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Financial Advisors Influence on Private Investors' Financial Decisions

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Abstract

Most individual retail investors today rely on recommendations from financial advice when investing in stocks or bonds. Understanding the impact of financial advice on individual investors portfolio decision is thus of great importance, yet relatively little is known about this topic. This paper contributes to the understanding of the effects of financial advice on investors' asset allocation and examines whether clients act according to their estimated risk profile or if other determinants influence their decisions. Our results show that financial advisors exert little influence over their clients' asset allocation, and differences is rather due to clients' attributes, particularly risk tolerance and investment horizon. Further, we find no evidence that deviations from recommended investment (based on clients' attributes) are due to advisors' influence. Actually, the findings indicate a weak explanatory power of both client and advisor characteristics on equity deviation, and a remarkable difference in client's deviation from recommendations remains unexplained.

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1. Detailed Introduction

The purpose of this research is to understand financial advisors influence on private investors' financial decisions. Lack of financial literacy often lead to a deviation between private investors observed investment behavior and ideal behavior. An important element in reducing this deviation is financial advisors (Collins, 2012). They are the main source of information for private investors and the Norwegian Finance Industry Authorization schemes (FinAut) found that clients have high confidence in their advisor's recommendations (FinAut, 2018). Yet, finance literature has for a long time overlooked the role of financial advisors, and established models completely ignore this group as they assume that all investors act directly on capital markets (Gerhardt & Hackethal, 2009). Therefore, this topic is interesting to investigate and should be paid more attention to in the future.

However, after Campbell (2006) encouraged further research of financial intermediaries in household finance, there has been an increased interest in the field. A growing number of papers study private investors financial decisions, with some also studying the role of financial advisors. By analyzing the investment behavior of investors that have received advice, it is possible to gain increased understanding of financial advisors' behavior and recommendations. Yet, results from previous research are diverse. Some papers find a significant positive impact of financial advice on individual investors investment decisions, while others find a negative impact, or no effect at all. A study by Foerster, Linnainmaa, Melzer and Previtero (2017) reports that financial advisors have a significant impact on individual investors variation of risky shares in portfolios and that their recommendations reflect their own portfolio choices. Further, Linnainmaa, Melzer and Previtero (2016) showed that financial advisors have similar portfolios to those they advise to their retail clients. That is, the advisors' own beliefs and preferences drive their recommendations. With an event-study approach, they also found that clients of the same advisor often purchase the same mutual funds at the same time. Nevertheless, Hoechle, Ruenzi, Schaub and Scmid

(2013), documented that financial advisors in fact do not improve performance and portfolio choices.

This paper will contribute to the research on financial advisors and their influence on households and individual investors financial decisions. With a dataset from a well-known Nordic bank, our examination will be twofold: we will assess whether clients act according to their estimated risk profile or if other determinants influence their decisions, and examine the impact of financial advisors on their clients' asset allocations. Research addressing the latter exist, but is rather limited, while research on investors' deviation from their recommended investment has, to the best of our knowledge, never been done before. Hence, conducting an analysis on this will be of great interest. Using a Norwegian nation-wide dataset, we are able contribute to this field of study as such research of financial advisors' influence has not been conducted in Norway before. The dataset is unique and provide data not available on any open access database, making it even more interesting to study our topic. We focus particularly on the influence of advisors but will also look at demographic characteristics of the client such as age, gender, profession and location. The dataset shows deviations between clients' recommended investment, based on the results from a standardized questionnaire, and their actual investments. It includes data from 40+ branches across Norway which makes it possible to see trends in investments by clients of the same branch. As it is a known problem that many advisors are paid with incentives that may encourage them to direct money to specific funds with high fees (Beyer, de Meza, & Reyniers, 2013), we want to emphasize that this bank does not operate with such incentives for the advisors; the bank pays the advisors a fixed wage. As a result, we are provided with a more neutral dataset, that is not skewed by monetary incentives.

While most previous relevant studies focus on clients' overall portfolios, Hoechle, Ruenzi, Schaub, & Schmid (2013) investigated investors on a trade-by-trade basis. Our dataset provides investment decisions rather than overall portfolios; thus, we analyze the impact of financial advice on an "investment-by-investment" basis. Hence, our method has similarities with this article. To better understand the influence of advisors on investors' investment decisions, we analyze the effects of investors' and advisors' attributes by conducting two OLS-regressions using a data sample over the time period from 2016 to 2019. We divide the time period into four parts, one for each year, to capture the influence of aggregate trends in the data. In the first regression model we examine investors' deviation in percentage equity from what they were recommended, based on the results from a standardized questionnaire, and what they ultimately chose. Certain client attributes are economically significantly related to the probability of deviating. For example, older and more experienced clients with medium risk tolerance are more likely to deviate, and female clients deviate more than men. Further, clients tend to deviate less if the advisor is male and with the increase in cases per advisor. However, the most striking finding is that the model has a weak explanatory power with a R-squared of just 4% even with many variables, implying that deviations are poorly explained by clients' attributes and advisor characteristics. We extend the analysis by checking for advisory trends within the same branch and find that some branches clearly have more deviations than others. This might be due to different cultures across branches, but our model cannot prove this.

To further investigate the relationship between advisors and the clients' investment decisions, the second regression model analyze the variation in the proportion of equities (inherent risk of investment) in clients' investment decisions. Foerster et al. (2017) analyzed the portfolio risky share of investors with advisors using panel data with similar features as our dataset. Thus, our method and analysis have similarities with their article. We find that financial advisors' characteristics have a trivial impact on investment decisions, which is surprising as it contradicts with the results from Foerster et al. (2017). However, one important reason for this difference is that we use fewer advisor fixed effects. Also, the advisors in the Nordic bank use a digital advisory tool that provides a predefined portfolio recommendation for the clients based on the results from a standardized questionnaire that maps the client's attributes. As a result, the advisors follow a strict framework when giving advice. A key finding in our analysis is that a surprisingly large part of the variation in equity percentage in investment decisions is explained by the client's risk tolerance and investment horizon. The economically significance of these variables are higher in our model than the comparable model of Foerster et al. (2017), implying that the advisors of this bank emphasize them to a large extent. Hence, this result may be the reflection of the training the bank's advisors receives. Furthermore, males tend to invest more in equity than women and the proportion of equity declines with age of both client and advisor.

This paper starts by explaining our motivation for the study and continues by reviewing previous theory and literature addressing this topic in section 3. In section 4 and 5 we will present the dataset that will be used to investigate the research question and a description of the variables used in the regression models. The methodology is provided in section 6 and the results and discussions are presented in section 7. Finally, we will discuss limitations of the study in section 8 and present our conclusion in section 9.

2. Motivation

Hung et al. (2008) reports that 73% of the retail investors asked used a financial advisor before conducting a stock market or mutual fund transaction. A survey from DABbank back in 2004 provides similar results; 80% of Germans consult with a financial advisor before investing (DABbank, 2004). Clearly, the use of financial advisors is widespread, and yet there exist only a limited number of studies on the relationship between advisors and their clients' investment decisions. Furthermore, the studies that exist on financial advisors have somewhat contradicting results. This makes this field of study very interesting and the research can provide value. Conducting an analysis on a sample from a Nordic bank's Norwegian clients is of great interest, as such analysis has not been done in Norway before, to the best of our knowledge. This will add value to the understanding of the effects of advisors on (Norwegian) investors' investment decisions.

Another motivation is the limited availability of the dataset. The data is not public, leaving us with valuable information not available to everyone. To the best of our knowledge, most previous research focuses on advisors' effect on individual investors' total portfolios, while this dataset makes us able to analyze the impact on investor's individual investments. It enables us to differentiate clients fully relying on the advisor's recommendation, and clients consulting with their advisor but placing their order independently. Most of previous research do not consider this, making it problematic as clients often conduct investments of their own rather than based on advice.

3. Literature review

In the literature review, we will start by presenting basic theory of portfolio decisions and financial advice, and then we will focus on other relevant research that have been presented similar to the topic we are investigating.

3.1 Standard financial models

The mean-variance portfolio theory developed by Harry Markowitz in 1952 is important in modern investment decisioning and for emulating the effects on household portfolio decisions. The model is a static model used to assemble a portfolio of assets so that the expected return is maximized for a given level of risk. This gives a set of optimal portfolios that is known as the efficient frontier, and no investor should hold portfolios that are not on this line. Furthermore, if a risk-free investment is introduced, investors can borrow and lend at risk-free rate and thereby diversify away all risk but the covariance of the asset and the market portfolio. The efficient frontier then becomes a tangential line, called the *Capital Market line*. The market portfolio is obtained at the tangent point, and no one should hold any portfolio but the risk-free investment and the market portfolio. Even though the model is deemed as a quant revolution, it has some drawbacks that needs to be considered. The single period of the model has been criticized and the assumption of a fraction less financial market is rather unrealistic.

