Portfolio choice and financial advice*

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Abstract

This paper analyzes portfolio allocation decisions of individual investors. Our dataset records how individuals allocate their money among risky funds and a money-market fund, and also the characteristics of both the investors and the financial advisors who sell the products. These data offer a unique opportunity to investigate how portfolio decisions are affected by financial advisors. Our empirical strategy consists in studying the relationship between the share of the total capital invested in risky funds and the characteristics of buyers and sellers. Since the dependent variable is bounded between zero and one, we estimate a fractional response model. We find that the share invested in risky funds is larger when the advisor is more educated. Furthermore, male advisors sell larger shares of risky funds than female advisors. We offer possible explanations for these findings.

Key words: Portfolio choice; individual investors; impact of financial advisors.
Classification numbers: C24; D12; G11.

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1 Introduction

In most developed countries an increasing fraction of households participate in stock markets (Curcuru et al., 2009, and Guiso et al., 2003). One explanation for this trend is that publicly provided pension schemes are becoming less generous. People anticipate that their future incomes may be reduced and try to compensate for this loss by purchasing stocks. Another explanation is the growth of the mutual funds industry (Rydqvist, Spizman and Strebulaev, 2011) which simplifies the access to financial markets and lowers transaction costs.

The increased participation in stock markets comes with more responsibilities given to households who have to decide how to invest and diversify their wealth. Given the high risk premium earned by stockholders in the long term, the problem of allocating wealth between risky and safe assets is crucial for consumers' future standard of living. It is potentially also one of the most complex financial decisions they must make. The allocation problem requires, at least in theory, a deep knowledge about the functioning of financial markets. Investors must also confront themselves with the question of how much risk they are ready to take, which requires a good apprehension of their own risk tolerance in a complex stochastic environment.

Faced with such a difficult task, it is not surprising that people seek professional advice. They consult independent financial advisors or ask advice from counselors who work in banks or insurance retail branches. The demand for financial experts is widespread. Allen (2001) reports that more than 60 percent of individual investors in the U.S. rely on professional investment advice. In the Netherlands this figure is around 50 percent and in Germany around 80 percent (Kramer and Lensink, 2009). Financial experts also exert a potentially strong influence on households' investment decisions. Gerhardt and Hackethal (2009) report that 80 percent of clients of a German bank rely on advisors as their main source of information. According to a survey conducted by the Investment Company Institute (1997), around 15 percent of mutual fund shareholders who consult a professional financial advisor delegate all purchase decisions to the advisor; around 75 percent select a fund from among several recommended by the advisor. Given these facts it is important to apprehend the precise role played by financial advisors and the quality of their advice.

The empirical literature on the effect of financial advisors is nonetheless still small.[1] Most papers in this field have examined the influence of experts on the performance and composition

[1] As pointed out by Inderst (2009): "The academic literature, most notably the large literature on household finance, has almost completely ignored the role of the supply side. But for retail finance, this is crucial. Retail financial products are often 'not bought but sold': the initiative is taken by a broker or a client's relationship banker."

of investors' portfolios. Bergstresser et al. (2009) find that funds sold through brokers rather than through direct channels offer inferior returns, even before distribution fees. Hackethal et al. (2009) study investors' accounts from a major internet broker and show that, once the possible endogenous decision of the investor to ask professional advice is controlled for, accounts run by or with input from financial advisors offer on average lower returns and higher risk. Kramer and Lensink (2009) study equity investors of a Dutch bank, and also find that advisors negatively affect average portfolio returns. The portfolios of advised clients are, however, better diversified and have lower variability in returns. Gerhardt and Hackethal (2009) analyze a data set of detailed portfolio compositions and daily transactions of customers of a German direct bank. They report that advised customers hold less equities and trade more than non-advised customers. The portfolio returns of advised clients are, unlike the previous studies, slightly higher than those of non-advised clients.

There are also some papers on the individual determinants for seeking financial advice, and the influence of advice on the suitability of investors' portfolio allocations with their risk profiles. Bluethgen et al. (2008) use administrative data from a German retail bank and find that clients who seek professional advice are older, wealthier, more risk averse, and more likely to be female. Jansen et al. (2008) have survey data on the self-reported degree of risk aversion of customers (also of a German retail bank), and some advisor characteristics (gender, number of customers advised in past year, years of experience in securities advice). In addition they have comprehensive demographic information on the customers and their accounts. Regressing the equity share on the advisor-attributes (and customer demographics), they find that customers invest less in equities when they consult more experienced advisors. The advisor's gender and the number of clients advised do not, however, significantly affect the share of capital invested in equities. Jansen et al. furthermore report that advisors tend to incite customers to overinvest in equities relatively to what their risk profiles would call for. Berg et al. (2010) collect data from financial advisors and bank customers and investigate the decision process underlying portfolio choices. They show that most customers deliberately use a limited set of information.

Our paper contributes to this literature. Using a large administrative data set from a French financial company, we study how individual portfolio decisions are influenced by financial advisors. The data set records information about the investment accounts opened by individuals between January 2004 and December 2005 through the company's network of agencies. We observe the total amount of money invested by customers when they open an account, and how it is allocated among several risky funds and a money-market fund. By risky fund, we mean one of the eight "unit-linked" funds preselected by the company, and which are mostly composed of equities (see next section for more details about the funds). The money-market fund is composed of short-term debt and offers a close-to-riskless rate of return. We also observe information about the customers (their age and gender), and the financial advisors who sell the financial products (their age, sex, education, previous work experience, job tenure, family situation, parental status, and the region where the agency is located). Our empirical strategy consists in analyzing the relationship between the share of the total capital invested in risky funds and the characteristics of both customers and sellers. The share invested in risky funds is a good and simple measure of the riskiness of a portfolio allocation, and has frequently been taken as the dependent variable in the literature on individual portfolio behavior (see for instance Agnew et al., 2003, and Papke, 1998). Since the dependent variable is bounded between zero and one, we estimate a fractional response model proposed by Papke and Wooldridge (1996). In a first-best environment with well-informed and optimizing investors, asset allocation decisions should only depend on customer characteristics (their age, wealth, and variables that reflect attitudes towards risk). The characteristics of sellers such as their gender, age, or work experience, should not matter from the investor's point of view. As a result, such variables should not be statistically significant in our regressions. A significant impact of sellers' characteristics would instead reveal some frictions in the decision-making process that have to be elucidated.

