literate and cognitively able investors, namely, three times as large for investors in the highest literacy quartile. Within the portfolios of the most literate investors, derivatives appeared five times more often than in those owned by less literate investors. This difference rose to a factor of ten in the comparison pertaining to perceived literacy.

Table 5.VI. Advice-Seeking, Financial Literacy and Cognitive Ability Across Demographics

This table presents an overview of the demographics of the sample, also spit into advised (ADV) and self-directed (SD) and in groups based on financial literacy and cognitive abilities. All figures are percentages except when indicated otherwise.

	Sample		Investor		Measured Literacy Quartiles				Perceived Literacy			Cognitive Ability Score			
	N	%	ADV	SD	1^{st}	2^{nd}	3^{rd}	4^{th}	1-2	3-5	6-7	0	1	2	3
Investor															
Advised	320	68.5			25.6	22.5	29.4	22.5	18.2	67.1	14.7	22.6	21.8	30.5	25.1
Self-Directed	147	31.5			23.8	30.6	25.2	20.4	12.1	61.4	26.4	20.6	23.4	35.5	20.6
Pearson chi^2 (p-value)					3.62 (p=0.306)				9.92 (p=0.001)			1.44 (p=0.697)			
Education															
Primary / Preparatory intermediate vocational	72	15.4	54.2	45.8	56.9	19.4	15.3	8.3	30.4	60.9	8.7	50.0	20.0	22.0	8.0
Intermediate vocational	81	17.3	77.8	22.2	24.7	34.6	23.5	17.3	7.5	82.5	10.0	27.7	24.6	29.2	18.5
Higher secondary education / Secondary pre-university	33	7.1	66.7	33.3	18.2	45.5	21.2	15.2	13.8	75.9	10.3	27.3	18.2	31.8	22.7
Higher vocational / University	271	58.0	68.6	31.4	16.6	21.0	33.9	28.4	15.0	60.5	24.4	11.8	22.2	36.0	30.0
Other	10	2.1	100.0	0.0	50.0	30.0	20.0	0.0	33.3	55.6	11.1	50.0	33.3	16.7	0.0
Pearson chi^2 (p-value)			14.76 (p=0.011)		77.22 (p=0.000)				33.39 (p=0.000)			48.86 (p=0.000)			
Occupation															
Retired	165	35.3	70.9	29.1	30.3	26.7	26.7	16.4	19.3	66.5	14.3	22.8	22.8	30.1	24.4
Self-employed	89	19.1	64.0	36.0	12.4	24.7	33.7	29.2	10.5	62.8	26.7	16.9	23.9	36.6	22.5
Employee	167	35.8	67.1	32.9	22.2	22.2	29.9	25.7	14.6	65.9	19.5	21.3	18.9	33.9	26.0
Student	2	0.4	50.0	50.0	50.0	50.0	0.0	0.0	50.0	50.0	0.0	0.0	100.0	0.0	0.0
Social Services Benefit	21	4.5	71.4	28.6	47.6	33.3	4.8	14.3	30.0	60.0	10.0	18.2	54.5	9.1	18.2
Other	23	4.9	78.3	21.7	34.8	26.1	26.1	13.0	15.0	70.0	15.0	53.8	7.7	30.8	7.7
Pearson chi^2 (p-value)			2.84 (p=0.725)		28.99 (p=0.016)				13.12(p=0.217)			22.06 (p=0.106)			
Gender															
Male	359	76.9	66.3	33.7	18.7	25.1	29.8	26.5	12.6	66.6	20.9	18.8	20.6	34.2	26.5
Female	108	23.1	75.9	24.1	46.3	25.0	22.2	6.5	29.1	61.2	9.7	33.8	28.4	24.3	13.5
Pearson chi^2 (p-value)			3.57 (p=0.059)		42.18 (0.000)				19.11 (0.000)			13.46 (p=0.004)			

Table 5.VI. Advice-Seeking, Financial Literacy and Cognitive Ability Across Demographics (Continued)

	Sample		Investor		Financial Literacy Quartiles				Perceived Literacy			Cognitive Ability Score			
	N	%	ADV	SD	1st	2nd	3rd	4th	1-2	3-5	6-7	0	1	2	3
Age															
20-29	3	0.6	66.7	33.3	66.7	33.3	0.0	0.0	33.3	66.7	0.0	0.0	100.0	0.0	0.0
30-39	17	3.6	52.9	47.1	17.6	29.4	29.4	23.5	17.6	52.9	29.4	14.3	14.3	50.0	21.4
40-49	51	10.9	62.7	37.3	17.6	31.4	25.5	25.5	16.0	68.0	16.0	16.7	13.9	38.9	30.6
50-59	144	30.8	61.8	38.2	21.5	20.1	31.3	27.1	13.9	62.0	24.1	24.3	19.6	30.8	25.2
60-69	239	51.2	74.9	25.1	29.3	26.4	25.5	18.8	16.7	68.2	15.0	22.2	24.4	30.7	22.7
older than 70	13	2.8	69.2	30.8	15.4	23.1	53.8	7.7	30.8	53.8	15.4	25.0	41.7	25.0	8.3
mean age (years)			59.3	56.5											
Pearson chi^2 (p-value)			10.22 (p=0.068)		19.18 (p=0.205)				9.76 (p=0.462)			13.30 (0.579)			
Household composition															
Single, without kids	73	15.6	65.8	34.2	30.1	23.3	30.1	16.4	20.3	63.8	15.9	27.7	19.1	34.0	19.1
Single, with kids	14	3.0	85.7	14.3	42.9	21.4	35.7	0.0	0.0	92.9	7.1	58.3	16.7	0.0	25.0
Living together or married, without kids	218	46.7	73.4	26.6	26.6	25.7	25.7	22.0	19.6	64.0	16.4	22.0	24.4	31.1	22.6
Living together or married, with kids	148	31.7	61.5	38.5	16.2	25.0	32.4	26.4	11.2	64.3	24.5	15.8	19.3	36.8	28.1
Other	14	3.0	64.3	35.7	50.0	28.6	0.0	21.4	15.4	76.9	7.7	22.2	44.4	22.2	11.1
Pearson chi^2 (p-value)			8.09 (p=0.087)		22.29 (0.033)				14.06 (0.080)			20.11 (0.064)			
Gross Annual Household															
Below modal (< €33,000)	63	13.5	73.0	27.0	55.6	27.0	12.7	4.8	31.7	61.7	6.7	35.7	35.7	16.7	11.9
1x->1.5x modal (€33,000-<€50,000)	162	34.7	67.3	32.7	26.5	27.8	30.9	14.8	17.2	70.7	12.1	29.7	23.4	26.6	20.3
1.5-<3x modal (€50,000-<€100,000)	137	29.3	66.4	33.6	9.5	27.0	27.7	35.8	12.6	63.0	24.4	11.9	23.9	37.6	26.6
> 3x modal (>€100,000)	55	11.8	67.3	32.7	10.9	12.7	47.3	29.1	5.6	55.6	38.9	5.4	8.1	48.6	37.8
Don't know/no answer	50	10.7	74.0	26.0	40.0	22.0	18.0	20.0	17.0	70.2	12.8	26.7	10.0	36.7	26.7
Pearson chi^2 (p-value)			1.72 (p=0.786)		90.38 (0.001)				39.39 (0.000)			41.42 (0.001)			

Table 5.VI. Advice-Seeking, Financial Literacy and Cognitive Ability Across Demographics (Continued)

	Sample		Investor		Financial Literacy Quartiles				Perceived Literacy Groups			Cognitive Ability Score			
	N	%	ADV	SD	1st	2nd	3rd	4th	1-2	3-5	6-7	0	1	2	3
Investment Experience															
< 1 year	18	3.9	61.1	38.9	66.7	11.1	11.1	11.1	47.1	52.9	0.0	25.0	8.3	16.7	50.0
1-<5 years	80	17.1	71.3	28.8	35.0	28.8	23.8	12.5	23.1	67.9	9.0	29.1	16.4	32.7	21.8
>5 years	368	78.8	68.5	31.5	20.9	25.0	29.6	24.5	13.2	65.5	21.3	20.4	24.0	32.6	22.9
Pearson chi^2 (p-value)			0.73 (p=0.693)		27.88 (p=0.001)				23.35 (p=0.000)			8.49 (0.204)			
Wealth and portfolio															
Portfolio Value (€)		79,970	96,033	45,001	46,743	63,002	80,318	137,100	54,811	78,469	113,266	43,977	70,237	97,187	87,098
Equity allocation (%)		69.68	69.0	71.2	67.62	65.51	72.55	72.93	68.0	69.3	72.9	67.0	72.2	69.1	70.1
Bond allocation (%)		16.81	12.2	18.9	19.74	19.89	14.10	13.55	18.5	17.9	12.6	18.7	15.4	16.1	17.0
Fund Allocation (%)		47.81	56.8	28.4	49.70	40.41	52.33	47.95	51.1	51.0	33.6	49.9	48.5	44.7	49.0
Options (% of portfolios)		4.71	3.8	6.8	1.71	4.27	3.82	9.80	1.4	2.7	13.3	5.3	3.9	6.3	2.4
Other variables															
Risk tolerance (Scale 1-7)		3.64	3.40	4.07	2.46	3.45	3.97	4.53	2.32	3.68	4.54	3.14	3.41	3.91	3.93
Regret aversion (Scale 1-7)		2.96	2.75	3.06	3.12	2.99	2.69	2.59	3.26	2.74	2.78	3.34	2.66	3.00	2.82
Trust in people (Scale 1-7)		4.02	4.06	3.88	3.85	3.87	4.23	4.04	3.96	4.02	3.93	3.66	4.14	4.06	4.17
Trust in advisers (Scale 1-7)		4.10	4.14	3.82	3.95	3.88	4.22	4.11	4.00	4.09	3.94	4.12	4.05	4.05	4.21
Time preference (% impatient)		3.21	3.44	2.72	3.42	3.42	4.58	0.98	5.41	3.04	1.20	3.95	5.19	0.90	2.44

5.4.2. Impact of Financial Literacy and Cognitive Abilities on Advice Seeking

To determine whether financial literacy and cognitive ability influence the propensity to seek expert help, we estimated various linear probability models.[9] In Table 5.VII, we provide the results of our baseline estimations; they confirm results from prior studies on advice seeking (e.g., Bhattacharya *et al.*, 2012; Bluethgren *et al.*, 2008; Hackethal *et al.*, 2012). Less educated investors have a significantly lower propensity to seek advice; investors older than 60 years seek advice more often; portfolio size and being male relate positively to advice seeking.

We also include our literacy and cognitive ability measures in Table 5.VII. Both *measured* financial literacy and cognitive ability were unrelated to financial advice seeking (columns 2 and 4), but *perceived* financial literacy was strongly negatively associated with it (column 3), even after we added measured financial literacy and cognitive ability as additional regressors (column 5). It appears that how much people think they know matters more than how much they actually know, consistent with the competence hypothesis (Heath and Tversky, 1991). In line with Parker *et al.* (2011) we thus show that confidence matters more for behavior than actual knowledge. In column 6 we used an instrumental variable approach to control for possible reverse causality and confirmed the insignificant effect of measured financial literacy. Appendix 5.B contains the results of the underlying first-stage regression. Measured financial literacy related significantly positively to being self-employed, being male, having investment experience, and portfolio value; it related negatively to less education. Two instruments based on the amount of formal education in economics strongly predicted financial literacy, in the expected direction. We also could confirm our instrument relevance with an F-statistic for the excluded instruments equal to 11.18; they pass the Hansen J test of overidentifying restrictions with a p-value of 0.34.

5.4.3. Adding Preferences

Thus far, we have not taken heterogeneity in preferences into consideration, though preferences vary considerably and have significant effects on choice behavior. Therefore, preferences should be additional drivers of financial advice seeking, and excluding them from our estimations may lead to incorrect inferences as a result of omitted variables bias. We therefore included risk tolerance, time preference, regret aversion, and trust as additional controls in our analysis.