Based on Markowitz's work, other researchers developed the capital asset pricing model (CAPM) decades later. The theory simplifies Markowitz's portfolio theory by introducing the idea of specific and systematic risk. It provides the relationship between the risk of an asset and its expected return and is the most widely used model today.

A more suitable model for household portfolios is the dynamic extension of Merton (1969, 1971) that leads to the same optimal portfolio as Markowitz.

Merton's theory combines the problem of optimal portfolio choice and consumption rules for individual investors in a continuous-time model (Merton, 1969), making it possible to explain household's portfolio decisions over the life cycle. The theory takes changes in future investment opportunities into consideration, capturing an affect never appearing in static models. In a frictionless and complete market, portfolio choices can be made independently of consumption versus saving decisions (Merton, 1971).

3.2 Subjective expected utility theory

Subjective expected utility theory was introduced by Jimmie Savage in 1954. This theory of decision making under uncertainty is used to define choice-based subjective probabilities. In the model, where individuals chose a strategy that maximizes subjective expected utility, financial advice and other intermediates are ignored. Later empirical research has found considerable evidence contradicting with Savage's model (Bluethgen, Gintschel, Hackethal, & Müller, 2008). For instance, Kahneman and Tversky (1979) argued that the model fails to capture important features of subjects' choices over lotteries.

3.3 Behavioral finance

In standard financial models, expected returns are determined only by risk, and investors are assumed to be rational and predictable. Daniel Kahneman and Amos Tversky specialized on cognitive errors in the 1960s, causing individuals to engage in irrational behavior and this opened doors for early behavioral finance. Behavioral finance applies behavioral psychology to economic deciliation in order to understand why normal people make certain investment decisions and expands from standard finance models as it also distinguishes rational markets from hard-to-beat markets in the discussions of efficient markets (Statman, 2014). Statman (2014) presented a behavioral asset pricing model including utilitarian factors like risk, but also expressive or affect characteristics. Characteristics are interpreted as reflections of affect, a cognitive bias. Behavioral investors measure risk by the probability of failing to reach goals. They are risk averse like investors basing their choices on standard finance models, but they are not averse to high standard deviations of returns.

3.4 Theory of financial advice

Bluethgen et al. (2008) argues that cognitive errors and costly information acquisition give a basis for a theory of financial advice. Individual investors fail to reduce unsystematic risk by means of diversification as recommended by traditional portfolio theory. One important reason for this is cognitive errors. The subjective expected utility theory captures individuals' preferences correctly in simple lotteries, but individuals fail in more complex situations. Bluethgen et al. (2008) argue that in these complex situations, a financial advisor could be valuable in helping investors prevent mistakes. Because it is too complicated to present unique utility calculations for each individual investor, a possible solution would be to use a standardized questionnaire in order to find the risk profile of the client and then recommend a predefined model portfolio for clients with similar risk profiles.

Individuals also make suboptimal decisions because they lack information. Nonetheless, they make optimal choices based on the information available. Therefore, available information is crucial for making the right decisions. The problem is that the cost of acquiring information are perceived as larger than the benefits. Bluethgen et al. (2008) argue that an advisor could solve this problem by gathering and disseminating financial information to several investors. This will enable them to exploit economies of scale in the information acquisition.

3.5 Other relevant studies

Understanding the influence of financial advisors on household portfolios are of great importance, yet little previous literature regarding our problem is known, as most of financial literature assumes that private investors act directly on the capital markets (Gerhardt & Hackethal, 2009). To our knowledge, there has not been any empirical studies on whether client's deviations from recommended investment (based on the client's attributes) are due to advisor's influence or not. Further, only a few empirical studies have analyzed the relationship between client's portfolio decisions and financial advice. Among these studies there are evidence of both positive and negative effects of advisors on individual investor's portfolio performance.

Campbell (2006) encouraged research in household finance and stated that there exist deviations in private investors behavior from financial theory due to behavioral biases. More recent empirical studies show that most households rely on financial advisors in portfolio choices and implement the recommended trading decision from the advisor. This is grounded on the fact that investors often are unable to pick the right point on the efficient frontier, resulting in losses (Cavezzali & Rigoni, 2012). Hung et al. (2008) reports that advisors are widely used, and they should therefore also be trustable by customize the service by making tailor-made recommendations.

A paper by Bluethgen et al. (2008) was an early response to Campbell's call for further research within the field of household finance. In addition to sketching a theory of financial advice, they found that advised clients are older, wealthier, more risk averse and more likely to be female. By using a data set from a German retail bank, they found evidence in line with honest financial advice and that financial advisors have a significant impact on household investment decisions. Gerhardt and Hackethal (2009) confirms these results by comparing advised with non-advised investors using a much larger data set from at large German direct bank. They continued the research by conducting an analysis on the effects of financial advisors on the portfolios of private investors. They found that differences between advised and non-advised investors are not due to advisors' behavior alone. Hence, they concluded that the effect of financial advisors is probably less than assumed so far, although it does certainly exist.

Kramer and Lensink (2012) investigated the impact of financial advisors with a large data set of individual Dutch equity investors. When controlling for possible endogeneity problems they found empirical evidence that using an advisor benefits individual investors. Their results also show that advisors reduce risk. However, their results did not prove that advisors increase diversification as Gerhardt and Hackethal (2009) found in their studies. Another contrast between the two studies is how an advisor affect trading activity. While Gerhardt and Hackethal (2009) found that advisors trigger higher trading activity (due to portfolio restructuring), Kramer and Lensink (2012) showed that the number of trades declined after an advisory intervention. The main result from Kramer and

Lensink (2012) is that, if conflicts of interest are minimal, advisors improve portfolio decisions of retail investors.

Linnainmaa, Meltzer and Previtero (2016) provided a study using data from two Canadian financial institutions, including trading and portfolio information on more than 3 000 retail advisors and almost 500 000 clients between 1999 and 2013. They concluded that differences in advisors' beliefs affect the variation in the quality of their advice. The identity of the advisor is the single most important piece of information for anticipating most of the clients trading behavior. Then, not surprisingly, they found that clients of the same advisor often purchase the same funds at the same time. Mullainathan, Noeth, & Schoar (2012) support these results as they conclude that advisors often fail to de-bias their clients, and that the portfolio choices of the clients reflects biases that are in line with the financial interest of the advisor.

A paper analyzing a data set of 420 investment recommendations by 135 advisors (mainly Italian) over five years, contributes to the empirical research on investor advisory (Cavezzali & Rigoni, 2012). This study helps filling important gaps in previous research and analyses whether advice is influenced by characteristics of the investors, as well as the characteristics of the advisor. The findings show that the advisors' characteristic does not explain variability in recommendations to investors. A key element in this research of financial advisory is customization, and it concludes that risk attitude of investors is the most important for the mix of risky assets, and that demographic and social factors of investors have most impact on the amount of money invested. The conclusion of this study is that financial intermediates in household finance in fact can fill the gap between what the investor should do, and what they actually chose.

Hoechle et al. (2013) used a proprietary dataset from a large Swiss bank and analyzed the impact of financial advice on individual investors trading performance and behavioral biases on a trade-to-trade basis. By comparing advised and non-advised clients, they documented that financial advisors in fact do not improve performance and that advised clients in average perform significantly worse than non-advised clients when they control for client fixed effects.

On the other hand, using a unique dataset on Canadian households, Foerster et al. (2017) reports that financial advisors indeed have a significant impact on client's portfolio choices and the variation in risky shares across clients. By including advisor fixed effects, the variation in risky shares increased by 20 percentage points, implying that such advisor effects explain considerably more variation in portfolio risk than individual investors characteristics. They also concluded that the amount of risk an advisor takes in his or her own portfolio has a significant effect on the risk taken by his or her clients.

These former results are interesting and a first step into an important research area. A general conclusion from early previous literature is that financial advisors indeed have a significant impact on household investment behavior, but that the portfolio choice of investors may reflect biases that are in line with the financial interest or personal beliefs of the advisor. However, the results from more recent papers find a smaller impact or no influence of advisor on individual investors portfolio performance. While this topic has received a greater deal of attention in the recent years, no empirical research provides analysis on the Norwegian market for financial advisory. Thus, this paper will contribute to the research by investigating the Norwegian financial advisors and their influence on household and individual financial decisions.

4. Description of dataset

The dataset is obtained in collaboration with a well-known Nordic bank with more than 40 branches across Norway and contains investment data of retail clients that are assigned to a financial advisor at the local branch. Bluethgen et al. (2008) suggested that a standardized questionnaire could be used to group clients after their risk profile in order to recommend them a predefined model portfolio based on the results from the questionnaire. This bank operates with such a system, where a digital advisory tool provides a recommendation for the client. Our dataset stems from this tool and enables us to see each client's asset allocations, and whether or not clients made decisions deviating from their recommendation.