Although the data set records many seller characteristics, the empirical analysis mainly focuses on the role of two variables: the advisor's education level and gender. Our results show that the level of education has a statistically significant and positive effect on the share of capital invested in equities: highly educated financial advisors sell more risky mutual funds to their clients than lowly educated advisors. This finding is interesting in light of an empirical literature documenting a strong relationship between participation rates in equity markets for the population at large, and their education level and financial literacy. Rooij et al. (2011) document that financial literacy is a strong predictor of stock market participation. Guiso et al. (2003) show that education has a positive and significant effect on equity ownership in a series of European countries, even after controlling for differences in age, income and wealth among investors. Campbell (2006) finds a similar result with data from the U.S. We find that the predictive power of financial literacy and education that is found for individual investors holds for financial advisors as well. A possible interpretation of this finding is that less educated sellers may be incompletely and imperfectly informed about financial markets. These advisors may feel less at ease with relatively complicated financial products such as stocks or fixed-income securities, and therefore less inclined to recommend risky funds to their clients.

The seller's gender has also a significant effect: male advisors sell more risky portfolio allocations than female advisors. Our interpretation of this finding is that clients are influenced by the degree of risk aversion of sellers. The reasoning is as follows. It is a well-established fact from the literature that risk attitudes vary with the gender of individuals. A meta-analysis of 150 studies conducted by Byrnes, Miller, and Schafer (1999) reports that women are consistently more risk-averse in all sorts of contexts. Differences in risk tolerance across sex are particularly visible in financial choices. Sunden and Surette (1998) and Agnew, Balduzzi and Sunden (2003) find that household holdings of risky assets are significantly lower for women in retirement savings plans. Jianakoplos and Bernasek (1998) find a similar result based on a U.S. Survey of Consumer Finance. Barber and Odean (2001) exploit account data from a large discount brokerage and document that women hold on average less risky positions than men within their common stock portfolios. This relationship extends to financial professionals. Empirical studies show that female fund managers take less risk than male managers in their mutual fund investment decisions (Dwyer, Gilkenson, and List, 2002). This result is corroborated by Niessen and Ruenzi (2005) who also show that female fund managers follow less extreme investment styles. So there is support for the idea that female advisors are more risk-averse. In addition to this, the advice given by financial consultants may in part reflect their own risk preferences. Although advisors are trained to adapt their recommendations to objective information like customers' investment horizons or saving goals, they may not always be able to figure out the precise risk tolerance of their clients. It may therefore be difficult or impossible for them to give advice that perfectly suits the preferences and needs of customers. They may instead base their portfolio recommendations on their own risk profiles, explaining why, in our data, investors advised by female sellers hold less risky mutual funds in their portfolio than those advised by male sellers.[2]

These interpretations of our results may be incorrect if there are unobserved characteristics (of buyers or sellers) that determine the risky share of an investor, and are correlated with the regressors in the model (seller's education and gender in particular). In this case the estimated effects of seller's education and gender would partly pick up the impacts of the unobserved variables. This omitted-variables bias is potentially a problem in our study. Although we observe many advisors' characteristics (and hence unobserved seller variables will arguably play a minor role) little is known about the investors. In particular we do not know their education level, risk

[2]This kind of bias is not specific to the relationship between a financial marketing agent and an individual investor who seeks portfolio recommendations. It may occur whenever a 'decision-maker' who bears the consequences of a risky decision, consults an 'expert' who better apprehends the nature of the risk. We can think of a doctor who counsels a patient about several alternative medications, or a lawyer who instructs a client about the risks of pleading guilty or innocent. In these examples, the knowledgeable side may disregard the risk bearer's preferences, and formulate recommendations based on her own risk preferences.

profile, and wealth. These variables are known to be strong determinants of stock holdings.[3] It is possible that these variables are related to the seller's education and gender. For instance, wealthy or risk-loving investors may prefer to negotiate with male advisors. Our result regarding the seller's gender may then simply reflect that these categories of clients inherently invest more in equities, and not that male advisors sell riskier portfolios. Similarly, if more educated buyers prefer to interact with more educated sellers, our estimated effect of seller's education merely picks up this non-random matching of buyers and sellers. Since endogenous matching of clients and advisors can be an important issue, we also present results of the model including seller-specific effects. These individual effects are identified because most of the advisors in our data are observed more than once (on average they sign contracts with about twenty clients). The inclusion of seller-specific effects allows to control for endogenous matching. It turns out that the estimation of the extended model does not alter our main findings.

The paper is organized as follows. The next section describes the data, Section 3 presents the estimation methods and empirical results, and Section 4 concludes.

2 Data

Our data come from a large French financial company operating in the markets of insurance, personal protection, savings, retirement and financial planning. The company offers a large variety of financial products to French households. In this paper we study the main life insurance product marketed by the company in France (in the mid-2000s). Although the product analyzed by us is called a life insurance product (literal translation from French), it has actually little resemblance to the typical life insurance product sold in for instance the U.K. or in the U.S. Instead, the product is akin to a standard investment or saving vehicle in which savers are offered a menu of mutual funds. The main advantage of French life insurance products compared to other saving vehicles in France lies in their favorable tax regime. Taxes on accrued gains are nearly zero after eight years of holding, and subscribers may freely bequeath the capital with total exemption of inheritance tax up to a ceiling. Life insurance products are consequently very popular among French savers. They are held by around 13 million people. More than one third of aggregate financial wealth is invested in these contracts (Couleaud and Delamarre, 2009).

When investors purchase the product we are studying, they first have to decide how much money they wish to invest, and then how to allocate the total amount into different types of

[3] In the model we include, however, the average amount of money invested by other clients as a proxy for the wealth of an investor.

funds. Investors must split the total invested amount between a money-market fund, or euro-based fund (*fonds euro* in French), and eight preselected unit-linked funds (*fonds en unité de compte*), which are mostly equity funds. The capital invested in the euro-based fund is very close to being riskless as the return on investment is linked to the rate of return of the money market with a minimum return guaranteed by the company. The first line of Table 1 (given in the Appendix) shows the nominal rate of return of the euro-based fund proposed to investors between 2003 and 2009. During these years the nominal rate varied between 3.5% and 5%, with an average (calculated over the seven years) equal to 4.33 and standard deviation equal to 0.47.

Investors may also invest in eight unit-linked funds in which the amounts of benefits and premiums are not expressed in euros but in units of an investment vehicle, such as shares of a mutual fund or a real estate partnership. They make up the risky share of the product as benefits fluctuate directly with the market values of these units or shares. The eight funds mainly differ according to the level of risk and the geographical location of the firms in which the fund invests. The last eight lines of Table 1 show the nominal rate of return of the unit-linked funds between 2003 and 2009. For each unit-linked fund the standard deviation of the rate of return is considerably higher compared to the standard deviation of the euro-based fund rate. This illustrates the high level of risk taken by investors when they invest in unit-linked funds rather than in the euro-based fund.