Guiso, Sapienza and Zingales (2008) show that the level of trust affects economic decisions in general; Georagakos and Inderst (2011) specifically indicate that trust in

[9] A probit model is usually preferred for a bivariate dependent variable. We performed all the estimations using a probit model and achieved qualitatively and quantitatively similar results. The use of linear probability models is advocated with an instrumental variables technique; for example, Freedman and Sekhon (2010) state that nonlinearity in a probit model is an essential difficulty for a two-step correction. The error term of a linear probability may suffer from heteroskedasticity. Therefore, we used heteroskedastic-robust standard errors in all reported estimations.

Table 5.VII. The Impact of Financial Literacy and Cognitive Ability on Financial Advice Seeking, Baseline Results

This table presents coefficient estimates of various linear probability models on measures of financial literacy and cognitive abilities. De dependent variable is a dummy where 0 corresponds to investors that invest by means of execution-only, and 1 to investors that ask for financial expert-help at the bank of our sample or at any other bank. ***, **, * denote significance at the 1 percent, 5 percent, and 10 percent levels, respectively. P-values in parentheses based on robust standard errors.

	OLS (1)	OLS (2)	OLS (3)	OLS (4)	OLS (5)	IV (6)
Financial Literacy and Cognitive Abilities						
Measured Financial Literacy		-0.01			0.00	-0.12
		(0.79)			(0.90)	(0.35)
Perceived Financial Literacy			-0.05***		-0.06***	
			(0.00)		(0.00)	
Cognitive Abilities				0.00	0.01	
				(0.88)	(0.71)	
Education (base group is higher vocational or University)						
Primary or preparatory intermediate vocational	-0.17**	-0.18**	-0.21***	-0.17**	-0.19**	-0.24**
	(0.01)	(0.01)	(0.00)	(0.04)	(0.03)	(0.01)
Higher secondary education or secondary pre-university	-0.04	-0.04	-0.03	0.05	0.03	-0.04
	(0.60)	(0.60)	(0.77)	(0.63)	(0.81)	(0.63)
Intermediate vocational	0.08	0.08	0.09	0.07	0.08	0.07
	(0.15)	(0.15)	(0.13)	(0.26)	(0.21)	(0.24)
Age (Base group: age<40)						
Age 40-49	0.08	0.08	0.06	-0.07	-0.06	0.12
	(0.54)	(0.53)	(0.63)	(0.62)	(0.66)	(0.38)
Age 50-59	0.09	0.09	0.09	-0.01	0.01	0.11
	(0.47)	(0.46)	(0.43)	(0.95)	(0.95)	(0.37)
Age >=60	0.25**	0.25**	0.25**	0.15	0.17	0.27**
	(0.05)	(0.05)	(0.04)	(0.27)	(0.20)	(0.03)
Retired	-0.08	-0.08	-0.11	-0.21***	-0.22***	-0.05
	(0.29)	(0.30)	(0.13)	(0.01)	(0.01)	(0.49)
Self-employed	-0.09	-0.09	-0.12	-0.15	-0.14	-0.04
	(0.28)	(0.30)	(0.15)	(0.11)	(0.12)	(0.72)
Employee	0.02	0.02	-0.00	-0.06	-0.06	0.05
	(0.79)	(0.77)	(0.98)	(0.45)	(0.48)	(0.51)
Income (base group: >100.000)						
Income<33.000	0.08	0.08	0.02	0.13	0.06	0.05
	(0.32)	(0.34)	(0.79)	(0.16)	(0.55)	(0.57)
Income 33.000-<50.000	-0.04	-0.04	-0.07	-0.03	-0.06	-0.02
	(0.55)	(0.56)	(0.26)	(0.71)	(0.48)	(0.74)
Income 50.000-<100.000	-0.04	-0.04	-0.06	-0.08	-0.09	0.00
	(0.51)	(0.54)	(0.33)	(0.29)	(0.23)	(0.96)
Kids	-0.03	-0.03	-0.03	-0.07	-0.06	-0.04
	(0.53)	(0.53)	(0.62)	(0.24)	(0.27)	(0.46)
Married	0.07	0.07	0.05	0.03	0.01	0.05
	(0.25)	(0.26)	(0.35)	(0.68)	(0.85)	(0.39)
Male	-0.10**	-0.10*	-0.07	-0.05	-0.04	-0.03
	(0.05)	(0.07)	(0.19)	(0.41)	(0.59)	(0.77)
Experienced	-0.01	-0.01	0.03	0.00	0.05	0.02
	(0.85)	(0.88)	(0.59)	(1.00)	(0.41)	(0.73)
ln (Portfolio value)	0.05***	0.05***	0.05***	0.05**	0.05**	0.05***
	(0.00)	(0.00)	(0.00)	(0.01)	(0.02)	(0.00)
Constant	0.15	0.14	0.38*	0.35	0.55**	-0.04
	(0.49)	(0.53)	(0.09)	(0.15)	(0.03)	(0.88)
R^2	0.104	0.104	0.130	0.115	0.136	0.063
Number of observations	454	454	440	338	330	454
F-Statistic Excluded Instruments						11.18
Hansen J test p-Value						0.596
p-value exogeniety test						0.339

financial advice affects stock market participation, especially for less literate investors. Trust therefore may directly affect the decision to ask for help. Guiso and Japelli (2006) find that trust is positively associated with portfolio delegation. We include two trust variables in our analysis, adapted from the World Values Survey. Specifically, we asked about respondents' degree of agreement (seven-point scale, 1 = "totally disagree" to 7 = "totally agree") with two statements: (1) "Most people can be trusted" (which we label "trust general") and (2) "Most financial advisors can be trusted" ("trust advice").

Willingness to take risk also is heterogeneous across people (Dohmen *et al.*, 2011) and advised investors tend to be more risk averse (Bluethgen *et al.*, 2008; Gerhardt and Hackethal, 2009). Dohmen *et al.* (2010) use a survey question to measure risk aversion and show that it predicts behavior especially well when asked in reference to specific domains, such as financial matters. Lönnqvist *et al.* (2010) find the survey measure more reliable than a lottery choice task to assess appetites for risk (Holt and Laury, 2002). We therefore used a survey measure from Dohmen *et al.* (2011), measured on a seven-point scale: "How would you rate your willingness to take risks in financial matters?"

Simonson (1992) indicates strong correlation between regret and responsibility. We consider advice seeking a responsibility-shifting mechanism that helps the investor protect against the feelings of regret. Shefrin (2002) argues that handholding is the one of the most important services an advisor provides; if the investment decision turns out poorly, investors have the option of blaming the advisor. Therefore we included a question to assess the degree of regret aversion on a seven-point scale: "Image that your zip code wins a large price in the zip code lottery,[10] how much regret would you feel if you did not purchase a lottery ticket?"

Time preference relates to impatience and also may drive advice-seeking. Impatient people should be more likely to invest through an execution-only platform, because its barriers to executing investment decisions are lower, compared with contacting a financial advisor first, discussing the proposed trade, and then having it executed. To keep the survey length acceptable, we used one time preference trade-off as a rough approximation of the degree of impatience. Frederick (2005) found a large intergroup difference for the choice between €3.400 this month or €3.800 next month; both amounts and the difference between them were considerable,[11] but there is also a clearly rational choice, such that the impatient choice implies an annual discount rate of 280%.

In the lower panel of Table 5.VI we provide the scores on the preference questions: Advised investors scored lower on both risk tolerance and regret aversion but higher on

[10] The Dutch Zip Code Lottery provides a unique platform to measure regret. Even if people do not buy a lottery ticket, they receive a lottery number (i.e., their zip code). Thus people know the outcome of their decision, even if they do not participate, which may induce feelings of regret.

[11] Almost 80% of our respondents indicated a gross household income of less than €100,000 per year, which implies a net monthly income of approximately €4,000.

both trust variables. Although most respondents made the patient choice in the time preference question, more advised investors made the impatient choice. More literate and cognitively able investors were much more risk tolerant (Frederick, 2005), suffer less from regret aversion, and score higher on trust measures. These findings indicated that in estimating the effect of financial literacy and cognitive abilities on the choice to ask for financial expert help, preferences serve an important explanatory role.

Table 5.VIII. The Impact of Financial Literacy and Cognitive Abilities on Financial Advice Seeking, Adding Preferences

This table presents coefficient estimates of various linear probability models on measures of financial literacy and cognitive abilities. De dependent variable is a dummy where 0 corresponds to investors that invest by means of execution-only, and 1 to investors that ask for financial expert-help at the bank of our sample or at any other bank. ***, **, * denote significance at the 1 percent, 5 percent, and 10 percent levels, respectively. P-values in parentheses based on robust standard errors.

	OLS	OLS	OLS	OLS	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)
Measured Financial Literacy	0.01			0.02	0.01	-0.13
	(0.84)			-0.54	(0.75)	(0.52)
Perceived Financial Literacy		-0.03*		-0.03*	-0.03	
		(0.07)		(0.05)	(0.17)	
Cognitive Abilities			0.01		0.01	
			(0.68)		(0.63)	
Risk Tolerance	-0.06***	-0.05***	-0.06***	-0.05***	-0.06***	-0.04
	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.28)
Time Preference	0.14*	0.14*	0.21**	0.13	0.20**	0.18*
	(0.10)	(0.10)	(0.02)	(0.12)	(0.03)	(0.06)
Regret Aversion	-0.01	-0.01	-0.01	-0.01	-0.00	-0.01
	(0.36)	(0.37)	(0.65)	(0.38)	(0.75)	(0.34)
Trust General	-0.00	-0.00	-0.01	-0.00	-0.01	-0.01
	(0.78)	(0.80)	(0.71)	(0.82)	(0.63)	(0.64)
Trust Advice	0.04**	0.04**	0.05**	0.04*	0.04*	0.05**
	(0.04)	(0.05)	(0.04)	(0.06)	(0.06)	(0.03)
Other controls (see table 5.VII)	yes	yes	yes	yes	yes	yes
R^2	0.156	0.159	0.179	0.160	0.181	0.107
Number of observations	418	410	317	410	312	418
F-Statistic Excluded Instruments						5.74
Hansen J test p-Value						0.413
p-value exogeniety test						0.467

In Table 5.VIII we provide the results for our estimations, after adding the preference controls. As expected, risk tolerance was significantly and negatively associated with advice-seeking behavior. Time preference showed a positive association; contrary to our expectations, impatient investors chose advice more often. Trust in general bore no relation to propensity to ask for help, whereas trust in advisors indicated a positive association (Guiso and Japelli, 2006). Causality may run in both directions though: People who place more trust in advisors may be more inclined to hire one, and having an advisor may increase trust. The most important finding from Table 5.VIII was that our main conclusions remained unaltered: Perceived financial literacy lowered the propensity to ask for expert assistance in portfolio decision making; measured financial literacy and cognitive ability were unrelated.

5.4.4. Additional Results

Our univariate results in Section 5.4.1 indicated a possible U-shaped pattern between advice seeking and both measured financial literacy and cognitive abilities. We therefore included a squared term for both variables in Table 5.IX.

Table 5.IX. The Impact of Financial Literacy and Cognitive Abilities on Financial Advice Seeking, Adding Squared Terms and Dummies

This table presents coefficient estimates of various linear probability models on measures of financial literacy and cognitive abilities. De dependent variable is a dummy where 0 corresponds to investors that invest by means of execution-only, and 1 to investors that ask for financial expert-help at the bank of our sample or at any other bank. Ijn column 3, the base group is a cognitive ability of 0. ***, **, * denote significance at the 1 percent, 5 percent, and 10 percent levels, respectively. P-values in parentheses based on robust standard errors.