These clients must then have some determinants influencing their choice, and we are especially interested in whether this can be due to their advisor.

The dataset has a span of 32 months, from May 2016 to January 2019. We use accounts of private investors and exclude those owned by businesses as the main purpose of this study is to examine the effect of financial advice on individual investors. Advisory cases that lack information we consider to be of importance for our analysis, such as gender and age of investors, are also excluded. These considerations are based on other relevant literature reporting that these attributes are of great importance when determining individual investors investment decisions (Charness & Gneezy, 2012; Ameriks & Zeldes, 2004). The exclusion leaves us with a total of 3 539 observations in our final sample, including 3 089 clients assigned to 290 advisors. Demographic data of the clients are included as they may have a significant effect on the investors investments decisions and will make the result more accurate. These demographic data are collected by the bank on the date of the account opening and updated according to new information provided by clients and advisors. It includes variables such as gender, relationship status, age and location.

In addition, the dataset includes client attributes reflecting the investment strategy of investors, providing us insight in their behavior and investment profile. For each client, the dataset describes their responses to the questions in the questionnaire about risk tolerance, investment horizon, financial knowledge and financial experience and whether the client have a discretionary account or not. These attributes will be of great importance when advisors determine the appropriate allocation of equity for the clients' investment. Also, according to MiFID II, a new legislation implemented in the Norwegian law the 1st of January 2018, advisors are required to ask questions regarding attributes as risk tolerance and investment horizon and make their advice based on these (European Securities and Markets Authority, 2018).

Finally, advisors age, gender and which branch they work at are reported. The number of clients the advisor is responsible for is also included in the dataset. A precise description of each variable can be found in Appendix A.

4.1 Descriptive Statistics

Table 1 reports summary statistics for investors (Panel A) and financial advisors (Panel B). All variables are extracted from the bank's advisory tool in January 2019, but the advisory cases span from May 2016 to January 2019.

Table 1 Descriptive Statistics

Panel A: Investors *(N = 3 089)*

Characteristics	Statistics	# of obs.	Share	Mean	Std. Dev
Investor characteristics					
Demographic variables					
Gender	[% male]	1,670	54.06%	54.06	0.50
Age	[years]			48.31	14.45
Youth	[% youth]	143	4.63%		
Young Adults	[% young adults]	1,077	34.87%		
Old Adults	[% old adults]	1,514	49.01%		
Retired	[% retired]	355	11.49%		
Relationship status	[% married]	1,493	48.33%	48.57	49.98
Location					
Small municipality	[% small town]	574	18.58%		
Medium municipality	[% medium town]	1,583	51.25%		
Big municipality	[% big town]	930	30.11%		
Portfolio allocations					
Equity	[% in investment]			67.23	33.33
Product key	[% disretionary accounts]	168	5.44%		0.23

Investor attributes

Investment Horizon		Risk tolerance	
0-2 years	7.26%	Low	12.09%
3-8 years	30.06%	Medium	39.07%
9+ years	62.66%	High	48.81%

Financial knowledge		Financial experience	
None	52.85%	None	20.88%
Some	42.60%	Some	35.23%
Good	4.52%	Good	43.87%

Panel B: Financial Advisors *(N = 290)*

Characteristics	Statistics	# of obs.	Share	Mean	Std. Dev
Gender	[% male]	122	42.07%	43.42	0.50
Age	[years]			47.51	10.15
Youth	[% youth]	2	0.69%		
Young Adults	[% young adults]	101	34.83%		
Old Adults	[% old adults]	178	61.38%		
Unknown	[% unknown]	9	3.10%		
Clients advised		3089			
Advisory cases in total		3539			
Advisory cases per advisor				12.20	17.42

This table reports summary statistics for investors (Panel A) and financial advisors (Panel B). All variables are extracted from the bank's advisory tool in January 2019, but the advisory cases span from May 2016 to January 2019. "Youth" includes investors and advisors between the age of 16-24, "young adults" between the age of 25-44, "old audults" between the age of 46-66 and lastly "retired" between the age 67-92. "Location" provides information on where the clients live. "Small municipality" includes investors living in a municipality with maximum 30,000 inhabitants, "Big municipality" investors living i a municipality where the number of inhabitants exceeds 126,000 and "Medium municipality" investors living in a municipality with the number of inhabitants between these two.

Most of the investors are old adults, which means that they are between the age of 45 and 66. Further, a slight majority of the investors are male (54%), and about half of them are married (48%). There is variation in the level of financial knowledge and experience of the clients. About half of the investors (53%) declared that they have none financial knowledge, and only 4,5% states that their financial knowledge is good. Moreover, perhaps surprisingly as their financial knowledge is on average low, most of the investors have good financial experience (44%), with only 21% stating that their financial experience is low. Most investors (88%) reports their risk tolerance to be either medium or high, and the majority have chosen an investment horizon of 9 years or longer. About half of the investors (51%) lives in a medium sized municipality and 30% lives in a big municipality. The remaining 19% lives in a small municipality. The categorization of size of municipalities is defined in section 5.1.1.

We assess advisors influence over investment decisions by examining percentage invested in equity from 0 to 100%. Table 1 represents an overview of the clients' investment allocations, where the average of equity invested is 67%. This corresponds to the average high-risk tolerance of the investors, as equity share determine to a large extent the overall investment risk. Further, only 5% of the clients invests in discretionary funds. This segment is often related to clients with higher capital shares[1], and the low share might indicate that the number of wealthier clients in the dataset is small, that clients prefer other investment opportunities or that these funds are not recommended to the clients by the advisors.

The age and gender distribution of advisors are similar to that of investors. The advisors are on average 48 years old, and 61% is between the age of 45 and 66. Further, the majority are female (58%). There are 3 539 advisory cases in total split (unevenly) on 290 advisors, and since the number of clients advised is 3 089, the average of cases per advisor is about 12. Hence, most clients only make one investment decision in the period, but there are exceptions. By keeping the exceptions, we have about 14% additional cases which we believe adds more value to our research.

[1] According to representatives in the Nordic bank

5. Model Estimation

To analyze financial advisors influence on private investors' financial decisions the following multiple regression models are estimated:

(1) $Y_{1,iat} = \beta X_{it} + \lambda_a + \sigma_i + \varepsilon_{ia}$

(2) $Y_{2,iat} = \beta X_{it} + \lambda_a + \sigma_i + \varepsilon_{ia}$

For regression (1) the dependent variable is the deviation between the equity percent in the client's actual investment and the recommended equity percent defined by the bank's questionnaire (in absolute values) of advisory case *i* of advisor *a* in year *t*. Other relevant literature has examined the impact of advisors on private investors financial decisions using datasets with both advised and individual trades. For example, Hoechle et al. (2013) classified each trade as either advised or independent allowing them to compare these on a trade-by-trade within-person analysis. As our dataset only includes advised trades, it is interesting to investigate why some clients chose another investment decision than they were recommended. To our knowledge, this has never been done before, making our research different from other relevant literature, and a valuable contributor to previous research on this topic. With regression (1) we want to investigate whether these deviations are because of client attributes or if they may be due to advisors' influence. Therefore, vector X_{it} includes the client attributes risk tolerance, investment horizon, age, gender, financial experience, financial knowledge, marital status and geographic location. To capture potential unobserved characteristics of the client that are common for investors with the same advisor, we include advisor fixed effects age and gender by λ_a. The variable also includes the number of cases per advisor. Lastly, to investigate whether clients that invest in discretionary portfolios deviate more or less than other investors we include σ_i as a dummy variable taking the value 1 if the client invests in discretionary portfolios and 0 otherwise. As the bank states that clients investing in discretionary portfolios usually are wealthier, this variable indicates whether wealthier investors tend to deviate more or less than others.

Foerster et al. (2017) analyzed the variation in the proportion of equities in investors' portfolios with the allocation to risky shares as the dependent variable. Inspired by this approach, we apply chosen equity percent as the dependent variable to investigate closer what determines a client's asset allocation. This enables us to explore whether advisors tailor the investment risk to their client's characteristics, or if the proportion of equity is influenced by the advisor. In this regression we include the same regressors as in model (1).

To fully see the effect of advisor attributes on both the deviation between the equity percent in the clients actual investment and the recommended equity percent, and the chose equity percentage, we run two main regressions for both models; one including advisors attributes and one excluding λ_a to measure the explanatory power of investor attributes alone.

The variables will be explained in more detail in the following section.

5.1 Investor-specific Control Variables

Based on previous research we have identified several investor-specific characteristics that are likely to affect investment decisions. We include control variables to account for these effects.