After the initial purchase date of the contract, investors may at any time invest supplementary amounts of money. These subsequent investments may again be made in both the euro-based and the unit-linked funds. The accumulated capital (invested sums of money plus the returns to investments) can be partly or completely withdrawn at any time.

The company markets the life insurance product through different channels. In our database we observe the contracts that were purchased by clients through the company's network of agencies. The agencies are located throughout France. Each agency is directed by one or several agents (*agents généraux)*. These agents are not directly employed by the company. Instead, they act as independent managers who are mandated to sell the company's whole range of insurance and financial products. They earn commissions from the sale of company's products. Commissions vary with the type of product and premium size. In the case of life insurance products, they keep a fraction of the front loads, which are fees proportional to savers' payments, and level loads that are charged as a percentage of the total amount invested each year. Some of the managers are assisted by a few employees. The managers are, however, in principle the ones who counsel and negotiate with the clients visiting the agency. They provide them with information about the product, and give portfolio allocation advice.

Our database is a contract-based data set. It records all contracts signed between January 2004 and December 2005. We exclude from the initial sample the contracts concluded in agencies that are directed by more than one manager. Although we know in these cases the characteristics of each manager, we cannot tell which manager contracted with a given client. Also excluded from the initial sample are the contracts with missing observations on characteristics of clients or managers. The final sample consists of 24,375 contracts. These contracts were sold in 1,215 different agencies (and hence by 1,215 different managers). For each contract, the data set records the characteristics of the client, the characteristics of the manager who sold the contract, the district where the agency is located (France is made up of 98 administrative districts), the date at which the contract was sold, and the contract parameters.

Table 2 shows summary statistics on the characteristics of the clients and managers. For both clients and managers we observe their age and gender. For managers we observe some additional characteristics: their education, job-tenure, work experience before their current job, their family situation, and whether the managers have children that are still financially dependent on them. All characteristics are measured at the date of contract signature.

Table 2: Statistics on characteristics of clients and managers

Variable	Mean	Std. Dev.	Min	Max
Age client	49.0	15.0	18	101
Gender client (1=male)	0.52	0.50	0	1
Age manager	44.72	8.28	25	71
Gender manager (1=male)	0.93	0.25	0	1
Education manager:				
Autodidact	0.0093	0.096	0	1
Low level vocational training	0.05	0.23	0	1
General certificate of secondary education	0.05	0.22	0	1
High school diploma	0.22	0.42	0	1
Two years of higher education	0.33	0.47	0	1
Between two and four years of higher education	0.14	0.35	0	1
Four years of higher education and more	0.20	0.40	0	1
Job tenure manager	8.48	7.32	0	42
Work experience manager before current job:				
Experience in insurance	0.56	0.50	0	1
Experience in sales	0.79	0.41	0	1
Experience in administration	0.76	0.43	0	1
Family situation manager:				
Single	0.13	0.34	0	1
Married	0.73	0.45	0	1
Separated, divorced, or widow(er)	0.04	0.21	0	1
Cohabitant or engaged	0.10	0.30	0	1
Manager has financially dependent child(ren)	0.75	0.43	0	1

Clients are on average 49 years old, and about half of them are men (52%). Managers are on average younger (just under 45) and they are primarily male (93%). There is much variation in the education level of managers. A few of them (almost 1%) declared they had not followed any formal education at all beyond primary school (autodidact). 5% just had a basic vocational training (comparable to the level-1 National Vocational Qualification in the U.K. system), and 5% only earned a general certificate of secondary education (the first diploma pupils can obtain after 4 years of high school). 22% of managers declared to have a high school diploma. The remaining managers studied beyond high school: 33% had two years of higher education, 14% between two and four years of higher education, and 20% more than four years of higher education. On average the tenure of the current job was almost 8.5 years. 56% of the managers stated they had previous work experience in insurance, sales (79%), and administration (76%). The large majority of managers were married (73%), but there were also singles (13%), managers who were separated, divorced or widow(er)s (4%), and managers who were engaged or cohabited with someone else (10%).

Fig. 1 shows how many products the 1,215 managers in our sample sold per month. In most months managers succeeded in selling between 900 and 1400 new policies. In June, August and November 2004, and in May and August 2005, they were less successful as they sold between 300 and 700 new contracts.

Insert Fig. 1 around here

The average number of contracts sold per manager during the observation period (i.e., between January 2004 and December 2005) is 24,375/1,215=20.06 contracts. The minimum number of policies sold is 1 (recall that our data set is contract-based, so each manager included in the data has necessarily sold at least one contract during the observation period), and the maximum number is 175. Figure 2 plots the number of contracts sold (in intervals) against the sample frequency.

Insert Fig. 2 around here

276 agents have thus sold between 1 and 5 contracts, 215 agents between 6 and 10 contracts, etc... The figure indicates that there is much heterogeneity in the sales figures. This heterogeneity may stem from geographical variations in the demand for life insurance products (recall that agencies are located all over France), or from variations in the sales capacities of the different managers in our sample.

The contract parameters we observe are the total capital invested at the enrollment date, and the allocation of this amount among the money-market fund and the unit-linked funds. We do not observe how much money is invested in each of the eight unit-linked funds separately, but just the total amount invested in the unit-linked funds.[4] We do not observe either possible investments made after the opening of the life insurance account. The decisions made at the opening date are, however, the most interesting ones for the purpose of this study since we are sure that at this moment the client and manager actually met each other. In contrast, later investment decisions can be made via Internet or mail, i.e., without any interaction between the client and manager. Table 4 gives summary statistics on the total capital invested per contract, and the corresponding amounts invested in the money-market fund and unit-linked funds.

[4] As an example, one client in the sample invested a total capital equal to 15,000 €, of which 6,000 € was invested in the euro-based fund, and 9,000 € in the unit-linked funds.

Table 4: Statistics on invested capital per contract

Variable	Mean	Std. Dev.	Min	Max
Total capital	9,430	30,282	120	900,000
Capital in money-market fund	7,842	27,321	0	900,000
Capital in unit-linked funds	1,588	9,335	0	612,245

On average the total capital invested per client equals 9,430 €. The smallest total amount invested by a client equals 120 € and the largest 900,000 €. The average amount invested per client in the money-market fund (resp. unit-linked funds) equals 7,842 € (resp. 1,588 €). The average client clearly invested much more in the riskless assets than in the risky ones.[5] This is confirmed by the summary statistics on the share of the total capital invested in the unit-linked funds, reported in Table 5 (line indicating full sample).