	OLS	OLS	OLS	IV
	(1)	(2)	(3)	(4)
Measured Financial Literacy	-0.15			-0.09
	(0.14)			(0.36)
Measured Financial Literacy Squared	0.03			0.02
	(0.11)			(0.38)
Cognitive Ability		-0.13		
		(0.11)		
Cognitive Ability Squared		0.04*		
		(0.06)		
Cognitive Ability=1			-0.08	
			(0.27)	
Cognitive Ability=2			-0.07	
			(0.34)	
Cognitive Ability=3			0.02	
			(0.75)	
Other controls & preferences (see table 5.VIII)	yes	yes	yes	yes
R^2	0.162	0.188	0.188	0.106
Number of observations	418	317	317	418
F-Statistic Excluded Instruments				9.67
p-value exogeniety test				0.530

Although the signs for measured financial literacy supported the U-shaped relationship, the coefficients were insignificant. Using instruments for measured financial literacy (column 3, Table 5.VII) made no difference. That is, measured financial literacy does not drive financial advice-seeking behavior, nor is financial advice an adequate solution to substitute for a lack of financial literacy. Adding the squared term of cognitive ability confirmed the U-shaped pattern (column 2), though it was significant only for the squared term. To assess the robustness of this result, we added a specification with three cognitive ability dummies (column 3). The signs were in line with the U-shaped relationship, but the coefficients were not significant. Therefore we conclude, that for both measured financial literacy and cognitive ability, neither a linear nor a U-shaped relationship could be observed.

The help-seeking group consisted of two possible types of advice, so we also repeated our estimations separately for the two relevant subsamples (see Table 5.X). In Panel A, we provide results for portfolios of less than €100,000; they are basically unaltered. Only perceived financial literacy was negatively associated with advice seeking. In Panel B, the results for investors with portfolios of more than €100,000 (i.e., excluding those who opted for delegated portfolio management) reflected a drastically reduced sample size, with decreased significance levels, but they still generally confirmed our previous findings.

5.4.5. Financial Literacy, Cognitive Ability, and Perceptions of Advice Seeking

To determine what drives the negative relationship between perceived financial literacy and the propensity to ask for financial expert help, we analyzed three additional questions that appeared in our survey. First, we asked investors which information sources they used in their investment decisions. Second, we asked them about their motives for hiring an advisor or not. Third, we measured perceptions of financial advice and execution-only investing.

The overview in Table 5.XI pertains to information sources used by advised and unadvised investors. A financial advisor was among the most frequently mentioned sources for advised investors, of course; they also used non-investment advisors significantly more. Self-directed investors relied on information from family and friends, as well as television, newspapers, and financial websites. This interesting result implies that advisors serve as a substitute source of information. Furthermore, we observe large differences in the information sources used by more and less financially literate people. The highest literacy quartile relies significantly more on all information sources, though the differences are even greater for non-advisor information sources. The least literate group most commonly indicated: “I don’t use any sources.” Thus, financially literate investors use all information sources more frequently, which even may drive their higher literacy. For cognitive ability, the group differences showed a similar pattern, though not as pronounced. In Table 5.XI, we note that financial websites were used significantly more often among the highest cognitive ability group; all other differences were insignificant.

Table 5.X. The Impact of Financial Literacy and Cognitive Abilities on Financial Advice Seeking, Subsamples.

This table presents results based on two subsamples. Panel A presents the coefficient estimates for the subsample of investors that choose for delegated portfolio management or execution-only; panel B is based on the subsample of investors that choose between financial advice or execution-only. ***, **, * denote significance at the 1 percent, 5 percent, and 10 percent levels, respectively. P-values in parentheses based on robust standard errors.

	OLS (1)	OLS (2)	OLS (3)	IV (4)
Panel A: Delegated Portfolio Management vs. Self-Directed				
Measured Financial Literacy	0.00			-0.19
	(0.91)			(0.46)
Perceived Financial Literacy		-0.06***		
		(0.01)		
Cognitive Abilities			0.01	
			(0.70)	
Other controls & preferences (see table VIII)	yes	yes	yes	yes
R^2	0.157	0.171	0.203	0.057
Number of observations	289	283	219	289
F-Statistic Excluded Instruments				4.2
Hansen J test p-Value				0.345
p-value exogeniety test				0.406
Panel B: Advised vs. Self-Directed, and Portfolio Size > €100,000				
Measured Financial Literacy	-0.03			-0.14
	(0.72)			(0.81)
Perceived Financial Literacy		-0.07		
		(0.13)		
Cognitive Abilities			0.18*	
			(0.05)	
Other controls & preferences (see table 5.VIII)	yes	yes	yes	yes
R^2	0.274	0.306	0.336	0.258
Number of observations	71	71	51	71
F-Statistic Excluded Instruments				0.41
Hansen J test p-Value				0.728
p-value exogeniety test				0.836

Table 5.XII contains the overview of investors' motives for choosing help or execution-only investments. The most important reason investors ask for help (56% of advised investors) was their belief that advisors had more investment knowledge. Other important motives included portfolio monitoring (39%), finding relevant information (38%), creating a better portfolio (36%), and saving time (29%), consistent with economic theory. Thus, economies of scale in portfolio management and information acquisition, as well as the potentially better investment decision-making abilities of advisors, appear to help investors

Table 5.XI. Information sources used before making an investment decision, Advised vs. Self-Directed and over Financial Literacy and Cognitive Ability Groups

This table tabulates relative frequencies to the following question: "What are the most important information sources you use before making an investment decision?" (Shown in random order; multiple answers are allowed). For brevity we do not exhibit the middle categories. ***, **, * denote significance at the 1 percent, 5 percent, and 10 percent levels, respectively.

	All	Investor			Financial Literacy Quartiles			Perceived Literacy Groups			Cognitive Ability Score		
		Advs.	SD	Advs.-SD	1 (low)	4 (high)	high-low	1-2 (low)	6-7 (high)	high-low	0 (low)	3 (high)	high-low
Financial Adviser of this bank	33.0	45.0	6.8	38.2***	32.5	38.2	5.8	27.0	20.5	-6.55	27.6	39.0	11.4
Accountant, Insurance Agent, Solicitor or other non-investment adviser	4.1	5.6	0.7	4.9***	2.6	5.9	3.3	2.7	1.2	-1.50	5.3	4.9	-0.4
Family, friends or relatives	10.3	6.9	17.7	-10.8***	10.3	11.8	1.5	9.5	9.6	0.18	15.8	8.5	-7.3
TV	19.9	15.6	29.3	-13.6***	6.8	28.4	21.6***	13.5	27.7	14.2**	23.7	17.1	-6.6
Newspaper	41.8	35.6	55.1	-19.5***	17.9	58.8	40.9***	14.9	62.7	47.8***	34.2	42.7	8.5
Financial Websites	23.8	16.3	40.1	-23.9***	6.0	42.2	36.2***	5.4	45.8	40.3***	11.8	26.8	15.0**
Financial Magazines	15.2	14.4	17.0	-2.6	3.4	29.4	26.0***	4.1	37.3	33.3***	14.5	18.3	3.8
Newsletter from this bank	11.6	12.2	10.2	2.0	7.7	11.8	4.1	8.1	7.2	-0.88	18.4	11.0	-7.4
Financial Adviser other bank	10.9	14.7	2.7	12.0***	6.0	16.7	10.7**	4.1	9.6	5.58	9.2	12.2	3.0
Other Sources	6.9	6.3	8.2	-1.9	1.7	11.8	10.1***	4.1	12.0	8.0*	2.6	6.1	3.5
I don't use any sources	16.3	17.2	14.3	2.9	30.8	6.9	-23.9***	37.8	7.2	-30.6***	18.4	13.4	-5.0
I don't know	3.0	3.1	2.7	0.4	6.8	1.0	-5.9**	5.4	0.0	-5.41	3.9	2.4	-1.5

(Hackethal, *et al.*, 2012). According to Stoughton *et al.* (2011), small investors use financial advisors to economize on information costs as well. Finally, advisors serve as stress relievers; "peace of mind" was mentioned by 32% of the respondents. This finding may relate to advisors' ability to minimize regret (Shefrin, 2002). However, self-control ("an advisor makes sure that I put aside enough money") appears to play no role.

In contrast, entertainment or thrill-seeking motives (Dorn and Sengmueller, 2009) appeal to self-directed investors (Panel B, Table 5.XII); "investing on my own is more fun" was the second most important reason to opt for execution-only investing. The most important reason was a feeling of control over the portfolio. Agency issues leading to moral hazard behaviors were not major drivers for these execution-only respondents, but cost considerations were. Only 19% of the respondents indicated conflicts of interest with an advisor as a major reason to opt for execution-only, while 30% indicated lower costs.

When relating these motives to (perceived) financial literacy and cognitive ability, some interesting patterns emerged. Literate investors regarded advisors as a sounding board in their investment decisions (Panel A, column 7, Table 5.XII), consistent with the idea that advisors provide complementary sources of information for literate investors. Time saving was a more important motive for more literate investors, who may have higher time-related opportunity costs. These investors also believe that advisors are better able to find relevant information (column 4), though those who perceive themselves to be more literate (column 7) are driven less by their belief in advisors' greater investment knowledge.

The three most important reasons for self-directed investing became especially pronounced among the more literate group (Panel B, Table 5.XII). Cost, control, and fun were critical to the most financially literate; the least literate mentioned "don't know" as their motive more often. The differences between perceived literacy groups were similar but not significant. Those who perceived themselves as highly literate also perceived more potential conflict of interest problems (Column 7, Panel B) and believed they could invest just as well, or better, than a financial advisor.

We applied a more robust test to the possible motives for this choice between advised and self-directed investing. In Table 5.XIII we list the estimates of the effects of financial literacy and cognitive abilities on perceptions of (dis)advantages of investing execution-only or with help. We used six statements related to the (dis)advantages of execution-only and six statements about the (dis)advantages of financial advice. The exact wording and univariate statistics appear in Appendix 5.C.

Perceived literacy (Panel B, Table 5.XIII) better explained the degree of agreement with all 12 statements than did measured financial literacy (Panel A) or cognitive abilities (Panel C). When we included the three literacy and ability variables in our specifications simultaneously (Panel D), perceived literacy emerged as the main driver of beliefs. Perceived financial literacy was positively associated with the judgment of advantages of

Table 5.XII. Motives for choosing advised or self-directed investment services, across financial literacy and cognitive ability groups

This table tabulates relative frequencies of reasons to choose for financial advice or for being self-directed. Answers were shown in a random order and more than one anwser was allowed. The question in panel A was given to people that made use of advisory services at the bank of our sample, the question in panel B to investors that used the execution-only services at the bank of our sample. Reasons are presented from most to least mentioned for all investors. ***, **, * denote significance at the 1 percent, 5 percent, and 10 percent levels, respectively.

		Financial Literacy Quartiles			Perceived Literacy Groups			Cognitive Ability Score		
	All	1 (low)	4 (high)	high-low	1-2 (low)	6-7 (high)	high-low	0 (low)	3 (high)	high-low
Panel A: "I choose to invest by means of a financial advisor, because a financial adviser:" (N=301)										
has more investment knowledge than myself	55.5	53.1	52.4	-0.7	52.6	35.9	-16.7	65.2	54.4	-10.8
monitors my portfolio	39.2	29.6	38.1	8.5	35.1	48.7	13.6	39.4	43.9	4.5
is better able to find me relevant information than myself	38.2	27.2	47.6	20.5**	33.3	43.6	10.3	40.9	40.4	-0.6
creates a better portfolio than I would do by myself	36.2	34.6	31.7	-2.8	35.1	33.3	-1.8	37.9	42.1	4.2
gives me peace of mind	31.9	37.0	33.3	-3.7	45.6	30.8	-14.8	40.9	26.3	-14.6*
saves me time	29.2	12.3	38.1	25.7***	22.8	30.8	8.0	25.8	29.8	4.1
reduces my risks	22.3	21.0	19.0	-1.9	19.3	17.9	-1.3	28.8	22.8	-6.0
is a sounding board to me	21.9	13.6	39.7	26.1***	10.5	41.0	30.5***	13.6	22.8	9.2
pays attention to my personal circumstances	16.9	16.0	17.5	1.4	19.3	20.5	1.2	21.2	12.3	-8.9
avoids investment mistakes	15.6	19.8	11.1	-8.6	10.5	12.8	2.3	22.7	10.5	-12.2*
improves my return	14.3	13.6	15.9	2.3	17.5	12.8	-4.7	21.2	14.0	-7.2
aids in clarifying my financial goals	9.3	11.1	7.9	-3.2	10.5	10.3	-0.3	16.7	7.0	-9.6
is responsible for investment decisions	8.6	8.6	3.2	-5.5	7.0	2.6	-4.5	10.6	5.3	-5.3
makes sure I put aside enough money	2.7	3.7	1.6	-2.1	3.5	2.6	-0.9	6.1	3.5	-2.6
finds me bargains	2.3	1.2	3.2	1.9	1.8	2.6	0.8	4.5	1.8	-2.8
improves my social status	0.7	1.2	0.0	-1.2	0.0	0.0	0.0	1.5	0.0	-1.5
Other reasons	9.0	6.2	14.3	8.1	3.5	17.9	14.4**	1.5	14.0	12.5***
Don't Know	7.6	14.8	4.8	-10.1*	14.0	7.7	-6.3	9.1	8.8	-0.3