5.1.1 Demographics

Various demographic data are used to control for investor attributes in the regression. Charness and Gneezy (2012) found strong evidence for gender differences in risk taking and several studies report the same conclusion, namely that women are more risk averse than men. Therefore, we include investors' gender as a dummy variable that takes the value of 0 for female and 1 for male. In line with earlier studies we expect a positive relationship between gender (male) and equity percent in the investment. Another important aspect of investment decision is how the portfolio allocation changes with age. Professional financial advisors often recommend that the fraction of wealth that people hold in the stock market (i.e. risky shares) should decline with their age (Ameriks & Zeldes, 2004). Inspired by the approach of Hoechle et. al (2013), we include age as a categorical variable, differentiating the clients in different stages of life from youth (16-24 years), to young adults (25-44 years), to old adults (45-66 years) and lastly to retired (67-92 years). Benzoni, Collin-Dufresne and Goldstein (2007) found effects that suggest a hump-shaped function of stock proportion over the life cycle. This is consistent with empirical observation and we expect our results to show a tendency towards this hump-shape.

Hanna & Yao (2005) studied the effect of gender and marital status on financial risk and found that both characteristics provides differences in risk tolerance for individuals. They found that if a person is married, he or she has a lower risk tolerance. Further, the individual preferences in our dataset may give a flawed measure of households' joint preferences. Married clients may be influenced by their partner and thus deviate from their self-reported preferences. Therefore, we also include marital status as a dummy variable taking the value of 1 if a person is married and 0 if not. We expect the variable to have a negative relationship with equity percent in investments and a positive effect on deviations.

To control for potential differences related to where the clients live, we include a categorical variable for their location – small, medium and big municipality, ranged after number of inhabitants in the respective municipality. "Small" represents clients living in a municipality with maximum 30,000 inhabitants, and "Big" represents clients living in a municipality where the number of inhabitants exceeds 126,000. Lastly, clients living in a municipality with the number of inhabitants between these two are represented in the variable "Medium". In the category "Big" we find the four municipalities in Norway with most inhabitants. We find it interesting to investigate whether this variable has a significant impact on our dependent variables or not.

5.1.2 Risk profile

Jansen, Fischer and Hackethal (2008) reports that risk aversion is negatively correlated with the proportion of equity in investor's portfolio. We include the investors risk profile as a categorical variable which takes the value low, medium or high for each investor. The advisors modify their recommendations based on client characteristics and the risk tolerance is a particularly important factor. As expected, more risk-tolerant investors are both recommended and chose riskier investments. Foerster et al. (2017) reported that client's risk tolerance stands out for its statistical and economic significance in explaining differences in risky share. In line with their results, we expect a positive relationship between higher risk profile and equity percent in the investments. However, it might be less clear how risk profile affects deviations from recommended investment, and it will be interesting to investigate this.

5.1.3 Investment horizon

Clients' investment horizon should also be of high importance when determining the appropriate allocation to risky assets. Generally, when investors have a shorter investment horizon, they are willing to take on less risk. Many researchers have found evidence supporting this, e.g. Foerster et al. (2017) who found that investors with longer investment horizon takes on about 7 percentage points more equity risk than those with very short horizons. We include this as a categorical value by separating the clients' investment horizon in short (0-2 years), medium (3-8 years) and long (9+ years). We expect our results to be in line with earlier studies with regards to the risk taking and time horizon relationship. However, it will be interesting to investigate whether time horizon has a significant effect on deviations from recommended investment or not.

5.1.4 Financial knowledge and experience

Financial knowledge and experience may be correlated with equity allocations and the use of financial advisors when investing. Previous research states that financial knowledge is positively related to the use of any type of financial advice, especially with using advice related to investing (Robb, Babiarz, & Woodyard, 2012). Further, both Hackethal, Haliassos and Japelli (2012) and Collins (2012) finds that investors that are less financial sophisticated are less likely to take recommendations from an advisor. However, Foerster et al. (2017) found limited variation in risk taking across different levels of financial knowledge. Hence, there is reason to believe that there exists a correlation between taking advise and financial sophistication, but we do not expect the variables to be particularly important in risk taking. Nevertheless, both variables are included in the regressions as categorical values, taking the values none, some or good experience/knowledge.

5.1.5 Product key

The product key variable is measured by a dummy-variable which takes the value of 1 if the client's investment decision is made at the portfolio manager's discretion, that is if the client has invested in discretionary funds. The value will be zero otherwise. According to the bank, this segment is often related to wealthier clients that invest in higher volumes (typically in discretionary funds), and it would be interesting to investigate whether such clients stands out from other clients. Cohn, Lewellen, Lease & Schlarbaum (1975) reported a positive impact of income on the risky-asset fraction of investors' portfolios, and thus we expect similar results.

5.2 Advisor-specific Control Variables

Based on previous research, we have also identified some advisor characteristics that are likely to have a significant impact on our results. Actually, previous studies have found that client's observable characteristics have surprisingly low explanatory power for asset allocations. Foerster et al. (2017) found that these characteristics jointly explain only 12% of the cross-sectional variation in risky share and other studies have a comparable or even lower explanatory power. Therefore, advisor-specific control variables need to be elucidated when analyzing the decision-making process in order to get more accurate results.

5.2.1 Gender and Age

As discussed in section 5.1.1, we expect that gender and age will have a significant effect on investors investment choices. This is likely to hold for advisors as well, because recommendations given by financial advisors may in part be reflected by their own personal preferences. Foerster et al. (2017) found that the age of advisors is of high statistical significance for their clients' portfolios in regards of risky shares. Their results suggest that older advisors direct their clients into considerably more risky portfolios than younger advisors. This contradict with the suggestion that financial advisors reflect their own personal preferences, and with the studies showing a hump-shape pattern with age in risky shares. By contrast, the same study by Foerster et al. (2017) found the gender of the advisor to be unrelated with the risky share in the clients' portfolio. This result might be surprising considering gender differences in risk taking. Further, Hoechle et al. (2013) found that it is a higher probability that clients of female advisors and younger advisors (below 30 years) trade on advice. The different results discussed makes it interesting to use the advisor-specific control variables in our regression, in order to analyze their impact on their clients' investment choices.

Hence, we include advisor's gender as a dummy variable that takes the value of 0 for female and 1 for male. Age is included as categorical variables with the same groups as for clients, with the retired group being a natural exception.

5.2.2 Number of clients per advisor

Foerster et al. (2017) found a weak relation between the risky share in client's portfolios and number of clients per advisor. Their results suggest a small tilt toward less risky portfolios among advisors with more clients. Further, Hoechle et al. (2013) reports that advisors responsible for fewer clients are associated with a higher probability of their client trading on advice. We include this variable in our regressions and use it when we investigate correlations between client and advisor characteristics.

6. Methodology

To estimate financial advisors influence on private investors financial decisions we conduct a panel data model analysis. Using Matlab, we estimate regression models using OLS including advisor and investor fixed effects. Panel data modelling is appropriate for datasets with both cross-sectional and time series aspects. As many of the investors have missing years for the cross-sectional units in the sample, our dataset is an unbalanced panel (Wooldridge, 2016, pp. 440). Unlike Foerster et al. (2017), our dataset provides investment decisions rather than overall portfolios; thus, we analyze the impact of financial advice on a "investment-by-investment" basis. The following will provide a detailed description of our methodology.

6.1 Fixed effects model

Because of the likelihood of omitted variables that are correlated with the variables in our model, we derive a fixed effects model for our panel data. Using a fixed effects model may provide a method for controlling for omitted variable bias (Wooldrige, 2016).

6.2 Year fixed effects

Foerster et al. (2017) includes year fixed effects in their regressions to absorb common variation in portfolios. Our dataset covers a period of four years, making it possible that there have been economic fluctuations that will affect all individuals in the sample. Such fluctuations can be interest rate increase/decrease or changes in stock prices. Year fixed effects deal with this. To capture the influence of aggregate trends and thereby variation in the data, we test whether we should include year fixed effects in our data models by including dummies for each year in our dataset. We exclude the year of 2016 to avoid multicollinearity. Further, we test whether the coefficients for all dummies are jointly equal to zero and find evidence that the results are significant for all models except the model analyzing the impact on chosen equity percentage for investors not including advisor fixed effects. Year fixed effects are therefore included for all models except this one. When year effects are fixed, they will have the same impact on the investors, making us able to remove correlations between observations in the same period. This leaves us with a model with less biased standard errors.

6.3 Issues of dependence

Issues of independence, such as serial correlation, occurs when the error terms of a time series regression correlate with each other across time. We test for first order serial correlation in the error terms using the Durbin-Watson (DW) test. The DW test statistics are 1.66 and 1.77 for regression (1) and (2), respectively. As both statistics are near 2, there is little evidence of autocorrelation (Brooks, 2014, pp 196). Foerster et al. (2017) estimated the OLS with standard errors clustered by advisor to account for correlations in errors over time and between clients who share an advisor. Brooks (2014) however, argue that approaches in panel data that ignore cross-sectional dependence is widely used in the empirical literature. This is mainly because dealing with cross-sectional dependence satisfactorily makes an already complex issue substantial harder (Brooks, 2014, pp 551). Based on our results from the DW test and Brooks' (2014) argumentation, our regression does not account for correlations in errors over time.