Table 5: Statistics on fraction invested in unit-linked funds

	Mean	Std. Dev.	Min	p50	p75	p90	p95	p99	Max
Full sample	0.194	0.285	0	0	0.3	0.6	1	1	1
Lowly educated Manager	0.184	0.274	0	0	0.3	0.5	0.8	1	1
Highly educated manager	0.200	0.290	0	0	0.3	0.6	1	1	1
Client female × manager female	0.151	0.247	0	0	0.21	0.5	0.6	1	1
Client female × manager male	0.174	0.268	0	0	0.3	0.5	0.8	1	1
Client male × manager female	0.174	0.270	0	0	0.3	0.5	0.7	1	1
Client male × manager male	0.218	0.301	0	0	0.4	0.7	1	1	1

Clients invested on average 19% of the total capital in risky funds at the opening of their investment account. Since the 50th percentile is zero, more than 50% of the clients did not invest at all in the unit-linked funds (more precisely, 58% did not). At the other extreme, more than 5% of the clients invested all their capital in these funds.[6] Figure 3 plots the share of the total capital invested in the unit-linked funds against the sample frequency. It shows that the distribution of the fraction invested in the unit-linked funds has a lot of mass not only at the extreme values 0 and 1 (as indicated already in Table 5), but also at the points 0.1, 0.2, 0.3, ..., 0.9. Roughly 95% of the observations take the discrete values 0, 0.1, 0.2, ..., 0.9, 1, and the

[5]In a regression of the fraction invested in unit-linked funds on the total capital invested, the coefficient on total capital is positive and statistically significant. Since total money invested can be seen as a proxy for the wealth of clients, this estimation suggests that richer investors choose riskier portfolio allocations.

[6]This concentration of observations at the extreme values zero and one is also observed in Agnew et al. (2003).

remaining 5% are continuously distributed between 0 and 1. The estimation method presented in the next section acknowledges this feature of the data.

Insert Fig. 3 around here

As explained in the introduction, we primarily focus on the role played by manager gender and manager education. We wish to allow for the possibility that manager gender has different effects on the risky share according to whether the client is male or female. In the empirical analysis we therefore interact the indicator of manager gender with the indicator of client gender. We also slightly redefine the education variable. Instead of distinguishing the initial seven education levels, we define a new binary education variable that indicates whether a manager is highly educated (if the initial education variable falls in one of the three highest categories) or lowly educated (if it falls in one of the four lowest categories).

Table 5 reports summary statistics on the share invested in risky funds by education level, and by gender-client/gender-manager combination. On average, lowly educated managers sell a share of 0.184, whereas highly educated managers sell 0.200. The hypothesis that the share has the same mean within the two subgroups is rejected at the 1% level. When both the client and manager are female, the lowest share in risky funds is generated (the average share in this case is 0.151), and the highest share is generated when both are male (0.218). The two other combinations, i.e., when client and manager are not of the same gender, generate intermediate levels (both means equal 0.174). We can again reject at the 1% level the hypothesis of equal means within each possible pair of subgroups (except when we contrast the combinations client female $\times$ manager male and client male $\times$ manager female). This means in particular that female managers sell significantly lower risky shares than male managers, regardless of the client's gender. Since the difference in means between the first two interaction variables is smaller than for the last two, the impact of manager gender is stronger for male clients than for female clients.

Before turning to the next section, we wish to comment on the advantages and drawbacks of our data. A clear advantage is that the data are administrative. Compared to data sets where information on investment decisions come from surveys, our data are probably less subject to measurement errors. Another, and for this paper crucial, advantage of our data is that they include information about the characteristics of the financial advisors who advised the clients in their portfolio decisions. Compared to the database used by Jansen et al. (2008) (the only other paper we are aware of that has information on advisor characteristics), we have more detailed information on sellers. There are also some important disadvantages. One is that we know relatively little about the clients. Another drawback is that we do not have information about the subsequent returns on the assets chosen by the customers at the opening of their accounts (as in some of the studies cited in the introduction). Because of this, we cannot for instance study whether clients who were advised by a female seller had lower or higher returns on their (more prudent) investments. Yet another drawback is that we do not know anything about the trading activities of the investors following the opening of their accounts. Therefore we cannot assess the effect of managers' characteristics on later portfolio reshuffling. Finally, we have no access to other investment or saving accounts that clients possibly hold.

3 Methods and results

In this section we first present the econometric model that we use to estimate the link between the share invested in risky funds on the one hand and the characteristics of clients and sellers on the other hand. Then we present and discuss the main empirical results. Finally we present some additional estimations to check for the robustness of our conclusions.

3.1 Econometric model

Our dependent variable is the share of the total capital invested in the unit-linked funds. Let s_{ijt} be the random variable representing the share purchased by client i in period t, when this client negotiated and contracted with manager j. This variable is a fraction and is therefore necessarily between 0 and 1. If it is relatively small (resp. large) the client's choice is relatively riskless (resp. risky). From Figure 2 we know that the dependent variable is partly discrete and partly continuous. To account for this discrete/continuous nature of s_{ijt}, one possibility would be to estimate the doubly-censored model used by Agnew et al. (2003). However this model would not be fully appropriate in our case as it implicitly assumes that the dependent variable is continuously distributed between the two censoring points (zero and one). This is clearly not the case in our data since the distribution of s_{ijt} also has a lot of mass at the deciles 0.1, 0.2, ..., 0.9. Another possibility is to define the distribution of s_{ijt} as a mixture of a discrete and a continuous distribution and then estimate the parameters of the model by maximum likelihood. The drawback of this approach is first that the resulting likelihood is rather complicated, and second that the results are likely to be very sensitive to distributional assumptions.