Table 5.XII. Motives for choosing advised or self-directed investment services, across financial literacy and cognitive ability groups (Continued)

		Financial Literacy Quartiles			Perceived Literacy Groups			Cognitive Ability Score		
	All	1 (low)	4 (high)	high-low	1-2 (low)	6-7 (high)	high-low	0 (low)	3 (high)	high-low
Panel B: "I choose to invest by myself because:" (N=166)										
Investing on my own, gives me control over my own portfolio	42.8	25.0	53.8	28.8**	29.4	50.0	20.59	35.5	40.0	4.5
Investing on my own is more fun than by means of an adviser	31.9	22.2	41.0	18.8*	29.4	29.5	0.13	35.5	36.0	0.5
Investing on my own is cheaper than by means of an adviser	29.5	13.9	53.8	40.0***	23.5	31.8	8.29	22.6	20.0	-2.6
A financial adviser is only meant for large, wealthy clients	25.9	25.0	20.5	-4.5	17.6	22.7	5.08	35.5	24.0	-11.5
A financial adviser puts the banks' interest above mine	18.7	11.1	12.8	1.7	0.0	27.3	27.3**	9.7	28.0	18.3*
I find all necessary investment information on the internet	16.9	8.3	23.1	14.7*	5.9	20.5	14.57	19.4	28.0	8.6
I can invest just as good (or even better) than an adviser	8.4	2.8	5.1	2.4	0.0	15.9	15.9*	3.2	12.0	8.8
other reasons	24.7	33.3	20.5	-12.8	23.5	27.3	3.74	19.4	24.0	4.6
Don't know	4.8	13.9	0.0	-13.9**	17.6	0.0	·17.6***	9.7	0.0	-9.7

execution-only (statements 1–3) and negatively with its disadvantages (statements 4–6). It related negatively to advantages of a financial advisor (statement 7–9) but not to judgments of possible disadvantages (statements 10 and 12).

The findings in this table also imply that people with lower self-assessed literacy believe advisors make better decisions (statement 8), have more information (statement 9), and think that investing on their own would lead to more investment mistakes (statement 4) and more risks (statement 6). Advisors thus serve a substitute role mainly for those who think they lack financial knowledge. Investors with higher self-assessed literacy believe in the advantages of being self-directed: It is fun and grants more control to the investor.

5.5. Conclusions and Discussion

We found self-reported evidence that advisors serve a substitute role. Advised investors use various information sources (other than advisors) significantly less than self-directed investors. A substitute role for advice would predict a negative linear relationship between financial literacy or cognitive ability and the propensity to seek expert help. We found no such relationship for measured financial literacy and cognitive ability, but there was strong evidence that *perceived* financial literacy negatively affected the choice to use expert help, even when we controlled for actual knowledge.

Perceived financial literacy also explained significant differences in the beliefs about the advantages and disadvantages of advised and self-directed investing. People who assess their own financial knowledge as lower agree more about the advantages of financial advice and the disadvantages of being self-directed. These findings confirm the role of advisors as substitutes when investors think they lack the financial literacy needed to make sound financial decisions, in line with the competence hypothesis (Heath and Tversky, 1991). If people feel more competent (perceive literacy as higher), they rely more on their own judgment (execution-only).

Although we found no relationship of measured financial literacy or cognitive ability with financial advice-seeking behavior, advisors clearly served different roles for more and less literate and cognitively able investors. Investors with higher literacy and cognitive ability rated the “sounding board” function of advice higher, which implies a substitute role. The time-saving function of advice also was more relevant for literate investors. When investors lacked cognitive abilities, advisors instead served as stress relievers and means to avoid investment mistakes.

For policy makers, these findings have several relevant implications. Financial institutions offering investment services to retail investors must assess the suitability and appropriateness of any financial service or product for the individual client. The creation of an appropriate client profile should include self-assessed levels of investment expertise, because it relates strongly to perceptions, motives, and choice, and thus could help identify appropriate services for different perceived literacy groups.

Table 5.XIII. Perceptions on Financial Advice and Execution-Only

This table presents results on the impact of financial literacy and cognitive ability on perceptions about execution-only and financial advice using ordered probit regressions. The dependent variable is the degree of agreement on 12 different statements that highlight various (dis)advantages of investing by means of execution-only or by making use of a financial adviser using a 7-point scale from (1) "Totally Disagee to (7) "Totally Agree". The exact wording and the univariate statistics of the statements are given in Appendix 5.C. ***, **, * denote significance at the 1 percent, 5 percent, and 10 percent levels, respectively. P-values in parentheses based on robust standard errors.

	Statements on Execution-Only						Statements on Financial Advice					
	More Fun	More Control	Cheaper	More Mistakes	More Time	More Risks	Peace of Mind	Better Decisions	More Information	Bank's Interest	Takes Responsibility	Knows Less
	1	2	3	4	5	6	7	8	9	10	11	12
Panel A: Measured Financial Literacy												
Measured Financial Literacy	0.08	0.00	0.07	-0.15*	-0.04	-0.12*	-0.06	0.03	0.05	-0.05	-0.20***	-0.03
	(0.29)	(0.98)	(0.31)	(0.07)	(0.59)	(0.08)	(0.42)	(0.70)	(0.53)	(0.51)	(0.00)	(0.67)
Other Controls (see Table 5.XIII)	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Pseudo R^2	0.014	0.009	0.014	0.020	0.027	0.022	0.012	0.031	0.019	0.015	0.040	0.023
Number of observations	391	384	358	379	394	401	405	399	413	391	406	403
Panel B: Perceived Financial Literacy												
Perceived Financial Literacy	0.12***	0.07*	0.04	-0.17***	-0.17***	-0.14***	-0.12***	-0.15***	-0.12***	0.01	-0.05	0.08*
	(0.01)	(0.08)	(0.39)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.77)	(0.23)	(0.08)
Other Controls (see Table 5.XIII)	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Pseudo R^2	0.019	0.012	0.016	0.029	0.037	0.028	0.018	0.039	0.028	0.014	0.033	0.029
Number of observations	382	377	351	374	385	393	397	391	402	383	399	393

Table 5.XIII. Perceptions on Financial Advice and Execution-Only (Continued)

	Statements on Execution-Only						Statements on Financial Advice					
	More Fun	More Control	Cheaper	More Mistakes	More Time	More Risks	Peace of Mind	Better Decisions	More Information	Bank's Interest	Takes Responsibility	Knows Less
	1	2	3	4	5	6	7	8	9	10	11	12
Panel C: Cognitive Ability												
Cognitive Ability	0.02	-0.02	0.05	0.06	0.07	0.08	-0.06	-0.08	-0.03	-0.01	-0.15**	-0.08
	(0.81)	(0.75)	(0.47)	(0.33)	(0.26)	(0.20)	(0.27)	(0.18)	(0.60)	(0.85)	(0.02)	(0.21)
Other Controls (see Table 5.XIII)	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Pseudo R^2	0.026	0.013	0.018	0.032	0.033	0.024	0.017	0.036	0.022	0.028	0.034	0.024
Number of observations	298	296	275	288	303	309	307	300	312	297	308	305
Panel D: Financial Literacy and Cognitive Ability												
Measured Financial Literacy	-0.06	-0.06	0.13*	-0.01	0.08	0.01	0.01	0.10	0.16	0.06	-0.17**	-0.13
	(0.48)	(0.52)	(0.10)	(0.92)	(0.32)	(0.88)	(0.87)	(0.35)	(0.11)	(0.48)	(0.05)	(0.14)
Perceived Financial Literacy	0.11**	0.11**	0.02	-0.15***	-0.17***	-0.15***	-0.12***	-0.12**	-0.12**	-0.01	-0.01	0.07
	(0.03)	(0.02)	(0.65)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)	(0.85)	(0.78)	(0.12)
Cognitive Abilities	0.01	-0.04	0.03	0.09	0.09	0.11*	-0.04	-0.07	-0.03	-0.02	-0.11*	-0.09
	(0.93)	(0.54)	(0.62)	(0.13)	(0.18)	(0.09)	(0.47)	(0.29)	(0.66)	(0.79)	(0.08)	(0.20)
Other Controls (see Table 5.XIII)	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Pseudo R^2	0.031	0.020	0.022	0.041	0.044	0.034	0.023	0.043	0.034	0.028	0.036	0.031
Number of observations	293	291	270	285	297	304	301	296	305	291	303	298

In addition, there is an ongoing debate about whether financial advice actually provides help by substituting for a lack of financial literacy or cognitive ability. Our findings indicate it does not; neither financial literacy nor cognitive ability exhibit a relationship with the propensity to seek financial advice. Financial advice thus appears to be an inadequate mechanism to assist those who need it the most.

Appendix 5.A. Factor Loadings Financial Literacy Questions

Question	Answer	Factor Loadings
1. Which statement describes the main function of the stock market?	Correct	0.605
	Don't Know	-0.708
2. Which statement about mutual funds is correct?	Correct	0.646
	Don't Know	-0.754
3. What should happen to bond prices if interest rates fall?	Correct	0.469
	Don't Know	-0.599
4. Buying a company stock usually provides a safer return than a stock mutual fund that invests worldwide?	Correct	0.699
	Don't Know	-0.666
5. Stocks are normally safer than bonds, true or false	Correct	0.674
	Don't Know	-0.688
6. Considering a long time period, which asset normally gives the highest return?	Correct	0.538
	Don't Know	-0.526
7. Normally, which asset displays the highest fluctuations over time?	Correct	0.675
	Don't Know	-0.636
8. What happens to the risk of losing money when an investors spreads money among different assets?	Correct	0.541
	Don't Know	-0.599

Appendix 5.B. First Stage Regressions on Measured Financial Literacy

	(1)	(2)
Instruments (Base Group: Little Economics Education)		
A lot of Economics Education	0.43***	0.29***
	(0.00)	(0.00)
Some Economics Education	0.32***	0.18*
	(0.00)	(0.05)
Education (Base group is higher vocational or University)		
Primary or preparatory intermediate vocational	-0.58***	-0.62***
	(0.00)	(0.00)
Higher secondary education or secondary pre-university	0.05	0.07
	(0.73)	(0.60)
Intermediate vocational	-0.16	-0.14
	(0.15)	(0.22)
Age (Base group: age<40)		
Age 40-49	0.34	0.40*
	(0.15)	(0.07)
Age 50-59	0.18	0.25
	(0.40)	(0.23)
Age >=60	0.12	0.33
	(0.61)	(0.15)
Retired	0.25	-0.05
	(0.19)	(0.77)
Self-employed	0.49**	0.10
	(0.02)	(0.57)
Employee	0.31	0.02
	(0.15)	(0.91)
Income (Base group: >100.000)		
Income<33.000	-0.24	-0.14
	(0.23)	(0.44)
Income 33.000-<50.000	0.13	0.13
	(0.30)	(0.30)
Income 50.000-<100.000	0.34***	0.34***
	(0.00)	(0.00)
Kids	-0.08	-0.05
	(0.37)	(0.62)
Married	-0.13	-0.22*
	(0.27)	(0.05)
Male	0.57***	0.43***
	(0.00)	(0.00)
Experienced	0.25**	0.28**
	(0.04)	(0.02)
ln (Portfolio value)	0.06***	0.05**
	(0.00)	(0.01)
Risk Tolerance		0.16***
		(0.00)
Time Preference		0.24
		(0.20)
Regret aversion		-0.00
		(0.93)
Trust general		-0.03
		(0.34)
Trust in Adviser		0.06*
		(0.07)
Constant	-1.77***	-1.97***
	(0.00)	(0.00)
R^2	0.321	0.378
Number of observations	454	418
F-Statistic Instruments	11.18	5.74

Appendix 5.C. Univariate Statistics on Statements about Financial Advice and Execution-Only.