6.4 Issues of multicollinearity

To avoid problems of multicollinearity, we will omit the categorical variables for the lowest levels of each category. This is the same approach as used by Foerster et al. (2017) and Hoechle et al. (2013). The estimated coefficients on the remaining dummies represent the average deviation of the dependent variables for the included categories from their average values for the excluded category (Brooks, 2019). Hence, the omitted categories are our base cases.

6.5 Matching dummy variables

As there might be some matches of advisors and clients that harmonize better than others, we extend the previous models by adding independent variables based on gender-matching and age-matching between clients and advisors. This approach is inspired by Hoechle et al. (2013). We include four new dummy-variables on the gender of the clients and advisors: male-male, female-female, male-female and female-male. The variables take the value 1 if the combination exist and zero otherwise. Further, three new matching-variables on age of clients and advisors are made, one taking the value 1 if the advisor and clients are of similar age (zero otherwise), one taking the value 1 if the clients are older than the advisor (zero otherwise), and one taking the value 1 if the advisor are older than the client (zero otherwise). The previously used categorical variables for age and gender for both the advisors and clients are replaced by these new variables. In order to prevent entering a dummy variable trap, and to avoid multicollinearity, we exclude the dummy variable for male-male and the one for clients and advisors being of similar age.

The re-estimated regressions are:

(1) $Y_{1,iat} = \beta X_{it} + \lambda_a + \sigma_i + \gamma_{ia} + \varepsilon_{ia}$

(2) $Y_{2,iat} = \beta X_{it} + \lambda_a + \sigma_i + \gamma_{ia} + \varepsilon_{ia}$

where γ_{ia} includes both the age and gender matching-variables.

6.6 Correlation matrix

To further avoid problems of multicollinearity we compute a correlation matrix between the variables. This allows us to determine which variables that have the strongest relationship with the dependent variables and whether some investor or advisor characteristics are highly correlated. Highly correlated variables can make it very difficult to assess the effect of the independent variables on the dependent variables, as the results will be unstable parameter estimates of the regressions. This needs to be accounted for. The correlation matrix is reported in Table 2. As the pair-wise correlations between the variables are not particularly high (all under 0.5), we will continue conduct the analysis including all variables as regressors.

Table 2 Corrlation Matrix

	Gender client(d)	Age client (in years)	Inv. Horizon (in years)	Relationship status	% equity	Deviation %	Location	Risk-profile (d)	Product key	Financial experience	Financial knowledge	Gender Advisor (d)	Age advisor	# of clients
Gender client(d)	1.000	0.122*	(-0.106)*	0.137*	0.017	(-0.022)	(-0.027)	0.0711*	(0.065)*	0.141*	0.102*	0.079*	(-0.014)	(-0.023)
Age client(in years)	0.122*	1.000	(-0.465)*	(0.310)*	(-0.309)*	0.102*	(-0.016)	(-0.260)	0.245*	0.313*	0.123*	(-0.039)	0.130*	0.026
Inv. horizon (in years)	(-0.106)*	(-0.465)*	1.000	(-0.078)*	0.471*	(-0.139)*	(-0.072)*	0.322*	(-0.146)	(-0.176)*	(-0.104)*	0.053*	(-0.058)*	0.062*
Relationship status client(d)	0.137*	(0.310)*	(-0.078)*	1.000	0.009	0.008	(-0.100)*	(-0.004)	0.085*	0.152*	0.049	0.014	0.015	0.014
% equity	0.017	(-0.309)*	0.471*	0.009	1.000	-0.353	(-0.099)*	0.660*	(-0.114)*	(-0.087)*	(-0.047)	0.049	(-0.073)*	(-0.026)
Deviation %	(-0.022)	0.102*	(-0.139)*	0.008	(-0.352)*	1.000	0.046	(-0.062)*	(-0.114)*	0.087*	0.033	(-0.078)*	(0.076)*	(-0.028)
Location	(-0.027)	(-0.016)	(-0.072)*	(-0.100)*	(-0.099)*	0.046	1.000	(-0.101)*	0.007	(-0.009)	0.054*	(-0.062)*	(-0.055)*	0.049
Product key (d)	(0.065)*	0.245*	(-0.146)	0.085*	(-0.114)*	(-0.114)*	0.007	(-0.060)*	1.000	0.221*	0.131	0.004	0.017	(-0.032)
Risk-profile	0.0711*	(-0.260)	0.322*	(-0.004)	0.660*	(-0.062)*	(-0.101)*	1.000	(-0.060)*	(-0.0193)	0.001	0.003	(-0.015)	-0.008
Financial experience	0.141*	0.313*	(-0.176)*	0.152*	(-0.087)*	0.087*	(-0.009)	(-0.0193)	0.221*	1.000	0.359*	(-0.042)	0.057*	(-0.059)*
Financial knowledge	0.102*	0.123*	(-0.104)*	0.049	(-0.047)	0.033	0.054*	0.001	0.131	0.359*	1.000	(-0.048)	0.013	0.092*
Gender Advisor (d)	0.079*	(-0.039)	0.053*	0.014	0.049	(-0.078)*	(-0.062)*	0.003	0.004	(-0.042)	(-0.048)	1.000	(-0.347)*	(-0.023)
Age Advisor	(-0.014)	0.130*	(-0.058)*	0.015	(-0.073)*	(0.076)*	(-0.055)*	(-0.015)	0.017	0.057*	0.013	(-0.347)*	1.000	0.179*
# of clients	(-0.023)	0.026	0.062*	0.014	(-0.026)	(-0.028)	0.049	-0.008	(-0.032)	(-0.059)*	0.092*	(-0.023)	0.179*	1.000

This table present correlaton coeffisients between the dependent, independent and control variables of both clients and advisors from May 2016 til Januar 2019. (d) indicates dummy variables. Significance at 5 % significans level are reported by *. Decription of the variables are reported in Appendix A.

7. Results and Discussion

7.1 Regression results and discussion

The main results from estimating the panel data regressions are presented in table 3. The coefficient estimates are presented in column 2-7. Column 2-4 and 5-7 replicate regression (1) and (2), respectively, with the different independent variables included in the models. This table can be found on page 31 for the reader's reference.

7.1.1 Regression (1): Equity deviation as the dependent variable

We estimate three regression models with equity deviation as the dependent variable to analyze the relationship with the different independent variables. The regression presented in column 2 in table 3 include only investor attributes as independent variables. The intercept of the regression, 6.07, is the average equity deviation in 2016 of investors who is in the lowest (omitted) category for every variable. Our findings show that older and more experienced clients are more likely to deviate from recommended equity percent. Assuming the deviations are not triggered by the advisor, these results contradict to the findings from earlier studies where clients in these categories have been proven to be more likely to rely on financial advice (Bluethgen et al., 2008; Hackethal et al., 2012). As financial experience has a positive impact on deviations, it is rather surprising that higher financial knowledge has a negative relationship with deviations compared to clients with none financial knowledge. This variable, however, is not of statistical significance. Furthermore, male clients deviate 1.79 percentage points less from advice than female clients. This result is statistically significant. According to Bluethgen et al. (2008), advised clients are more likely to be female as their risk attitude tends to be lower than for men. Hence, a higher deviation for female clients, as our results suggest, is not as expected and is one of the most striking findings in this model. Relative to the excluded "short" category, clients with long investment horizons deviate less, while those with medium investment horizons deviate more from recommended equity percent. Both *location* and the dummy variable *product key* are of statistical significance. The former shows higher deviations when the client lives in a medium or big municipality relatively to a client living in a small municipality, while the latter shows that wealthier investors tends to deviate more. Risk tolerance is an important factor in decision-making, and with regards to deviations from recommendations, clients with medium risk tolerance deviate the most; 3.13 percentage points more than those with low risk tolerance. The dummy for marital status also has a negative relationship with deviations, meaning that married clients are less likely to deviate from recommended investment. This might be surprising as married clients could be influenced by their partner and thus deviate from their self-reported preferences. Relationship status, however, are not of statistical significance. Nevertheless, this model's adjusted R-squared is only 3.99%. Hence, a remarkable amount of variation remains unexplained.

The second regression model (column 3) modifies the first by adding advisor fixed effects. Data on advisor characteristic allows us to investigate whether clients' deviations from their recommendations are due to influence from the advisors or not. Our results show that if the advisor is male, the client will deviate 2.65 percentage points less from their recommendations than if the advisor is female. Moreover, the older the advisor is, the more his or her clients deviate. Advisor age is, however, not statistically significant in our model. Further, increase in cases per advisor results in less deviation in equity percent. When adding advisor characteristics, the coefficients on investor attributes stays about the same. The model's adjusted R-squared is still low (4.00%), implying that a remarkable difference in clients' deviation from recommendations remains unexplained.