A simpler method to take into account the features of our dependent variable is to use the estimation method proposed by Papke and Wooldridge (1996). The method does not require that the distribution of the dependent variable is fully specified. It is only necessary to correctly specify the mean conditionally on the explanatory variables. The unknown parameters in the conditional mean are estimated by maximizing a quasi-likelihood function. To be more precise, let x_{ijt} be the vector of explanatory variables, and assume that the share invested in the unit-linked funds can be written as $s_{ijt} = G(x_{ijt}\beta)\epsilon_{ijt}$, where β is a vector of parameters of interest, $G(\cdot)$ a cumulative distribution function, and ϵ_{ijt} an error term capturing all characteristics of clients and managers not included in the vector of explanatory variables. We assume in addition that the error term is independent of the explanatory variables and has mean one, i.e., $E(\epsilon_{ijt}|x_{ijt}) = 1$. This implies that the conditional mean of s_{ijt} conditional on x_{ijt} is

$$E(s_{ijt}|x_{ijt}) = G(x_{ijt}\beta). \tag{1}$$

The assumption that $G(\cdot)$ is a distribution function guarantees that the predicted values of s_{ijt} are between 0 and 1 for all values of the explanatory variables and parameters. The dependent variable s_{ijt} may be continuous, discrete, or mixed continuous/discrete (as in our specific case).

Papke and Wooldridge propose to estimate the parameter vector β by maximizing a Bernoulli log-likelihood function. The contribution of an observation to the log-likelihood is

$$l_{ijt}(b) = s_{ijt} log[G(x_{ijt}b)] + (1 - s_{ijt}) log[1 - G(x_{ijt}b)]. \tag{2}$$

The quasi-maximum likelihood estimator of β is defined as the maximum of the quasi-likelihood function:

$$\max_b L(b) = \max_b \sum_{ijt} l_{ijt}(b).$$

The estimator converges to the true parameter vector β if the conditional mean of s_{ijt} is correctly specified, i.e., if it is indeed given by (1). A powerful result is that since (2) belongs to the family of linear exponential functions, the consistency result holds even if the true likelihood function of the data does not coincide with the quasi-likelihood $L(b)$ (this follows from the general theory on pseudo-maximum likelihood methods developed by Gouriéroux et al., 1984). Another advantage of the approach is that it is not necessary to specify the conditional variance of s_{ijt} given x_{ijt} (as one should if the parameters in (1) are estimated by non-linear least squares).

The asymptotic variance-covariance matrix of the estimator can be estimated by (see Papke and Wooldridge, 1996):

$$\hat{A}^{-1}\hat{B}\hat{A}^{-1}$$

where

$$\hat{A} = \sum_{ijt} \frac{\hat{g}_{ijt}^2 x'_{ijt} x_{ijt}}{[\hat{G}_{ijt}(1-\hat{G}_{ijt})]},$$

$$\hat{B} = \sum_{ijt} \frac{\hat{u}_{ijt}^2 \hat{g}_{ijt}^2 x'_{ijt} x_{ijt}}{[\hat{G}_{ijt}(1-\hat{G}_{ijt})]^2}$$

and $g(z) = dG(z)/dz$, $\hat{G}_{ijt} = G(x_{ijt}\hat{\beta})$, $\hat{\beta}$ is the quasi-maximum likelihood estimator, $\hat{g}_{ijt} = g(x_{ijt}\hat{\beta})$, and $\hat{u}_{ijt} = s_{ijt} - G(x_{ijt}\hat{\beta})$ is the residual (difference between observed share and estimated conditional expectation).

3.2 Empirical results

Table 6 gives the quasi-maximum likelihood estimation results of the parameter vector β appearing in the mean (1) for the case where $G(\cdot)$ is the logistic cumulative distribution function, i.e., $G(z) = exp(z)/[1 + exp(z)]$. We report the results for several specifications of the vector of explanatory variables x_{ijt}. Column 1 presents the results for the simplest specification: the vector contains only a constant, the age of client i, and our four primary variables of interest: the three interactions between the gender of client i and gender of manager j (we omit the category client-female $\times$ manager-female as the reference variable) and the dummy indicating whether manager j is highly educated or not.

As column 1 indicates, the client's age is strongly significant and has a negative sign: older clients appear to invest less in risky assets than younger clients. This is in line with the results obtained in the literature on individual portfolio choices in large U.S. pension plans (see for example Papke, 1998, and Agnew et al. 2003). Since the variable client-female $\times$ manager-male has a positive and significant effect, female clients invest more in risky assets when they contract with male sellers than with female sellers. Similarly, since client-male $\times$ manager-male has a larger effect than client-male $\times$ manager-female and the two variables are significantly different from each other (at the 1% level), male clients choose riskier asset portfolios when they contract with male sellers than with female sellers. In line with our earlier results (see Table 3), we thus find that male managers sell more risky portfolio allocations than female managers, and, since 0.424-0.152=0.272>0.171, this influence of manager gender is more substantial for male clients than for female clients. However, unlike our earlier findings, we cannot reject the null hypothesis that this difference equals zero (the test-statistic of the Wald test equals 1.119, while the 5% critical value of the chi-square distribution with one degree of freedom is 3.84).[7] The education

[7]It is a well-known result from the literature that men invest more in stocks than women (See for instance

dummy is positive and significantly different from zero, indicating that highly educated managers sell more risky funds than lowly educated managers. This is also in line with the results reported in Table 5.

Table 6: QML estimation of model (1) (G is the logistic cdf)

	(1)	(2)	(3)	(4)
Constant	-1.076^{***} (0.079)	-1.281^{***} (0.118)	-1.837^{***} (0.133)	-2.217^{***} (0.269)
Age client	-1.465^{***} (0.076)	-1.506^{***} (0.077)	-1.467^{***} (0.077)	-1.494^{***} (0.079)
Client female × manager male	0.171^{**} (0.069)	0.180^{**} (0.070)	0.152^{**} (0.070)	0.146^{**} (0.074)
Client male × manager female	0.152 (0.093)	0.145 (0.092)	0.141 (0.092)	0.136 (0.093)
Client male × manager male	0.424^{***} (0.069)	0.435^{***} (0.070)	0.416^{***} (0.070)	0.406^{***} (0.073)
Highly educated manager	0.096^{***} (0.025)	0.072^{***} (0.026)	0.067^{**} (0.026)	0.056^{*} (0.030)
R^2	0.331	0.335	0.358	0.393
Other controls	No	Yes	Yes	Yes
Month dummies	No	No	Yes	Yes
District dummies	No	No	No	Yes

Notes: Asymptotic standard errors in parentheses. $***$: significant at 1% level; $**$: significant at 5% level: $*$: significant at 10% level. The variable "client-female × manager-female" is the reference variable. "Age client" is in years divided by 100. R^2 is defined in the main text. "Other controls" include all other manager characteristics, and the average total invested capital (calculated over all clients of manager j except the i-th). "Month dummies" include twenty three month-indicators (January 2004 is the reference month), and "district dummies" ninety five district indicators (there are ninety eight districts in France; district 75, Paris, is the reference district, districts 96 and 97 are omitted because no agencies are located in them).