This table reports average scores and differences in scores on 12 statements about investing by means of execution-only (Panel A) or by using a financial adviser (Panel B). Investors were asked the following: "Please indicate your opinion on the statements below using a 7-point scale ranging from (1) "totally disagree" to (7) "totally agree". Statements were shown in random order. For brevity we do not exhibit the middle categories. ***, **, * denote significance at the 1 percent, 5 percent, and 10 percent levels, respectively.

		Investor			Financial Literacy Quartiles			Perceived Literacy Groups			Cognitive Ability Score		
	N	Advs.	SD	Advs.-SD	1 (low)	4 (high)	high-low	1-2 (low)	6-7 (high)	high-low	0 (low)	3 (high)	high-low
Panel A: "Investing on your own (compared to investing using a financial advisor):"													
1. is more fun	402	4.06	4.89	-0.83***	4.16	4.50	0.34	3.83	4.41	0.59*	4.31	4.33	0.02
2. gives more control	395	4.22	4.70	-0.48***	4.33	4.18	-0.15	4.13	4.56	0.43	4.32	4.41	0.09
3. is cheaper	368	4.73	4.90	-0.17	4.61	4.96	0.35	4.72	4.88	0.16	4.69	4.91	0.22
4. leads to more investment mistakes	390	4.35	3.54	0.81***	4.46	3.95	-0.52***	4.61	3.49	-1.11***	4.20	4.16	-0.04
5. is more time consuming	404	5.24	4.38	0.86***	4.99	4.88	-0.11	5.37	4.47	-0.90***	4.80	5.25	0.44
6. leads to more risks	412	4.70	4.10	0.60***	4.78	4.46	-0.32	4.91	4.04	-0.88***	4.45	4.87	0.42
Panel B: "A financial advisor (compared to investing on your own):"													
7. gives more peace of mind	417	4.98	3.81	1.17***	4.87	4.62	-0.26	5.3	4.2	-1.06***	5.01	4.75	-0.26
8. makes better investment decisions	411	4.52	3.54	0.98***	4.33	4.06	-0.27	4.7	3.6	-1.14***	4.61	4.35	-0.27
9. possesses more investment information	425	5.76	5.21	0.55***	5.54	5.71	0.16	5.8	5.1	-0.65**	5.64	5.71	0.07
10. places the banks benefits above mine	402	4.46	4.62	-0.16	4.48	4.55	0.07	4.1	4.5	0.33	4.52	4.60	0.08
11. takes the responsibility of the investment decisions	418	3.71	3.21	0.50***	4.15	2.90	-1.25***	4.0	3.2	-0.79**	4.19	3.31	-0.87***
12. knows less on investing	414	2.77	2.85	-0.08	3.03	2.82	-0.21	2.7	2.8	0.13	2.87	2.54	-0.33

Chapter 6

Summary & Discussion

6.1 Summary of the Main Findings

This thesis aims to enhance our knowledge of the value of advisors. Whether advisors provide added value is not clear a priori. They may improve financial decisions because they share their expertise or debias their clients. They may decrease the quality of their client's financial decisions because they lack expertise, induce their own biases, or stimulate biased reasoning by their clients. In addition, their interests may conflict with the interests of their clients.

To determine the added value of financial advisors, this thesis offers three empirical contributions. In two of them, I investigate the value of financial advisors in terms of portfolio composition, performance, and trading activity. In the third, I report on what retail investors have to say about their choice of hiring an advisor or not, then test whether an advisor actually corrects for a lack of financial literacy and/or cognitive abilities of the investor. As an introduction to these three empirical contributions, I provide a framework and literature overview. This summary describes each of the previous five chapters in more detail.

Chapter 1 introduces economic and behavioral approaches to the study of investment decision making, the role(s) of financial advisors, and the specific elements of the environment in which the empirical studies take place. The economical approach provides a normative framework in which rationality, expected utility, and portfolio theory are key ingredients. The behavioral approach, which is descriptive in nature, uses people's bounded rationality as a starting point. Boundedly rational agents make judgments and decisions that may be frame dependent and driven by heuristics. Also judgment and decision making are subject to emotions, self-attributes, self-deception, and social forces. Financial advisors serve several roles, such as financial economist, financial psychologist, personal advisor, relationship manager, salesperson, and teacher. In each advisory relationship, each role may be present to greater or lesser extents. The Dutch institutional environment is strongly influenced by the legal framework of the Dutch Wft and European MiFID, which distinguish investment advice from execution-only investment services when mandating the required level of due care. New institutional developments include the Dutch banking code (Nederlandse Vereniging van Banken [NVB], 2009) that requires banks to put client interests first and a new financial markets directive (Dutch Ministry of Finance, 2012) that proposes a ban on commission sales and introduces a bankers' oath.

Chapter 2 provides an overview from the literature of previous empirical research on the actual behavior of individual investors. Although such behaviors naturally are rather heterogeneous, some stylized facts emerge about portfolio compositions, trading frequency, and buying and selling decisions. The portfolio of a typical retail investor is characterized by a limited amount of diversification, as a result of naïve diversification and/or proximity-driven investments (e.g., overweighing of own-company, local, own-industry, or own-country stocks). Trading frequency may be either excessive, or an investor may not trade at all. Buying and selling behavior is influenced by various heuristics, emotions, and framing effects. Such behavioral induced effects are partly mitigated by introducing sophistication into portfolio decision making, while studies on the effects of advisory interventions provide mixed results.

Chapter 3 is an empirical study comparing the investment portfolios held by advised and execution-only individual investors. The results indicate significant differences in their characteristics and portfolios but no evidence of differences in their risk-adjusted performance. Portfolios of advised investors are better diversified and carry significantly less idiosyncratic risk. In addition, an analysis of investors who switch to advice taking indicates that improved diversification reflects the effect of advisory intervention. After the advisory intervention, advised portfolios for example contain more mutual funds and more asset classes.

Chapter 4 investigates the impact of financial advisors on portfolio returns, risk, trading, and diversification. This chapter uses an improved methodological approach to deal with the self-selection bias that is inherent in any comparison of two groups whose members themselves choose to receive a treatment (advice) or not. With a more limited data set using individual stocks only, I facilitate this comparison. The Hausman-Taylor panel estimation technique is applied, which can solve the estimation of endogenous variables that are time invariant. These estimations confirm prior experimental results about the benefits of advisory interventions that control for moral hazard behavior and endogeneity as a result of self-selection. Advice marginally improves risk-adjusted equity returns and strongly reduces ideosyncratic risk. In addition, advisors reduce trading activity, as proxied by the frequency of trades.

Chapter 5 is an analysis of survey data collected from a randomly selected, representative sample of Dutch retail investors. It aims to identify possible links between financial literacy, cognitive ability, and the propensity to seek help from financial experts. The chapter also provides evidence about drivers of advice seeking, according to retail investors. The main result indicates that *perceived* financial literacy is negatively associated with asking for help from financial experts. Apparently, people opt for advice when they believe they lack investment knowledge. Consistent with this finding, perceived financial literacy negatively relates to the perceived advantages of advised investing and perceived disadvantages of execution-only investing. Financial advice thus serves a substitute role for people who view themselves as less financially literate. Furthermore, neither *measured* financial literacy nor cognitive ability relate to advice seeking, which implies that advice is not a sufficient remedy for less literate or cognitively able persons. Other interesting determinants of advice seeking emerge though: Less educated and more risk-tolerant investors exhibit a lower propensity to seek advice, whereas wealthy, older investors who place trust in advisors seek advice more often. Finally, I determine investors' motivation to use a financial advisor. The main motivations relate to reduced information costs, in that they believe the advisor has more knowledge, creates a better portfolio, finds more relevant information, and saves time. People opt for execution only because it provides them with control over portfolio decisions, and because they believe it is more fun.

6.2. Discussion

Chapter 2 revealed that many households could benefit from guidance. Many people are poorly informed and make inferior financial decisions, which is driven by the complexity of financial decision making combined with poor financial capability and will power. Therefore, an important finding of this thesis is that financial advice may provide a helpful mechanism for improving investment decisions—though only, of course, for those who choose to take (and presumably follow) that advice. Those who may benefit the most from advisory expertise (i.e., those with financial literacy and/or cognitive abilities) are not necessarily more inclined to hire an advisor. Financial advice in and of itself thus is not enough a remedy for inferior financial decision making. I propose instead using financial advice within a broader framework designed to improve financial decisions. In addition to possible benefits of financial education and choice architecture, I offer some suggestions for improving the skills and value of financial advisors.

6.2.1. Financial Education

Financial literacy appears crucial to ensuring people have a financially healthy future. To improve financial knowledge and understanding, financial education seems a plausible remedy. But measuring the impact of such education is not easy, and evidence about its impact on behavior is mixed. Roa García (2011, p. 11) summarizes evidence on the effect of financial education: "rather than the differences in financial knowledge, it is psychological differences that underlie differences in individuals' financial capabilities." De Meza (2008) finds that financial capability is mainly a matter of psychology, which implies a relatively modest effect of information-based approaches. Financial education requires the motivation to learn and a certain level of cognitive ability. If courses are not compulsory, people may not be motivated to join; if they are compulsory, people may not pay attention. Even if people join, pay attention, understand the material, and intend to use it, they still may not change their behavior. Financial education even could cause harm, in that it fosters overconfidence. Highly educated finance specialists make mistakes and exhibit biased behavior too, in anecdotal support of my assertion that education alone is not enough.

However, contrasting evidence indicates that long-lasting, continued exposures at an early age to financial information encourages the internalization of knowledge and thus improves financial decisions later in life. Financial literacy programs during mandatory school years might be an appealing idea. Financial education programs appear to have greater effects when received over time, such as through five- to seven-year mandatory programs taught in schools. De Meza (2008) finds that in the United States, long-term compulsory financial education grew more effective the longer it was in place, though he recognizes other possible reasons that behavioral changes result from mandatory financial literacy programs.

The form of the educational intervention makes a huge difference as well. Based on a randomized control experiment, Drexler, et al. (2010) provide evidence on improved financial behavior and outcomes that result from rule-of-thumb financial literacy training, while no effect emerges from traditional courses. People are thus inclined to change behavior when exposed to simple, sensible, easy-to-implement and practical rules. In a similar vein, Roa García (2011) suggests ways to enhance the effect of educational interventions: Students must gain experience by putting their lessons into practice, education programs must be complemented with protection policies, and education must be ongoing.

6.2.2. Choice Architecture.

Sunstein and Thaler (2003) introduced the concepts of choice architecture and libertarian paternalism. Choice architects organize the context in which people make decisions. Presenting choice options to patients or clients makes a doctor or advisor a choice architect, such as when they design enrollment forms (e.g., for the company healthcare or retirement plan). Choice architects become libertarian paternalists if they attempt to steer people's choices in welfare-promoting directions, without eliminating freedom of choice. They benefit greatly if they are equipped with a good understanding of bounded rationality and bounded self-control findings.

A powerful steering device (or so-called nudge) is the default choice method. Default choices work because people prefer to remain in their current situation, due to their status quo bias (Samuelson and Zeckhauser 1998), which leads to inertia and procrastination. Default choices also work because of an endorsement effect, in the sense that the default provides implicit advice about what is the wise decision. Johnson and Goldstein (2003) find strong evidence of the power of default options outside the financial domain: Enrollment in European organ donation programs was 97% for countries that made enrollment the default option but only 18% in other countries.