In the third regression (column 4) we replace some of the independent variables with client-advisor matching characteristics. We interestingly find significant impact on equity deviations from the gender-match dummies with female advisor and client, and male client and female advisor. All gender-match dummies display a positive impact, implying that the involvement of a woman either as an advisor or client contributes to more deviations from recommendations, as the male-male variable is our base-case. The effect when a female client is matched with a female advisor is especially economically large compared to the others (4.18). These results are interesting but not very surprisingly, as earlier research states that there exists prejudice against women in finance (Niessen-Ruenzi & Ruenzi, 2013), which perhaps is a signal of doubt in using women for professional advice. There are not statistically or economically significant impact on equity deviations of any of the age-matched dummies. Our previous results are mainly unaffected by the additional variables as the regression model provides almost the same R-squared as regression one. However, the R-squared is slightly lower (3.39%), implying that this is a weaker model than the two others in explaining cross sectional variation in clients' deviation from recommendations.

The most striking finding for regression (1) is that, even with a lot of regressors, the explanatory power of the model is low. This means that client's deviations in equity percent from what they are recommended are hard to explain. Deviations can be caused by individuals' preferences or be due to influence from advisors. However, our results show that advisor characteristics are of little impact when analyzing the effect on equity deviation. To our knowledge, no previous research has investigated deviations in the way we do, thus no comparison can be made to this result. This might be because it is necessary with a special dataset that reveals both what the client ideally should invest in, based on e.g. a set of standardized questions, and what the client chose. Also, the low explanatory power of our model may be because deviations are due to unobservable variables. Bergstresser, Chalmers and Tufano (2009) investigate the value of brokers for helping clients select mutual funds. They conclude that advisors deliver intangible benefits which we cannot measure and that there exist material conflicts of interest between advisors and their clients. Exclusion of such unobservable variables might be a reason for the low explanatory power. Besides, how the advisors convince that their advice is valuable can be of great importance as bad convincing may lead the clients to choose other investment decisions than what the advisor recommend. We extend the analysis by checking for advisory trends within the same branch in section 7.3. Nevertheless, this field of study could benefit from further analysis with more datasets in order to give useful answers.

7.1.2 Regression (2): Equity percentage as the dependent variable

Further, we estimate three regression models with equity percentage (i.e. inherent risk of investment) as the dependent variable. These models try to explain which attributes determining a client's equity percent in an investment decision. Again, we start with a regression including only investor attributes as independent variables, presented in column 5 in table 3. The intercept of this regression, 1.85, is the average equity percent in 2016 of investors in the lowest (omitted) category.

Risk tolerance and investment horizon stands out for their statistical and economic significance in explaining variation in risk-taking. Not surprisingly, the equity percent increase with higher risk tolerance. Relative to the omitted “low” category, clients with medium and high risk-tolerance invest 25.09 and 48.49 percentage points more in equities, respectively. These findings are in accordance with the results by Foerster et al. (2017). Investment horizon is also positively related to investments in equity. Foerster et al. (2017) found that clients with longer investment horizons invest only about 7 percentage points more in equity than those with very short horizons. Our results show that clients with medium and long horizons invest 25.03 and 41.91 percentage points, respectively, more in equity than those with short horizons. Our result suggest that the bank emphasizes risk tolerance and investment horizon to a great extent when giving recommendations to clients. Financial knowledge is in general not important economically nor statistically in explaining variation in risk taking. This is expected as Foerster et al. (2017) found limited variation in risk taking across different levels of financial knowledge. Clients with reported good financial experience, however, have a statistically significant negative relationship with equity percent relative to the clients with low experience. On average, male clients invest 1.20 percentage points more in equity than women. This is an expected result, considering that previous research finds strong evidence for gender differences in risk taking (Charness and Gneezy, 2012). Also, Foerster et al. (2017) found women’s risky shares to be on average 1.4 percentage points below those of men, which is a result very similar to ours. However, in our model this result is not statistically significant. Further, the investors age was expected to be important in explaining variation in risk-taking. Clients classified as young adults invest more in equity than younger clients, but after this age-group the clients invest less in equity compared to the youngest group of investors, hitting its lowest with the retired clients. These results are in line with the hump-shaped function of equity proportion over the life cycle. However, except from the retired category, the coefficients for age are not statistically significant. Marital status is significant, and married clients invest 2.34 percentage points more in equities than unmarried clients. This is surprisingly, as Hanna & Yao (2005) found a negative relationship between risk tolerance and marriage. Also quite surprisingly is the result that clients investing in discretionary portfolios (*product key*) invest in 4.61 percentage points less in equity than other clients. As these clients often tend to have higher capital share, this suggest that wealthier clients invest less inn equity than less wealthier clients. This is contrary to Cohn et al. (1975) who found that wealthier investors tend to invest in riskier assets. Further, we find very limited variation in risk-taking across size of municipality (locations). The model's adjusted R-squared is 57.2%. Hence, our regressors explain a relatively big part of the cross-sectional variation in equity percent.

The next regression model (column 6) modifies the previous by adding advisor fixed effects. The adjusted R-squared increases a little, from 57.2% to 57.5%. Adding advisor characteristics allows us to investigate whether these characteristics are of significance for the client's investment in risky shares. If the advisor is male, the client will invest 2.09 more percentage points in equity than if the advisor is a woman. This is statistically significant and of more economic significance than if the client itself is male, making our results different from other relevant research where the advisor's gender tends to be unrelated with the risky share in the client's portfolio (Foerster et al., 2017). However, the result is not a big of surprise due to differences in risk taking between men and women. The older the advisor is, the less the client invest in inherent risk of investment. Young adults and old adults invest in 8.55 and 11.14 percentage points, respectively, less equity than those of younger advisors. Advisor age is, however, not statistically significant in our model. Lastly, increase in cases per advisor is not of economically nor statistically significance in this model. When we add advisor characteristics to the model, the coefficients on investor attributes stays about the same. The relatively small increase in the explanatory power suggest that our advisor attributes are inconclusive. This is consistent with the results from Cavezzali & Rigoni (2012). However, Foerster et al. (2017) more than doubled their adjusted R-squared by adding advisor fixed effects. An important difference from our model is that they had access to advisors' portfolio allocations. However, their "new" R-squared (30.2%) is still lower than for regression (2).

Our results are again almost unaffected by the addition of client-advisor matching variables. However, certain matches of clients to advisors harmonize better than others and have a significant impact on the percentage of equity invested. The results are reported in the last regression (column 7). We find significant and negative impact from the female client to female advisor dummy, implying that the involvement of both female client and advisor contributes to an investment decision of less equity, compared to cases where both the client and the advisor are men. This is consistent with theory as women tends to be more risk-averse than men (Bluethgen et al., 2008). Further, the age-dummy with older advisor have significant and positive impact with a coefficient of 2.86. As our base category is the case when advisor and client is of the same age, this result shows that clients with an older advisor invests in a higher percentage of equity than if both participants are of the same age.

Our results suggest that the advisors to a large extent base their advice on client's attributes, particularly risk tolerance and investment horizon. This is in line with the requirements that MiFID II outlines, and will from the bank's perspective imply a good finding. Differences in both these variables translate to significant differences in percentage of equity invested by the client, leaving us with a model with a high R-squared. However, even after adding advisor fixed effects, there is still a part of clients' investment decisions that remains unexplained, and again we find little evidence that cross-sectional variation is due to advisor characteristics. The explanatory power of our model is comparable to or even higher than previous research. In comparison, Foerster et al. (2017) could only explain one-eighth of the cross-sectional variation in risky shares before adding advisor fixed effects to their model. A reason for this might be that our dataset provides client information from a bank offering a limited selection of investment funds while other studies might explain the variation in risky shares with a larger variation in client investment-opportunities. Another explanation can be the standardized questionnaire the bank operates with which is, partly, due to MiFID II. The results from this tool provides the advisor with a complete view of investors investment attributes, and a predefined model portfolio, probably making their recommendations accurate to the client's preferences. Thus, legislation might influence the advisor's performance and our results.