In the specification of column 2 the other manager characteristics listed in Table 6 are included in the vector x_{ijt} as well. We also include the average total invested capital, where the average is calculated over all clients of manager j (during the observation period, i.e., between January 2004 and December 2005) except the i-th. This variable is intended to capture the wealth of client i. The implicit assumption made here is therefore that other clients contracting with manager j make similar investments as client i, and total capital invested is a good proxy for a person's

Agnew et al. 2003). Column 1 implies, however, that this well documented gender effect only holds when the seller is male (men purchase significantly more risky funds than women when they deal with a male seller, but purchase similar stock levels when they deal with a female seller).

wealth.[8] For ease of exposition we do not report the estimated coefficients associated with these variables (the table just indicates that the specification corresponding to column 2 includes the additional controls). As column 2 shows, the results regarding our four primary variables of interest remain unchanged. All conclusions that were drawn on the basis of the first column remain exactly the same.

The specification of column 3 adds twenty three month indicators (the observation period has twenty four months from which we omit the reference month January 2004). Focussing on our primary variables of interest, we see that the results remain unchanged except that the dummy for higher education is no longer significant at the 1% level, but at the 5% level only (p-value is 0.011). Finally, the specification of column 4 adds ninety five district indicators (France is made up of ninety eight administrative districts from which we have omitted the reference district 75, the city of Paris, and the districts 96 and 97, in which there are no agencies). The results regarding our main variables remain again unchanged except that the dummy for higher education is now significant at the 10% only (p-value is 0.06). Table 6 also contains an R^2 for each specification. The measure of goodness-of-fit we use is the one proposed by Papke and Wooldridge (1996), and is defined as $R^2 = 1 - \sum_{ijt} \hat{u}_{ijt}^2 / \sum_{ijt} s_{ijt}^2$. As the table shows, the R^2 augments from 0.331 (column 1) to 0.393 (column 4).

To summarize, we find that, even after controlling for a large set of variables (client's age, a proxy for clients' wealth, seller characteristics, time and district dummies), the gender of the seller matters in portfolio choices of individual investors: for both male and female clients, the risky share is higher when the manager is male. Furthermore, more educated managers sell higher shares of risky funds than less educated managers. In the next subsection we present some additional estimations to check for the robustness of these conclusions.

3.3 Robustness checks

The estimates reported in the previous subsection may be misleading if managers do not contract with all the clients that come to their agencies. It may be that some managers primarily contract with the "big" clients (i.e., those investing large amounts of money at the enrollment date), and let their assistants deal with the "small" clients. If this is indeed the case, the manager characteristics included in the model may be measured with error (in the subsample of small contracts), implying

[8] We omitted the i-th observation in calculating the average to avoid possible endogeneity problems (total capital invested by i may be explained by the same unobserved client characteristics as the risky share). For the observations corresponding to the 66 managers who sold just one contract we cannot, however, do this trick and had to define the average simply as the total capital invested by i.

that the estimates reported so far are biased and have no causal interpretation. To check for this possibility, we have re-estimated model (1) on different subsamples, first excluding all contracts for which the total invested capital is smaller than 1,000 €, then all contracts smaller than 2,000 €, then all contracts smaller than 3,000 €, ..., until all contracts smaller than 30,000 € (which amounts to eliminating 91% of the initial sample).[9] As more and more observations are dropped, the coefficients on the three interaction variables tend to increase slightly. The first and third interaction variable remain significant for practically all subsamples (as in column 1 of Table 6). The second interaction variable becomes significant once we reach the selection threshold of 7,000 € (and remains significant for all other subsequent subsamples). The coefficient on the education variable stays relatively constant. It remains significant (as in column 1) until the threshold of 5,000 € is reached, and is insignificant for practically all subsequent subsamples. The results of the previous subsection thus appear relatively robust to dropping the contracts purchased by small investors.

The estimates reported in the previous subsection may also be misleading if there are unobserved characteristics of advisors and clients (captured by ϵ_{ijt}) that are determinants of risky shares and correlated with the observed explanatory variables x_{ijt}. Since our data set reveals little information about clients, it is possible that there are unobserved and important client characteristics that are correlated with observed regressors. If these unobserved client characteristics are related to observed advisor variables then we have a problem of endogenous matching of managers and clients. It could for example be the case that female sellers attract less rich buyers.[10] Since client wealth is an unobserved variable[11] that affects portfolio decisions of households (richer people invest more in risky funds, see for example Agnew et al., 2003), this may generate a problem of endogenous matching. As a consequence, the coefficients associated with our three gender-interaction terms would partly pick up the fact that female managers deal with clients that are inherently less interested in risky funds. A bias resulting from endogenous matching may similarly arise when less educated sellers attract less educated investors. Endogenous matching is potentially a problem as financial advisors have various easily detectable traits that may be important for clients in choosing their appropriate agency. In addition, the first and last name of

[9]Since these subsequent selections drastically reduce the sample size, we have estimated the specification with the fewest parameters, i.e., the one corresponding to column 1 in Table 6.

[10]This may happen if female sellers were stereotyped as being less skilled by wealthy investors. Using a dataset from a mutual fund, Niessen and Ruenzi (2005) document that female fund managers generate significantly lower inflows in their managed funds. Niessen and Ruenzi hypothesize that investors may consider women as less able to manage money.

[11]As discussed above, a proxy for the wealth of clients is included in our vector of regressors.

the manager is written on the facade of each agency, and clients who wish to open an investment account know in advance the gender of the person who runs a particular agency. If gender is an important issue for clients, they can therefore easily use this criterion to select their agency.

If endogenous matching is indeed an issue we expect that not only the unobservable client characteristics but also the observable ones are correlated with the observed manager variables. To check this we present in Table 7 regressions of three manager characteristics (gender, age, and education) on various client characteristics : age, gender, the total capital invested, age crossed with gender, and total invested capital crossed with gender. What emerges from these regressions is that only few variables of clients and managers appear to be correlated. In the model where manager gender is the dependent variable, no client variable has a statistically significant effect. In the model with manager age as the dependent variable, only client's age has a significant effect. Its coefficient is positive indicating that older clients tend to match with older managers. Finally, in the model with manager education as the left hand side variable, only total capital invested by the client has a significant impact. The coefficient is positive implying that clients who bring in more capital tend to negotiate with more highly educated managers. So overall these results do not give the impression that endogenous matching is overwhelmingly present.