An interesting application using choice architecture, developed by Thaler and Benartzi (2004), is the Save More Tomorrow retirement plan. People hate to lose (i.e., do not want their paychecks to decrease), so the saving in this plan is financed by raises. Increases in saving rates (paid from future wage increases) are automatic, such that the plan uses people's inertia to their own advantage. Because people also tend to discount future negative emotions, signing up for a plan that involves future, rather than immediate, payments mitigates self-control issues. Combining the plan with automatic enrollment has led to its great success, such that a majority of eligible people "decided" to join, and saving rates increased dramatically. Default options also might be effective in nonretirement saving and investment decisions. When opening an account, a sensible default might be that whenever the current account reaches a certain limit (e.g., twice the average monthly expenses), any surplus is automatically transferred to a savings account. Then when the savings account reaches a certain limit (e.g., six times the average monthly expenses), any surplus gets transferred to an investment account with a sensible asset allocation to low cost investment funds. At any time, these "choices" can be reversed, stopped, or altered, which ensures freedom of choice. However, one caveat cannot be overlooked: From a micro perspective, such a default product provides evident benefits, but from a macro perspective, it may introduce systemic risks in case it operates for large amounts of people at the same time.

Choice architecture also could apply to the development of products. Designing sensible, simple, transparent, and low cost investment products with just a few choice options may help people overcome their hesitation about investing. A Dutch financial intermediary called "Brand New Day" offers a good example. It offers a simple Internet-based investment product that requires only two choices: the initial and/or periodical amount to be invested, and the relative allocation to fixed income investment (i.e., a low cost, triple A, Euro government inflation-linked bond fund), with the rest invested in a low cost, global equity index fund. The default investment horizon is 20 years, but it can be adapted if desired. Ten years before this horizon is reached, the product invests at least 55% in fixed income, then increases the fixed income allocation automatically by 5% each year. Although more optimal portfolios, strategies, and/or products may exist, for many private investors, such a product may be very beneficial, in that it helps them to mitigate inertia and procrastination by reducing choice complexity and choice overload.

De Meza (2008) advocates sensible, easy-to-remember rules of thumb as good nudges. Simple slogans may shift norms and thus change behavior, as did the phrases "don't drink and drive" or "safe sex" in other contexts. Warnings added to financial advertisements, like "borrowing is costly" or "past performance is no guarantee of future results," may have similar benefits. Other sensible rules of thumb might "pop up" when investors execute an online trade. Whether such nudges really help is an empirical question that needs further inquiry, but the evidence of Drexler, et al. (2010) on rule-of-thumb financial literacy training, provides preliminary support for the positive effect of easy-to-remember rules as nudges.

6.2.3. Improving Financial Advice

This thesis concludes that financial advice has the potential to improve investors' decisions. In turn, there are benefits to be gained from improved training of advisors and changing their incentives.

The current education of financial advisors typically aims at improving financial-economic, social, and commercial skills. In describing the roles of financial advisors in Chapter 1, I introduced the "financial psychologist," who can help investors assess their susceptibility to judgment and decision-making biases, as well as provide ways to mitigate them. Adding investor psychology to the education curricula of advisors may help them accomplish that role better.

Debiasing is typically successful when people confront quick, unambiguous feedback. In financial decision making, feedback instead tends to be slow, such that it can take years to determine the outcome of a retirement portfolio decision, while outcomes also depend on factors outside the investor's control. Shefrin (2007) therefore notes that mitigating biases is not easy; it requires an explicit procedure, discipline, and effort. Kahneman and Riepe (1998) provide some practical help to attain discipline: Ask yourself what may go wrong, keep track of all unsuccessful efforts, and list all reasons the proposed trade is not a random choice (see also Appendix 1.A, Chapter 1).

A first step in a debiasing strategy may be for advisors to recognize their own biases, which requires them to overcome their bias against recognizing their own biases. Nofsinger (2011) states that recognizing one's biases (and those of others) is an important step for avoiding them. Although financial advisors may already be aware of the existence of decision-making fallacies in financial matters, such awareness does not automatically eliminate their judgmental biases. A nice illustration comes from the well-known Müller-Lyer optical illusion (Nofsinger, 2005, p.2). Even when a viewer knows that two horizontal lines are of the same length, one of the two still looks longer. Cognitive illusions are not easily eliminated, because the underlying psychological phenomena are deeply ingrained in human brains and result from automatic "system I" processes (Kahneman, 2011). It thus is safe to assume that advisors are not free from biases in their judgment and decision making. For example, they may be just as overconfident as laypeople or are susceptible to framing and anchoring effects. Investor psychology training may help both clients and advisors realize their own limitations. Some success in debiasing financial advisors has come from having advisors attend lectures on investor psychology (Kaustia and Pettula, 2011).

If they know more about investor psychology, advisors also may be better equipped to assess their clients' risk attitudes. Before building a portfolio, the advisor's main goal should be to get a clear picture of the investor. It is standard practice to assess investment goals and horizons, investor knowledge, experience, and risk attitudes before any advisory relationship begins. Specific personality traits may be equally important. For example, in assessing how a client perceives risk, advisors should recognize that risk may be perceived as volatility or as downside risk, the risk of losing money, the amount of money that may be maximally lost, or the risk of not reaching a specified goal. In this respect, Kahneman (2009) notes the "the myth of risk attitudes" and the importance of a temporal perceptive. Financial advisors should help clients perceive their future emotions when they experience various outcomes, which may deviate considerably from their perceptions at the moment of the decision. Assessing their propensity for regret is a key aspect; others include the degree of overconfidence, optimism, loss aversion, or use of mental accounts.

To improve financial advice, the current incentive structure of advisors also needs attention. Many academics believe that an important deterrent to unbiased financial advice is the way advisors are paid: They receive kickback fees from financial product suppliers or charge commissions on a trade. Although current legislation requires advisors to be transparent about the fees they receive, it may not help much. A recent survey by the Dutch Financial Markets Authority (AFM, 2012) indicated that 73% of advised customers had no clue about the costs of advising. More promising than transparency rules may be a change to the incentives of advisors. A proposed ban in the Netherlands on sales commission is promising, though it could come at some cost. Practitioners have suggested introducing hourly or fixed annual fees as two ways to adapt their remuneration model, though such cost transparency may limit the number of people who seek advice, such that they lean toward execution-only trades, which may cause more damage. Fixed annual fees also create an incentive for advisors to be inert, while hourly fees give them an incentive to pay too much attention to any single investor's portfolio.

6.3 Limitations and Further Research

There are some important limitations of the empirical contributions of this thesis. First, using data about investors at only one bank in the Netherlands introduces a potential sample selection bias that limits the external validity of my findings. Specific investor characteristics may drive the choice to invest at this particular bank, and the specifics of the Dutch institutional environment or culture may influence the results. Second, advice is operationalized and limited to a dummy variable. Investors receive advice or they do not. Yet advice may take different forms, with varying frequency, by advisors with different characteristics and skills, and may or may not be followed. Third, the choice to receive advice creates a potential self-selection bias, as noted previously. Although the difference-in-difference methodology in Chapter 3 and instrumental variable approach in Chapter 4 both aim to address this issue, by using field data that was not collected for my own research purposes, it becomes difficult to satisfy the causality question fully. It should be complemented with more robust methods designed to control for self-selection. In the next paragraphs, I suggest three complementary studies that address the concerns mentioned above.

The gold standard for detecting treatment effects is a randomized (field) experiment (Antonakis *et al.,* 2010). This ideal is often achieved in medical research, where the use of randomized, double-blind, and placebo-controlled trials is commonplace. Neither the subjects nor the doctors know who has been randomly assigned to the groups that receive the medicine or placebos. If executed properly, the health outcome differences after the experiment must be caused by the medicine. Such a research strategy could solve some of the limitations of my data set, though not all of them. In particular, when they receive a medication, patients have no discretion over the effects of the medicine, whereas recipients of financial advice have the option to ignore the advice, so an element of selection inherently remains. Hung and Yoong (2010) implement a randomized treatment laboratory study to the impact of financial advice, which may serve as a good starting point for an experimental study.

Another promising research stream pertains to audit studies, which would provide in-depth analyses of what happens during advisory meetings. Such studies would require the recruitment of auditors who, after extensive training, take on roles as (potential) investor and visit banks for advisory meetings, without those financial advisors knowing that they are taking part in research. Such a research strategy is akin to mystery shopper techniques used in marketing. So far, to the best of my knowledge, only one such study has been executed (Mullainathan *et al.*, 2012).

Finally, in this thesis, the advisors themselves were not the subject of inquiry. It would be worthwhile to survey a group of financial advisors about what they believe their roles to be, their added value, and whether their advisory strategy is useful to their clients. This information also could be used to take advisor heterogeneity into consideration in various specifications.

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Samenvatting (Summary in Dutch)

Dit proefschrift heeft tot doel onze kennis over de waarde van beleggingsadviezen door beleggingsadviseurs voor particuliere beleggers te vergroten. Inzicht in die waarde is belangrijk. Veel huishoudens maken namelijk gebruik van de diensten van een adviseur bij het nemen van financiële beslissingen. Daarnaast is wereldwijd een tendens waar te nemen om de huishoudens zelf meer verantwoordelijk te maken voor hun financiële toekomst. Uit empirisch onderzoek naar het gedrag van huishoudens blijkt dat ze daarbij wel wat hulp kunnen gebruiken: veel huishoudens beschikken over een beperkte financiële kennis en nemen mede daardoor suboptimale financiële beslissingen.

Het is niet op voorhand duidelijk of beleggingsadviezen van adviseurs waarde toevoegen of niet. Het is mogelijk dat adviseurs suboptimale beslissingen van particuliere beleggers weten te voorkomen omdat ze over meer financiële expertise beschikken. Het zou ook kunnen dat adviseurs minder goede beslissingen nemen of dat zij zelfs de suboptimale beslissingen van beleggers stimuleren. In dat geval speelt de potentiële belangentegenstelling tussen de beleggingsadviseur en zijn klant een rol: omdat adviseurs vaak over een informatievoorsprong beschikken kan een adviseur, zonder dat de cliënt dit direct opmerkt, zijn eigen belang (of het bankbelang) nastreven. Dit fenomeen staat bekend als *moral hazard*. Vooral bij de advisering tot aankoop van bepaalde financiële producten zoals beleggingsfondsen speelt dit een rol. Zo weet een adviseur vaak exact wat een product kost, terwijl de klant daar minder goed inzicht in heeft.

Dit proefschrift beslaat zes hoofdstukken waarvan er drie empirisch van aard zijn. Deze empirische hoofdstukken beogen inzicht te geven in de waarde van beleggingsadviseurs inzake portefeuillesamenstelling, portefeuillerendement en handelsactiviteit. Ook beleggers komen aan het woord: welke voor- en nadelen zien zij van een beleggingsadviseur ten opzichte van zelfstandig beleggen. Andere vragen die aan bod komen zijn: wie kiest er voor advies en wie niet, en corrigeert advies voor een gebrek aan financiële kennis en cognitieve vermogens, de twee oorzaken van minder goede financiële beslissingen. Hieronder vat ik elk van de zes hoofdstukken kort samen.

Hoofdstuk 1 introduceert de economische en de *behavioral* benadering van de studie naar beleggersgedrag, de rollen die een beleggingsadviseur voor particuliere beleggers speelt, en de specifieke elementen van de institutionele omgeving waarbinnen beleggingsadvies zich afspeelt. De economische benadering biedt een normatief raamwerk waarbinnen concepten als rationaliteit, verwachte nutsmaximalisatie en de portefeuilletheorie centraal staan. De *behavioral* benadering, die meer beschrijvend van aard is, neemt beperkte rationaliteit als vertrekpunt. Beperkt rationele actoren worden beïnvloed door de context van de vraagstelling en heuristieken bij het beoordelen en beslissen. Mensen worden daarnaast beïnvloed door emoties, zelfdeceptie en sociale krachten. Een adviseur zou met beide benaderingen rekening moeten houden: hij of zij moet op de hoogte zijn van de normatieve uitgangspunten die de beleggingstheorie biedt, maar mag vanzelfsprekend niet blind zijn voor de empirische werkelijkheid waarin beleggers afwijken van normatieve gedragingen onder invloed van psychologische mechanismen. Kahneman en Riepe (1998) vatten dit uitgangspunt goed samen als ze stellen dat: "*advisors should maximize a client's overall well-being (which includes emotional as well as financial health*)".