Table 3 Main results

Independent variables	Model 1: Dependent Variable = Equity Deviation (1)	(2)	(3)	Model 2: Dependent Variable = Equity Precentage (1)	(2)	(3)
Constant	6.0651	1.9980	7.0747	1.8497	11.5810	2.0501
	(0.0134)**	-0.7560	(0.0006)***	-0.4772	-0.1033	-0.3695
Risk tolerance						
Medium	3.1303	2.8390	2.2549	25.0860	25.0090	26.0450
	(0.0071)***	(0.0145)**	(0.0501)*	(0)***	(0)***	(0)***
High	1.0474	0.7848	0.1237	48.4870	48.4850	49.6340
	-0.3830	-0.5119	-0.9166	(0)***	(0)***	(0)***
Financial knowledge						
Some	-0.1220	-0.2305	-0.1161	-1.3948	-1.6975	-1.8032
	-0.9109	-0.8323	-0.9153	-0.2364	-0.1572	-0.1349
Good	-0.6355	-0.4317	-0.6286	0.4873	-0.0066	0.3034
	-0.5516	-0.6858	-0.5565	-0.6549	-0.9955	-0.7972
Financial experience						
Some	1.6645	1.6145	1.8761	-0.8041	-0.7887	-1.2374
	(0.0459)*	(0.0526)*	(0.0241)**	-0.3776	-0.3901	-0.1778
Good	6.1301	5.1690	6.0918	-4.0713	-3.1155	-4.4758
	(0.0005)***	(0.0036)***	(0.0005)***	(0.0348)**	-0.1110	(0.0219)**
Investment Horizon						
Medium	0.0126	-0.6053	-0.4331	25.0300	25.3790	25.0860
	-0.9929	-0.6713	-0.7615	(0)***	(0)***	(0)***
Long	-3.1430	-3.6917	-3.7965	41.9070	42.2060	42.7470
	(0.0280)**	(0.0098)***	(0.0078)***	(0)***	(0)***	(0)***
Investor demographic variables						
Gender	-1.7930	-1.5335	-	1.2000	1.0127	-
	(0.0094)***	(0.0266)**		-0.1146	-0.1838	
Age						
Young Adults	1.0028	1.2704	-	1.4618	1.3326	-
	-0.5727	-0.4732		-0.4552	-0.4948	
Old Adults	2.4881	2.3770	-	-2.7475	-2.4097	-
	-0.1583	-0.1762		-0.1571	-0.2135	
Retired	5.1545	4.8640	-	-7.3553	-6.8379	-
	(0.0105)**	(0.0154)**		(0.0009)***	(0.0020)***	
Relationship status	-0.5825	-0.4910	-0.1317	2.3437	2.2338	1.7610
	-0.4124	-0.4877	-0.8511	(0.0027)***	(0.0042)***	(0.0227)**
Location						
Medium municipality	2.5647	2.5251	2.6102	-1.5078	-1.0768	-1.2726
	(0.0050)***	(0.0058)***	-0.0044	-0.1337	-0.3856	-0.2088
Big municipality	2.5137	2.3662	2.2896	-1.3835	-1.1708	-1.0014
	(0.0117)**	(0.0177)**	(0.0221)**	-0.2077	-0.2867	-0.3646
Investor portfolio allocations						
Product key	4.5124	4.6680	5.3031	-4.6108	-4.9515	-6.1115
	(0.0025)***	(0.0017)***	(0.0003)***	(0.0049)***	(0.0025)***	(0.0001)***
Advisor fixed effects						
Gender	-	-2.6450	-	-	2.0878	-
		(0.0001)***			(0.0063)***	
Age						
Young Adults	-	4.8742	-	-	-8.5492	-
		-0.4178			-0.1972	
Old Adults	-	7.6873	-	-	-11.1400	-
		-0.2004			-0.0922	
Cases per advisor	-	(-0.0261)	-0.0157	-	0.0050	-0.0095
		(0.0080)***	-0.1033		-0.6425	-0.3745
Client-advisor matching characteristics						
Female, Female	-	-	4.1768	-	-	-3.5512
			(0)***			(0.0004)***
Male, Female	-	-	2.2238			-1.7951
			(0.0142)**	-	-	(0.0729)*
Female, Male	-	-	0.3698			0.1733
			-0.7221			-0.8800
Older client	-	-	0.2682	-	-	-0.7107
			-0.7545			-0.4531
Older advisor	-	-	-0.6087			2.8622
			-0.4636	-	-	(0.0018)***
Time fixed effecs	Yes	Yes	Yes	No	Yes	Yes
# of observations	3539	3539	3539	3539	3539	3539
# of investors	3089	3089	3089	3089	3089	3089
# of advisors	290	290	290	290	290	290
Adjusted-R^2	0.0399	0.04	0.0339	0.572	0.575	0.57

This table presents the estimated coefficients from OLS regression of proportion of equity in investors investment decision and equity deviation from recommendations from advisor on investor attributes, advisor fixed effects and year fixed effects. The regression models are specified in model (1) and (2) in the main text. Regression (1) includes only investors attributes, (2) both investor and advisor attributes, and (3) both investor and advisor attributes but gender and age are replaced by client-advisor matching characteristics. Client-advisor matching variables are included as dummies taking on the value 1 if the given matching of characteristics exsist and 0 otherwise. We omit the indicator variables of the lowest categories."Young adults" includes investors and advisors between the age of 25-44, "old audults" between the age of 45-66 and lastly "retired" between the age 67-92. "Location" provides information on where the clients live. "Big municipality" includes investors living i a municipality where the number of inhabitants exceeds 126,000 and "Medium municipality" investors living in a municipality with th number of inhabitants is between 30,000 and 126,000. "Product key" provides information on whether the clients invested in dicretionary funds or not and "Relationship status" whether they are married or not. For all six regression-models we report the coefficient estimates, the p-value (in parantheses) and the significance level where 1%, 5% and 10% significance level are denoted by ***, ** and * , respectively. The data sample is retrieved from a well-known Nordic bank's digital advisory tool in the period from May 2016 to January 2019. Appendix A defines the variables. The Row "Adjusted-R^2" reports the adjusted r^2 of det models, that is reports the incremental explanatory power over the models.

7.2 Correlation between variables

The results of the correlation matrix in table 2 in section 6.6 supports the results from the regression models. Age of client and percentage of equity invested are significantly and negative correlated, suggesting that older clients tend to have a lower proportion of equity in their investment. Further, there exist a strong positive linear relationship between percentage of equity and both investment horizon and risk profile. This is in coherent with regression (2) that found these two client attributes to be the most important in explaining cross-sectional variation in equity percent. Deviation percentage also has a positive linear relationship with equity percent which indicates that clients investing in more equity tends to deviate more from what the results from the standardized questionnaire recommended. Further, the results provide low and insignificant correlations with deviation percentage and both investor and advisor characteristics. These results harmonize with the low explanatory power of regression model 2 and supports the result from our regressions.

However, some investor characteristics seems to be significantly correlated. Not surprisingly, age of clients and investment horizon are significant and negative correlated, while age of client and relationship status are positive correlated. This suggests that older clients tend to have shorter investment periods and tend to be married. Based on our previous results, we expect that the involvement of both female advisor and client will contribute to higher deviations. However, the correlation between the two gender-variables is relatively low, implying an almost non-existing linear relationship between the two variables. Moreover, the relationship between the client's age and the advisor's age indicates that older advisors tend to be matched with older clients. Even though this variable match has the highest correlation coefficient among client and advisor combinations, the relationship is rather weak. This is consistent with our previous findings. Actually, the table shows that almost all cases of such combinations have a low correlation coefficient and matches between clients and advisors seems rather random.

7.3 Advisory trends within the same branch

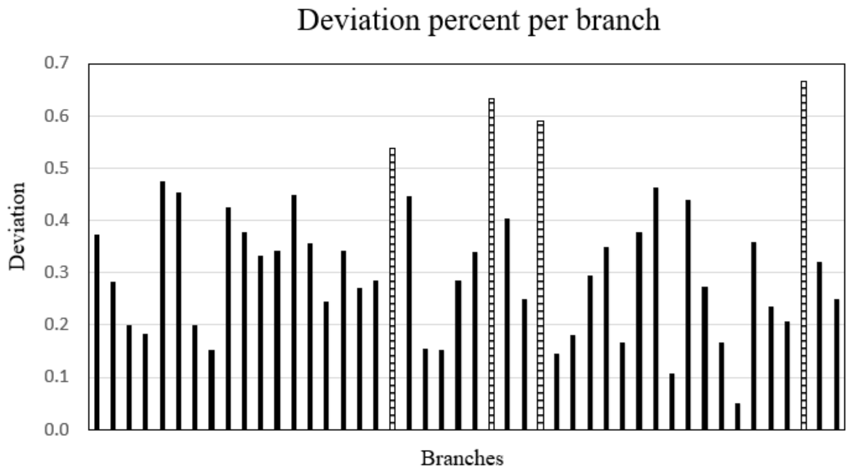
To investigate whether there are advisory trends within the same branch, we find the deviation percent as well as the average equity deviation of the different branches. In order to preserve the bank's anonymity but still be able to see the spread among the different branches, we omit the branches closest to the mean. The deviation percent is derived by the number of investment decisions where a client chose an equity percent that is different from the one recommended by the bank (through the standardized questionnaire) divided by the total number of investments in the branch for the period. The results are illustrated in figure 1, which shows the deviation percent as a function of the branches. The average deviation is 31.68%, and the result shows some large outliers; four of the branches have a deviation percent above 50% (marked with dotted lines).