Table 7: Correlation between characteristics of clients and managers

	Gender manager	Age manager	Education manager
Constant	0.936*** (0.008)	43.053*** (0.261)	4.062*** (0.044)
Client male	0.007 (0.011)	−0.146 (0.366)	0.074 (0.061)
Age client	−0.013 (0.016)	3.641*** (0.508)	−0.029 (0.085)
Client male × age client	−0.011 (0.022)	−0.297 (0.726)	−0.120 (0.122)
Total investment	−0.005 (0.079)	1.133 (2.575)	1.570*** (0.432)
Client male × total investment	0.060 (0.110)	4.506 (3.583)	−0.497 (0.602)
R^2	0.0002	0.0049	0.0009

Notes: Asymptotic standard errors in parentheses. $***$: significant at 1% level; $**$: significant at 5% level: $*$: significant at 10% level. The variable "Age client" is in years divided by 100. "Total investment" is total capital invested in euros divided by 10^6. "Gender manager" equal 1 if the manager is male and 0 otherwise. "Age manager" is in years. "Education manager" takes seven values (see text). The R^2 is the usual one defined in OLS regression.

The fact that the observable characteristics of both types of agents are not correlated does not exclude the possibility that unobserved clients variables are linked to manager variables. To address the unobserved-variables problem (and the problem of endogenous matching in particular) one would ideally specify the expectation of ϵ_{ijt} given x_{ijt} as a function of a client specific effect, a manager-specific effect, and a client/manager-specific effect. Since each client is only observed once in our data set (i.e., we do not observe multiple investment decisions for a given client), we cannot identify the client-specific and client/manager-specific terms (identification of the latter requires in addition that clients contract with different managers). Since managers have typically transacted with different clients the managers-specific terms are, however, identified. Formally, we specify $E(\epsilon_{ijt}|x_{ijt}) = \delta_j$. Note that this specification does not exclude the possibility that there are unobserved client variables in the error term ϵ_{ijt}. It only assumes that the conditional expectation of these unobserved variables does not vary with client i (but only with manager j). The conditional mean (1) becomes $E(s_{ijt}|x_{ijt}) = G(x_{ijt}\beta)\delta_j$. We can redefine $G(x_{ijt}\beta)\delta_j = G(x_{ijt}\beta + \mu_j)$, where μ_j can be seen as the seller-specific fixed effect. Once the fixed effects are included, we can no longer identify manager variables that remain fixed during the observation period (such as the education variable). One additional gender-interaction dummy is also no longer identifiable (we omitted the dummy "client female × manager male"). To estimate the extended model including the fixed effects, we have to drop the observations corresponding to managers who sold just one contract, and the observations corresponding to managers j for whom either $s_{ijt} = 0$ or $s_{ijt} = 1$, for all i and t (by inspecting the log-likelihood (2) it is easy to see that for such managers the individual effects are not identified). Estimation of the extended model consists in maximizing the quasi-likelihood function with respect to approximately thousand parameters (coefficients associated with the identified variables plus a fixed effect μ_j for each seller j).

The fixed-effects estimates of the primary coefficients of interest together with their standard errors are: -1.664 (0.085) ("age client"), 0.136 (0.094) ("client male × manager female"), and 0.266 (0.024) ("client male × manager male"). For comparison, we have also re-estimated model (1) without fixed effects using exactly the same reduced sample as in the fixed-effects estimation. The specification is the one corresponding to column 4. The estimates of the three coefficients and the corresponding standard errors are now: -1.490 (0.079), 0.135 (0.092), and 0.390 (0.074). The two models produce comparable results: the coefficients are of similar magnitude and the variables that are significant in the model without fixed effects remain so in the model with fixed effects. Furthermore, both models allow us to reject (at the 1% level) the hypothesis that the two interaction dummies are equal (implying that male clients purchase a larger fraction of risky funds when they negotiate with male sellers than with female sellers). The results with fixed effects are thus comparable to those of the previous subsection, so endogenous matching does not appear to play a very important role in our data.

4 Conclusion

This paper studies the impact of financial advisors on investment decisions. We use administrative data from a financial company on portfolio allocation decisions, and the characteristics of both investors and advisors who sold the contracts. A central message is that advisors' characteristics play an important role in portfolio choices of individual investors. We find that advisors with high levels of education sell riskier portfolio allocations (portfolios with larger shares of risky mutual funds) than advisors with low levels of education. The latter are possibly less informed about the precise functioning of stock markets, and may as a result recommend portfolios with less risky funds to their clients. Our second main finding is that female advisors sell less risky funds than male advisors. Our interpretation is that individual investors are affected by the degree of risk aversion of sellers.

A more general interpretation of our results is that investors do not have firm preferences over how much to invest in risky assets due to the high complexity of the decision problem. As a consequence, they are prone to follow outside advice and to be influenced by financial experts in a way that may reflect their preferences but also advisers' characteristics. As such, our results echo previous studies which show that personal portfolio decisions are influenced by peers such as co-workers (Duflo and Saez, 2002), neighbors (Hong, Kubik, and Stein, 2004) or spouses (Lyons, Neelakantan, and Scherpf, 2008), even though no attempt is made in these articles to relate peers' characteristics to investment decisions.

The content of our article is mainly positive. We point out that savers' decisions are affected by the profiles of financial experts from whom they seek advice. Our results do not allow us to judge whether advisors have a detrimental influence on savers' choices or not. It may be that experts' recommendations lead to portfolio decisions that somehow better reflect underlying preferences of customers (one paper cited in the introduction finds, however, the contrary). Financial advice may also augment portfolio returns (but again this seems contradicted by the small literature discussed in the introduction). Investors' behavioral biases such as overtrading or underinvestment may also be attenuated by professionals. More empirical work should be devoted in the future to these fundamental issues.

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APPENDIX

Table 1: Nominal rate of return (in percent) of the euro-based fund and unit-linked funds

	2003	2004	2005	2006	2007	2008	2009	Mean	S.D.	Skewness
Euro-based fund	5	4.65	4.41	4.35	4.35	4.05	3.5	4.33	0.47	0.58
European equity fund	20.71	38.07	27.19	51.91	-19.15	-44.35	37.62	16.00	34.81	-1.08
European bond fund	5.11	7.34	4.15	-1.02	-1.22	-1.21	10.98	3.45	4.81	0,42
European equity fund	15.74	6.91	24.1	15.73	3.54	-39.78	30.42	8.09	23.04	-1,79
French equity fund	16.23	7.71	27.96	19.59	3.88	-39.11	25.52	8.83	22.87	-1.89
International equity fund	8.12	8.12	29.1	8.63	-2.96	-39.24	14.77	3.79	21.29	-1.50
International bond fund	-5.24	1.15	7.21	-6.79	-2.71	9.41	-0.75	0.33	6.09	0.53
International equity fund	9.11	5.69	15.3	7.19	0.06	-23.94	16.05	4.21	13.59	-1.79
International equity fund	11.74	5.88	20.26	10.47	0.55	-32.46	18.67	5.02	17.88	-1.88

Notes: The first line indicates the nominal rate of return of the euro-based fund proposed to investors between 2003 and 2009, and the mean, standard deviation and skewness calculated over the seven years. Subsequent lines show the same information for the eight unit-linked funds.