Een adviseur kan diverse functies hebben die ik in dit proefschrift definieer als: financieel econoom, financieel psycholoog, persoonlijk adviseur, relatiebeheerder, verkoper en onderwijzer. In een adviesrelatie kan elke functie in meer of minder mate een rol spelen. De institutionele omgeving waarbinnen beleggingsadvies in Nederland zich afspeelt wordt beïnvloed door de Nederlandse Wet Financieel Toezicht (Wft) en de Europese *Markets in Financial Instruments Directive* (MiFID). Deze onderscheiden beleggingsadvies en *execution-only* vooral in de mate van de zorgplicht die wordt vereist. Nieuwe ontwikkelingen binnen de Nederlandse institutionele context zijn de "Code Banken" die het klantenbelang als uitgangspunt neemt en het "Wijzigingsbesluit Financiële Markten 2013". Twee elementen daarin zijn voor dit onderzoek met name van belang: de brede invoering van een bankierseed voor iedereen die in de bankensector werkt, dus ook voor beleggingsadviseurs en, wellicht nog belangrijker: per 1 januari 2014 geldt een provisieverbod bij het adviseren tot aankoop van complexe financiële producten. Na die datum mogen adviseurs geen provisie (zoals bestandsvergoeding, retourprovisies of plaatsingsvergoeding) meer ontvangen van een aanbieder van beleggingsproducten. Zij moeten hun klanten rechtstreeks laten betalen voor het advies. Hiermee beoogt de wetgever perverse prikkels uit het systeem te halen en de kosten meer transparant te maken.

In hoofdstuk 2 vat ik empirisch onderzoek naar het gedrag van particuliere beleggers van andere onderzoekers samen. Vanzelfsprekend is er veel heterogeniteit in dit beleggersgedrag waar te nemen, maar desalniettemin zijn er zijn enkele gestileerde gedragingen te observeren op het gebied van portefeuillesamenstelling, handelsgedrag en koop- en verkoopbeslissingen. Ten aanzien van portefeuillebeslissingen valt met name een onvoldoende mate van diversificatie op die mede wordt veroorzaakt door naïeve diversificatiestrategieën en de (psychologische) invloed van "nabijheid". Men belegt dan relatief te veel in het bedrijf of in de industrie waarin men zelf werkzaam is of in een bedrijf dat in de buurt van de eigen woonplaats of in het eigen land gevestigd is. Als we kijken naar het handelsgedrag valt op dat sommige groepen excessief veel handelen, terwijl andere groepen bijna nooit muteren in hun portefeuille. Koop- en verkoopgedrag blijken te worden beïnvloed door diverse heuristieken, emoties, en *framing*-effecten. Bij bestudering van deze door psychologische mechanismen beïnvloede gedragingen valt op dat meer professionaliteit en ervaring beleggingsbeslissingen verbeteren. Uit reeds verschenen publicaties over de invloed van advies komt overigens een gemengd beeld naar voren.

In hoofdstuk 3 presenteer ik empirische resultaten op basis van de bestudering van een grote database van een Nederlandse bank. Bij deze bank hebben alle beleggers de keuze of ze gebruik willen maken van het advieskanaal of van *execution-only*. Bij het vergelijken van de twee soorten dienstverlening die beleggers kozen, valt een aantal zaken op: de groep beleggers die voor advies kiest bestaat uit meer vrouwen dan mannen en de gemiddelde leeftijd is iets hoger dan die van de *execution-only* groep. Verder is er een duidelijk verschil in de portefeuilleomvang; die is namelijk bij de geadviseerde groep gemiddeld meer dan vier keer zo groot als bij de *execution-only* groep. Ook zijn er grote verschillen waar te nemen in de portefeuillesamenstelling. Zo bevatten de geadviseerde portefeuilles significant meer vastrentende beleggingen, meer beleggingsfondsen en meer gestructureerde producten. Daarentegen bevatten de *execution-only* portefeuilles meer aandelen (en binnen die *asset* class relatief meer individuele aandelenposities) en meer derivaten. Al met al valt hieruit op te maken dat *execution-only* portefeuilles gemiddeld genomen meer risico inhouden. Een andere belangrijk**e** bevinding volgt uit de bestudering van de rendementen van beide groepen. Hierbij worden drie soorten rendement bestudeerd. Zo worden de verschillen in de voor risico gecorrigeerde rendementstijdsreeksen van de gemiddelde geadviseerde belegger vergeleken met die van de gemiddelde *execution-only* belegger. Ook worden de rendementen onderzocht waarbij wordt gecorrigeerd voor cross-sectionele verschillen in beleggers- en portefeuillekarakteristieken. Ten slotte worden rendementstijdsreeksen met elkaar vergeleken waaruit timingvaardigheden zijn te destilleren. Al deze vergelijkingen leveren een identiek beeld op: tussen beide groepen beleggers wordt geen significant risicogecorrigeerd rendementsverschil waargenomen.

Hoewel bovenstaande resultaten veel interessante inzichten hebben opgeleverd, valt daaruit niet op te maken of de beleggingsadviseur al dan niet waarde toevoegt. Om de invloed van advies goed te meten heb je namelijk een goede *counterfactual* nodig en het is maar de vraag of de *execution-only* belegger die goede *counterfactual* biedt. Idealiter zou je namelijk willen weten wat de geadviseerde groep gedaan zou hebben indien deze niet voor advies had gekozen, en wat de *execution-only* groep gedaan zou hebben indien deze wél geadviseerd was. Helaas is dat in de werkelijkheid niet te observeren. In hoofdstuk vier staat dit probleem centraal, in hoofdstuk drie gebruik ik een methode die toch inzicht geeft over de invloed van advies. Hierbij wordt onderzocht wat het effect is op het portefeuillegedrag indien een belegger besluit over te stappen van *execution-only* naar advies. Omdat we kunnen waarnemen op welk moment dat gebeurt, kan het gedrag vóór en na de adviesinterventie met elkaar worden vergeleken, gecontroleerd voor het gedrag dat een vergelijkbare groep in diezelfde periode vertoont. Uit die analyse blijkt dat de adviseurs grote veranderingen in de portefeuille doorvoeren: er wordt meer geld belegd, de allocatie naar aandelenbeleggingen daalt en het aantal beleggingsfondsen in de portefeuille stijgt fors (zodat de invloed van “nabijheid”, de *home bias*, daalt) en er wordt in meer *asset classes* belegd. Deze bevindingen ondersteunen het beeld dat adviseurs zorgen voor een betere diversificatie in de portefeuille van particuliere beleggers.

In hoofdstuk 4 wordt specifiek ingegaan op het probleem dat de waarde van advies niet zonder meer kan worden bepaald door vergelijking van geadviseerde beleggers met *execution-only* beleggers. Omdat beleggers zelf de keuze maken welke dienstverlening ze kiezen en dus niet op basis van toeval in een van beide groepen terecht zijn gekomen, kan er sprake zijn van een z.g. zelfselectiebias. Een voorbeeld kan dit probleem wellicht verhelderen: veronderstel dat kundige beleggers er eerder voor kiezen om zelfstandig, dus zonder tussenkomst van een adviseur, te beleggen. Omdat zij kundig zijn presteren zij beter dan minder kundige beleggers indien die ook niet voor een adviseur zouden hebben gekozen. Zij kiezen er in dit voorbeeld juist wel voor om een adviseur te raadplegen. Bij vergelijking van de portefeuille-uitkomsten, zonder controle op het verschil in kundigheid, dat lastig is te meten, is er sprake van een zelfselectiebias. Indien blijkt dat beide groepen vergelijkbaar presteren, is de minder kundige belegger blijkbaar door het advies op hetzelfde niveau geraakt als de kundige belegger. Feitelijk heeft de adviseur hier dus voor een performanceverbetering gezorgd hoewel dat niet blijkt uit de directe performancevergelijking.

Omdat soortgelijke problemen veel voorkomen bij het evalueren van interventies die buiten een laboratorium plaatsvinden, zijn er diverse econometrische methoden ontwikkeld die een oplossing bieden. Zo kan er gebruik worden gemaakt van de panelstructuur van de data (er zijn dan van meerdere beleggers over verscheidene periodes observaties beschikbaar) of van zogenaamde instrumentele variabelen. Omdat de variabelen waarin we geïnteresseerd zijn geen tijdsvariatie kennen en we niet over externe instrumenten beschikken, wordt gebruik gemaakt van de Hausman-Taylor methode die specifiek voor die situatie is ontwikkeld. Indien de dataset een panelstructuur heeft, kunnen instrumenten worden gecreëerd uit transformaties van variabelen. Als aan bepaalde voorwaarden is voldaan kan zo de exogene variatie in de advieskeuze worden geïsoleerd en kan er worden gecorrigeerd voor zelfselectie. Daarmee wordt dan de causale relatie tussen de adviesinterventie en portefeuille-uitkomst duidelijk. De resultaten uit dit hoofdstuk bevestigen de resultaten uit hoofdstuk 3. Adviseurs zorgen ervoor dat portefeuilles minder idiosyncratisch risico bevatten en dus beter zijn gediversifieerd. Daarnaast wordt nu ook een (kleine) rendementsverbetering waargenomen en een lagere handelsactiviteit als gevolg van de beleggingsadviezen. Deze bevindingen ondersteunen het eerder genoemde voorbeeld dat juist de minder kundige beleggers kiezen voor advies.

In hoofdstuk 5 presenteer ik de resultaten van een survey-onderzoek onder een groep van 467 particuliere beleggers. Gegeven de in hoofdstuk twee genoemde bevinding dat met name de minder financieel geletterden en minder cognitief begaafden suboptimale financiële beslissingen nemen, is het een relevante vraag of er een relatie bestaat tussen financiële geletterdheid, cognitieve vermogens en de keuze voor een adviseur. Een adviseur zou het gebrek aan financiële kunde en cognitieve vermogens wellicht kunnen corrigeren. Er blijkt echter geen relatie te bestaan tussen de keuze voor advies of *execution-only* enerzijds en financiële geletterdheid en cognitieve vermogens anderzijds. Wel is er een verband tussen de eigen perceptie van de financiële geletterdheid en de keuze voor advies. Daaruit blijkt dat mensen die zichzelf als minder financieel kundig zien eerder voor een adviseur kiezen. De gepercipieerde financiële geletterdheid blijkt ook de meningen over beleggingsadvies en *execution-only* sterk te beïnvloeden. Zo schatten diegenen die zichzelf als minder geletterd zien de voordelen van advies groter in en de voordelen van *execution-only* als kleiner. De nadelen van advies waarderen zij kleiner, terwijl zij de nadelen van *execution-only* juist als groter beoordelen.

Naast financiële geletterdheid en cognitieve vermogens geeft dit hoofdstuk inzicht in andere factoren die bepalen of men kiest voor advies of niet. Daarbij blijkt dat laagopgeleiden en mensen met een hogere risicotolerantie minder vaak kiezen voor beleggingsadvies. Diegenen met een grotere beleggingsportefeuille, ouderen en ook andere beleggers met vertrouwen in adviseurs, kiezen juist wél voor advies.

Ten slotte biedt dit hoofdstuk inzicht in de vraag waarom beleggers kiezen voor een bepaald dienstverleningskanaal. Dan blijkt dat beleggers met name voor advies kiezen omdat het de informatiekosten verlaagt. Zo stellen geadviseerde beleggers dat zij kiezen voor een adviseur omdat die meer beleggingskennis heeft, de portefeuille in de gaten houdt, een betere portefeuille samenstelt, beter relevante informatie heeft en een tijdsbesparing oplevert. Consistent met die bevinding is dat geadviseerde beleggers veel minder dan zelfstandige beleggers financiële informatie verzamelen via andere kanalen (Tv-programma's, kranten, websites, familie en vrienden). Diegene die kiezen voor *execution-only* geven aan zelfstandig te willen beleggen omdat zij de controle willen houden over beslissingen, omdat zij meer plezier beleven aan het zelf doen en omdat het goedkoper is.