Figure 2 plots the average equity deviation in absolute terms of each branch. The equity deviation shows how much more or less the client invested in equity compared to what the results from the standardized questionnaire recommended. Only the advisory cases with deviation is accounted for in this figure in order to illustrate the extent of the deviations regardless of how many deviations each branch has in the period. The results are relatively smooth throughout the bank with some branches standing out with a higher average deviation. The branches closest to the mean is omitted to preserve the bank's anonymity. As the average is taken from the absolute values, this figure does not consider whether the client invested more or less in equity than recommended.

Figure 1 and 2 illustrate the extent of deviations across different branches. As they do not tell us the reason for the deviations, it is hard to explain trends. However, in figure 1 we can clearly see that some branches deviate more often than others. Worth mentioning is that some clients fill in the bank's standardized questionnaire more than one time, seemingly to achieve another result[2]. This makes it possible for a branch to influence the clients' investments without having reported deviations.

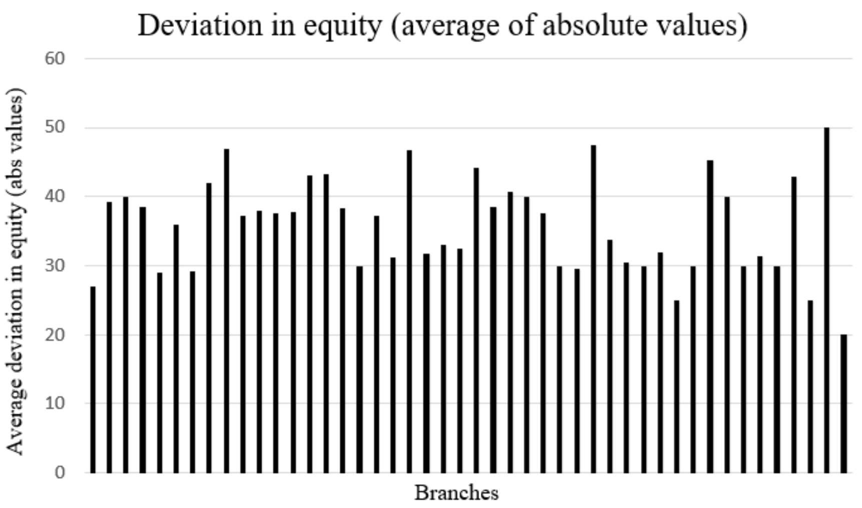
[2] According to representatives from the bank.

Figure 1 Deviation percent per branch



This figure shows the clients' deviation percent per branch in the period May 2016 to January 2019. A deviation is reportet if the client invest in more or less equity than recommended (based on the results from a standardized questionnaire). To preserve the bank's anonymity, branches closest to the mean is omitted from the graph. The four branches with the highest deviation percent (above 50%) are marked with dotted lines.

Figure 2 Deviation in equity per branch



This figure shows the average deviation in equity from what was recommended by the results from the bank's questionnaire (in absolute values) as a function of branches in the period May 2016 to January 2019. Only the advisory cases with deviation are accounted for in this figure in order to illustrate the extent of the deviations regardless of how many deviations each branch have in the period. To preserve the bank's anonymity, branches closest to the mean is omitted from the graph.

8. Limitations

One limitation of our data is that the individual's preferences, for example risk tolerance, may give a flawed measure of households' joint preferences. The married individuals in our sample may be influenced by their partner and thus deviate from their self-reported preferences. However, Foerster et al. (2017) found no evidence of measurement error among portfolios managed by married individuals. Moreover, it is important to mention that our results might be biased if there exist unobserved variables that affects our dependent variables and correlates with the other regressors. Our study might suffer from such an omitted variable problem, as we observe many important investor characteristics, but little is known about the advisors. Empirical research finds that other advisor characteristics may have a significant effect on investors investment decisions. Campbell (2006) reports positive and significant effects of education on equity participation, meaning that less educated investors will be less informed about financial markets. This importance of financial literacy will hold for advisors as well and may be a strong determinant of whether investors deviates from their recommendations or not. Further, it is also possible that this variable correlates with the investors financial knowledge as educated investors may prefer to interact with more educated advisors. Both Foerster et al. (2017) and Linnainmaa et al. (2016) found that advisor's own preferences drive their recommendations. Thus, a limitation in our data is that we miss information about the advisors' own investments. Another shortcoming of our dataset is that it only contains observations from one bank, which may cause client characteristics bias.

9. Conclusion

We examine the impact of financial advisors on individual's financial investment decisions and analyses why some clients deviate from their recommended investment that is based on the results from a standardized questionnaire. We are especially interested whether this is due to their advisor or not. Using a unique dataset from a well-known nation-wide Nordic bank and OLS-regression, we show that advisors' characteristics have little influence over their client's investment decisions. We present the following key findings. First, investors deviation in equity from recommendations based on their attributes are hard to explain. A weak explanatory power of about 4% in our regression model implies that deviations is neither due to individuals' attributes nor due to the advisors' characteristics we use in the model. Thus, there must be other omitted variables explaining why clients deviates from their recommendations. Second, the advisors tend to tailor their advice on asset allocation to their clients' attributes as our regressors explain a big part of the cross-sectional variation in equity percentage. The investors risk tolerance and investment horizon are the strongest predictors for risk taking, and the economically significance of these variables are higher in our model than the comparable model of Foerster et al. (2017). We confirm this result with a correlation matrix proving a strong positive linear relationship between percentage of equity and both investment horizon and risk profile. The strong significance of the two variables suggest that the bank emphasize these variables to a large extent and may therefore also illustrate the training of the bank's advisors. This is in line with the requirements that MiFID II outlines, and will from the bank's perspective imply a good finding. Advisor fixed effects, however, explain only additional 0.30 % of the variation in the regression, implying that financial advisors' characteristics included in our model have a trivial impact. This contradicts with the results from Foerster et al. (2017) that found advisor fixed effects to be of great importance. Nevertheless, an important reason for this difference is that we use fewer advisor fixed effects in our model. Also, this suggest that the results from the standardized questionnaire that the Nordic bank uses gives the advisors a framework they follow strictly when giving advice. Lastly, with further analyzes we find that some branches in the bank clearly have more deviations than others. The latter can be due to trends or different culture within branches, but our model cannot prove this.

A valid question is whether our data on clients and advisors is representative as all information comes from one bank only. Also, there might be country specific differences due to laws that advisors are constrained by. For this reason, further research should focus on the effect of financial advisors on individual investment decisions using information from another bank or several banks, with a wider dataset including for example skills and performance of the advisors.

Foerster et al. (2017) argue that there are probably other benefits by using financial advisors than investment advice. Clients of financial advisors are likely to receive advice on real estate and other areas in personal finance. Further research on financial advisors should also include these additional benefits of using advisors.

10. References

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11. Appendix

Appendix A

Appendix A: Variable descriptions

Variable	Definition
Dependent variables	
Deviation	Deviation between the equity percentage in the client's actual investment and the recommended equity percentage defined by the bank's questionnaire in absolut values.
% Equity	Choosen proportion of equity in investment, as percentage of whole investment.
Independent variables	
Client characteristics	
Gender	The client's gender (male/female; dummy-variable).
Age	Client's age (youth, young adults, adults and retired; categorical variables). Youth includes clients between the age of 16-24, young adults between the age of 25-44, adults between the age of 45-66 and retired between the age of 67-92.
Relationship status	The client's relationshipstatus (married/not married; dummy-variable).
Location	The clients location (whether the client lives in a small, medium or big municipality, based on the number of inhabitants; categorical variables). A small municipality has less than 30,000 inhabitants, a big municipality has over 126,000 inhabitants and a medium municipality has a number of inhabitants between these two.
Product key	The client's investmentaccount (discretionary account/not discretionary account; dummy-variable).
Investment horizon	Number of years the client aim to invest(Short/medium/long; categorical variables).
Risk tolerance	The client's tolerance for risk (low/medium/high; categorical variables).
Financial knowledge	Client's knowledge of financial markets (none, some, good; categorical variables).
Financial experience	Client's experience in financial markets (none, some, good; categorical variables).
Advisor characteristics	
Gender advisor	The advisors gender (male/female; dummy-variable).
Age advisor	Advisor´s age (youth, young adults and adults; categorical variables). Youth includes advisors between the age of 16-24, young adults between the age of 25-44, adults between the age of 45-66.
Clients advised	Number of clients managed per advisor.

The table defines the variables used in the empirical analysis.