Figure 1: Total number of contracts sold per month

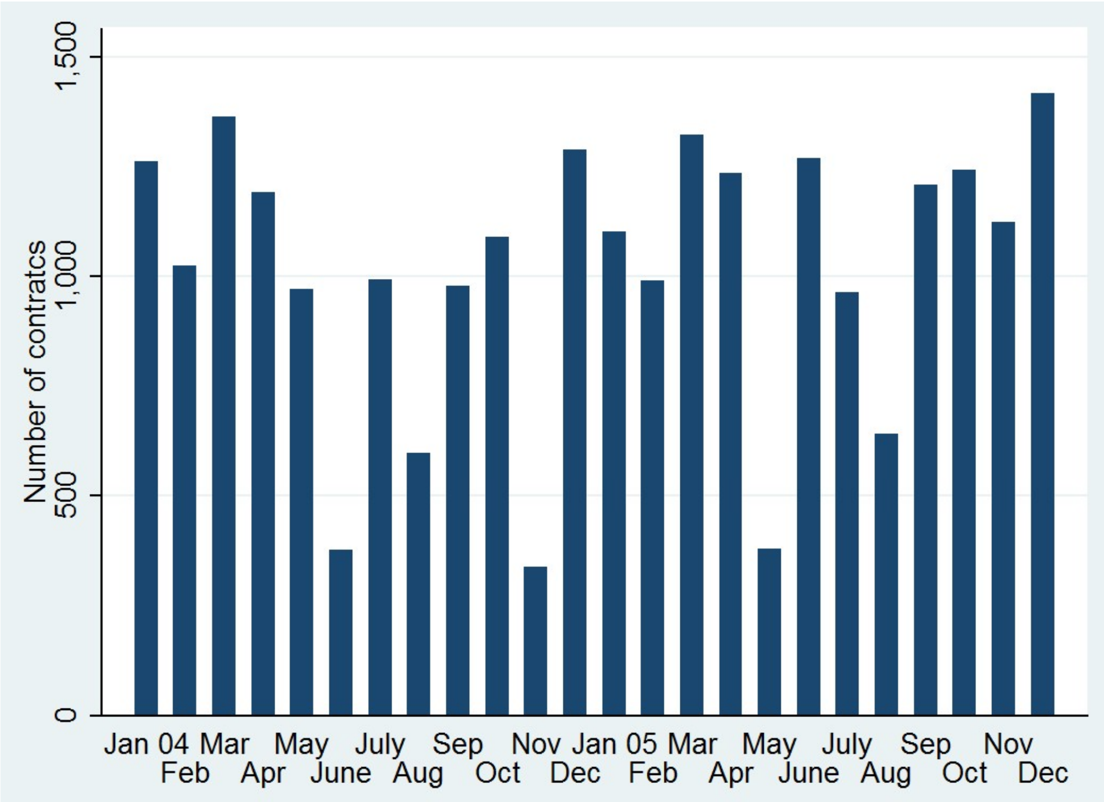

Figure 2: Frequency (in percent) of contracts sold per manager

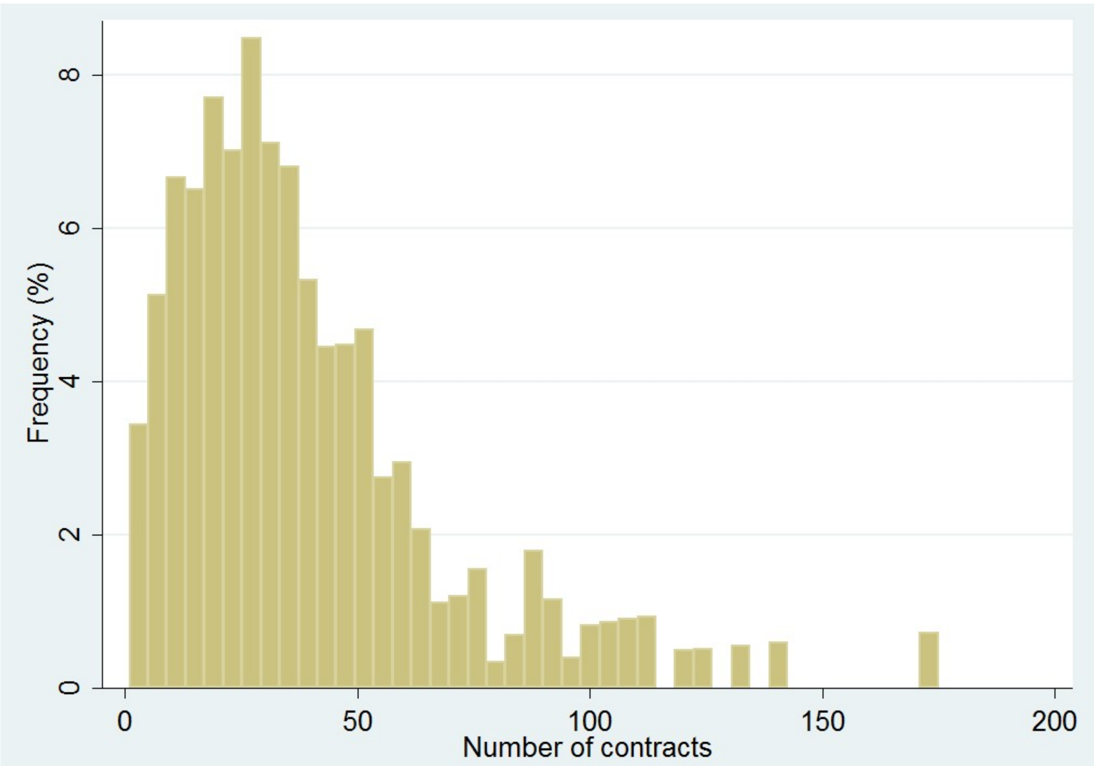

Figure 3: Frequency (in percent) of share invested in unit-linked funds