In het laatste, het zesde, hoofdstuk, bespreek ik de bovenstaande bevindingen in een bredere context. Mijn onderzoek toont aan dat advies waarde oplevert wat betreft beter gediversifieerde portefeuilles. Dat is een niet te onderschatten voordeel gezien de grote hoeveelheid empirische literatuur die erop wijst dat een gebrek aan goede diversificatie een van de grootste problemen is die uit de studie naar particulier beleggersgedrag naar voren gekomen is. Mijn onderzoek toont daarnaast aan dat er tussen financiële geletterdheid en cognitieve vermogens enerzijds en de keuze voor advies anderzijds geen relatie bestaat. Diegenen die meer voordeel bij advies zouden kunnen hebben, kiezen daar dus niet per se voor. Daarnaast is uit onderzoek door anderen gebleken dat als er al voor advies wordt gekozen, dit advies lang niet altijd wordt opgevolgd. De conclusie lijkt dus gerechtvaardigd dat advies wel waardevol is, maar dat het geen afdoende mechanisme is om financiële beslissingen van huishoudens te verbeteren. Ik stel dan ook voor advies als een onderdeel te beschouwen van een breed scala aan mechanismen die tot doel hebben huishoudens betere financiële beslissingen te laten nemen. Hierbij zijn zowel financiële educatie, keuzearchitectuur, regelgeving en het verbeteren van beleggingsadvisering van groot belang.

Financiële educatie lijkt een voor de hand liggende oplossing. Hiermee worden huishoudens zelf in staat gesteld om, door een toename van financiële kennis, goede beslissingen te nemen. Helaas komt uit empirische studies naar het effect van financiële educatie een gemengd beeld naar voren. Ook hier speelt de eerder genoemde kwestie van zelfselectie: diegenen die kunnen profiteren van educatie kiezen daar nu juist niet voor wegens gebrek aan motivatie of cognitieve vermogens. Verder blijkt het lastig om een relatie waar te nemen tussen een financieel opleidingstraject en een gedragsverandering. Het probleem daarbij is dat veel financiële keuzes niet frequent worden gemaakt, denk bijvoorbeeld aan het kiezen van een hypotheek, een verzekering of een beleggingsproduct. Financiële training kan ook leiden tot zelfoverschatting waardoor het effect juist negatief kan worden. Inmiddels zijn er aanwijzingen voor het feit dat financiële training een positief effect heeft, mits die eenvoudig te begrijpen en eenvoudig te onthouden vuistregels bijbrengt (een z.g. *rules-of-thumb* training).

Keuzearchitectuur is een begrip dat door Sunstein en Thaler (2003) is geïntroduceerd in combinatie met het begrip libertair paternalisme. Keuzearchitectuur is de context waarbinnen mensen keuzes maken. Libertair paternalisme is de poging om keuzes zodanig te structureren dat ze welvaartsverhogend zijn zonder dat het leidt tot een inperking van de keuzevrijheid. Een van de meest krachtige stuurmechanismen (z.g. *nudges*) is de standaardkeuze (z.g. *default*) Vaak kiest men de standaardoptie omdat de *default* als een impliciet advies gezien wordt en ook omdat mensen niet van veranderingen houden, soms gewoon lui zijn of aan uitstelgedrag lijden. Een “slimme” standaardoptie leidt dan automatisch tot een goede beslissing.

Een interessante applicatie van keuzearchitectuur is ontwikkeld door Thaler en Benartzi (2004). Zij ontwikkelden een pensioenspaarplan onder de naam *Save More Tomorrow* (of “SMarT”). Dit plan maakt slim gebruik van enkele psychologische mechanismen. Zo hebben de meeste mensen last van verliesaversie: het psychologisch fenomeen dat verliezen mentaal zwaarder wegen dan winsten van gelijke omvang. Daarnaast leiden veel mensen aan geldillusie: ze denken in nominale en niet in reële termen. Daarom financiert dit “SMarT” -plan de pensioenbijdrages uit salarisstijgingen zodat voor besteding beschikbare salarissen nominaal niet dalen. Elk jaar dat het salaris stijgt wordt de betaling aan het pensioenplan automatisch verhoogd totdat een vooraf vastgesteld maximum percentage van het salaris bereikt is. Het plan maakt daarmee handig gebruik van het feit dat veel mensen inert zijn en de eenmaal gemaakte keuzes liever niet meer veranderen. Daarnaast heeft men er vaak moeite mee om nu al een kostenpost te accepteren voor iets dat pas in de toekomst voordeel oplevert (dit heeft te maken met een gebrek aan zelfcontrole en het daaraan gerelateerde hyperbolisch disconteren). Daarentegen heeft men vaak minder moeite met een toekomstige kostenpost. Daarom begint de eerste inleg pas een jaar nadat een deelnemer zich heeft aangemeld. In de VS is dit plan bij diverse bedrijven geïntroduceerd in combinatie met de *opt-out* optie. De *default* is participeren in het plan tenzij je aangeeft dat niet te willen. plan blijkt een groot succes: veel Amerikaanse werknemers doen mee en als gevolg daarvan zijn hun pensioenspaarsaldi fors gestegen.

Keuzearchitectuur kan ook helpen bij het ontwikkelen van eenvoudig te begrijpen beleggingsproducten waarbij de keuzes beperkt en de kosten laag zijn. Deze kunnen de drempel om te gaan beleggen (die mede samenhangt met *choice overload* and *choice complexity*) verlagen en een goede keus mogelijk maken. Zo biedt bijvoorbeeld "Brand New Day" in Nederland een beleggingsproduct aan via het internet. Hierbij kiest een belegger voor een maandelijks en/of eenmalig te storten bedrag en er kan met een schuifbalkje worden aangegeven hoe dat bedrag moet worden verdeeld tussen enerzijds een wereldwijd gespreid indexfonds en anderzijds een triple-A obligatiefonds. De *default* is een looptijd van 20 jaar, waarbij zodra de einddatum in zich komt, de aandelenallocatie langzaam terug wordt gebracht ten gunste van het obligatiedeel. Hoewel dit product niet voor iedereen de optimale keuze zal zijn, is het waarschijnlijk superieur ten opzichte van veel alternatieve keuzes.

Hoewel uit dit proefschrift blijkt dat beleggingsadvies waarde toevoegt, is verbetering mogelijk. Hierbij denk ik aan de aanpassingen van de *incentives* en aan de opleiding van de beleggingsadviseur. Aan de *incentives* van adviseurs is al druk gewerkt. In Nederland is de wet aangenomen die per 1 januari 2013 voor een aantal financiële producten de provisies verbiedt. Per 1 januari 2014 gaan deze regels ook voor beleggingsproducten gelden. Op dit moment worden de kosten van een adviseur nog betaald uit transactievergoedingen, plaatsingsvergoedingen en bestandsvergoedingen. Hoewel sinds enkele jaren deze kosten transparant moeten zijn, lijken veel cliënten zich toch niet bewust van de werkelijke kosten van financiële producten. De wetgever heeft daarom besloten dat cliënten van hun financiële intermediair rechtstreeks een factuur voor het advies moeten ontvangen. Recent zijn door diverse financiële dienstverleners bijvoorbeeld de tarieven voor een hypotheekadvies bekend gemaakt, deze tarieven liggen tussen de €2.000 en €3.000. Ook voor beleggingsadviezen zullen dergelijke vergoedingssystemen worden ingevoerd. Op het eerste gezicht lijkt dit plan een goed idee. Klanten worden bewust gemaakt van de kosten van advies en zo kunnen zij een meer afgewogen oordeel vellen over de waarde die het advies oplevert en de kosten daarvan. Het uitbannen van perverse prikkels en de grotere transparantie zijn noodzakelijk maar het nieuwe systeem heeft, net als het oude systeem, zijn nadelen. Zo is voor veel mensen de waarde van een advies niet goed waar te nemen en zeker niet op korte termijn. De financiële consument zal nu wellicht eerder kiezen voor *execution-only*, dus beslissen zonder advies, en het is maar de vraag of dat tot betere uitkomsten leidt ook al zijn de directe kosten bij die keuze lager. Indien men wél voor advies kiest, moet men zich realiseren dat wanneer de prikkel bij de adviseur om een product te adviseren dat de hoogste provisie oplevert weggenomen is, er andere financiële prikkels voor in de plaats kunnen komen. In een systeem waarbij een adviseur bestede uren in rekening gaat brengen, heeft de adviseur misschien de neiging om het aantal te besteden uren te maximaliseren. Bij een vaste vergoeding, een vergoeding gebaseerd op *assets-under-management* of een doorlopende bestandsvergoeding op basis van een abonnement, ontstaat juist een prikkel om, nadat het advies eenmaal tot een beleggingsportefeuille heeft geleidt, daar niets meer aan te doen, omdat de inkomsten van de adviseur niet meer van enige verdere inspanning afhangen. Hoewel het lastig is om een systeem te ontwikkelen dat al deze problemen ondervangt, is het goed om zich te realiseren dat elk systeem zowel voor- als nadelen kent. De wetgever had er overigens ook voor kunnen kiezen om een zekere intransparantie te laten bestaan maar wél de hoogte van de provisie aan banden te leggen.

Ook over het opleidingstraject van adviseurs is het een en ander op te merken. In het bestaande curriculum van beleggings- en financiële adviseurs is er geen of slechts beperkte aandacht voor (beleggers)psychologie, terwijl juist psychologische mechanismen de beslissingen en evaluatie van uitkomsten in grote mate beïnvloeden. In hoofdstuk 1 heb ik daarom de rol van financieel psycholoog als een van de functies van een beleggingsadviseur geïntroduceerd. Inzicht in beleggerspsychologie maakt de adviseur bewust van de rol die psychologie speelt in de besluitvorming van cliënten en van de rol die zij speelt bij de eigen besluitvorming. Onderzoek heeft aangetoond dat, net als particuliere beleggers, ook adviseurs niet vrij zijn van *biases* in hun oordeels- en besluitvorming. Ter verduidelijking geef ik een voorbeeld waaruit blijkt hoe het inzicht in beleggerspsychologie behulpzaam kan zijn in een adviesrelatie: voordat advies wordt gegeven, wordt een zogenaamd cliëntprofiel opgesteld, waarin zaken als beleggingsdoelen, kennis, ervaring en preferenties zijn opgenomen. Centraal hierbij staat het bepalen van de risicobereidheid van een belegger. Op dit moment worden risico's veelal getoond als standaarddeviaties van historische rendementen behorende bij diverse *asset*-allocaties. Uit onderzoek blijkt echter dat de standaarddeviatie niet altijd aansluit bij de wijze waarop beleggers risico's percipiëren. Soms zijn beleggers geïnteresseerd in de kans om geld te verliezen, soms in de maximale omvang van dat verlies, en in andere gevallen in de kans om het beoogde doel niet te bereiken. Ook heeft een belegger vaak simultaan verschillende niveaus van risicobereidheid, afhankelijk van onder andere de beleggingsdoelen en de herkomst van het geld. Daarbij komt dat veel mensen moeite hebben om al vooraf toekomstige emoties in te schatten, men realiseert zich vaak pas achteraf dat de eigen risicobereidheid toch anders is dan men meende te weten. Het presenteren van risico als standaarddeviatie leidt dus niet per se tot een correcte cliëntprofilering.

Hoofdstuk zes wordt afgesloten met enkele suggesties voor toekomstig onderzoek. Ik stel voor om de waarde van advies in een experimentele opzet te onderzoeken. Het probleem van zelfselectie kan dan in de onderzoeksopzet al worden aangepakt in tegenstelling tot de correctie achteraf die in het proefschrift is gebruikt. Ook stel ik voor de adviseur zelf een stem te geven en door onderzoek bij beleggingsadviseurs meer inzicht te verkrijgen in hun eigen mening over de toegevoegde waarde van hun advies. Ten slotte stel ik een onderzoek voor waarbij gebruik gemaakt wordt van onderzoekers die zich voordoen als klant van een beleggingsadviseur. Zij laten zich adviseren zonder dat de adviseur weet van het onderzoek. Zo kan meer inzicht verkregen worden in datgene wat zich exact in het adviestraject voordoet.

Al met al, laten de resultaten zien dat adviseurs een nuttige bijdrage kunnen leveren bij het nemen van financiële beslissingen door huishoudens. Advies alleen is echter niet voldoende. In combinatie met financiële educatie, aangepaste regelgeving, en keuzearchitectuur, kan het leiden tot een gezondere financiële toekomst van particulieren.