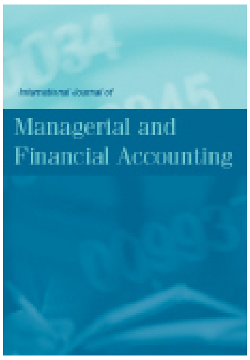

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'One size fits all' in private banking: implications for the wealth and asset management industry

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Abstract: We focus on discretionary portfolio management to examine the impact of advisory on strategic asset allocation and its dynamics. We use a unique and proprietary dataset from a large European private bank of 5,627 clients that covers the period from 2005 to 2013. While high-net-worth clients opt for customised advisory, we show instead that allocations are quite similar across a range of clients; advisors are conservative and favour low-risk profiles regardless of clients' age. We observe a low number of active clients and provide evidence of the low extra returns generated by changes in the portfolio asset allocation. Finally, we highlight that changes in risk attitude mainly depend on portfolios' past performance and/or past market performance, suggesting that advisors are not effective in mitigating extrapolation bias and self-attribution bias. Overall, we provide evidence of the low level of tailoring, suggesting a 'one size fits all' approach in private banking.

Keywords: asset and wealth management; advisory; behavioural biases; linear mixed model analysis; private banking; portfolio customisation.

JEL codes: G1, G2, G4, C6.

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1 Introduction

Investing requires financial knowledge. However, a vast amount of literature shows that individuals demonstrate low financial literacy (Klapper and Lusardi, 2020; Lusardi, 2008, 2012, 2019; Lusardi and Mitchell, 2011, 2014; Yakoboski et al., 2022) and are not well-equipped to deal with ever more complex financial instruments (van Rooij et al., 2011). Households can seek advice and guidance from qualified sources. As long as households can resort to the advice of experts for their financial decisions, external advice can be seen as a substitute for individual learning, thus avoiding the effort of acquiring financial expertise. Common motivations for the demand for professional financial advice are that advisors are more knowledgeable about financial instruments and markets than non-professional investors (e.g., because they can exploit economies of scale in information acquisition), and that they can mitigate households' behavioural biases (Calcagno and Monticone, 2015).

Although these two motivations – knowledge of the financial instruments and markets and mitigation of behavioural biases – are central to the choice of financial advice, few studies have focused on these aspects. We position our paper within this area of literature, with the purpose of filling the gap.

The literature on financial advisory is mostly focused on:

1 the comparison of mutual fund performance (Bergstresser et al., 2009; Hackethal et al., 2012; Chalmers and Reuter, 2013)

2 the impact of advisory fees on performance (Foerster et al., 2017; Linnainmaa et al., 2021)

3 the conflict of interest that fees may generate on asset allocation (Fecht et al., 2013; Inderst and Ottaviani, 2012).

Moreover, few studies have measured the value creation provided by the support of financial advisors (e.g., Chalmers and Reuter, 2013; Foerster et al., 2017; Hackethal et al., 2012; Kramer, 2012; Shapira and Venezia, 2001; von Gaudecker, 2015).

As for the investors' behaviour, several studies have shown that investors are prone to both cognitive and emotional biases that may harm their performance and lead to sub-optimal portfolio choices (Shefrin and Statman, 2000; Shefrin, 2018). As a matter of fact, while initial studies using the behavioural finance approach investigated market anomalies [see Rossi (2016b) and Rossi and Fattoruso (2017) for literature reviews] or criticised traditional neoclassic models such as the capital asset pricing model [see Rossi (2016a) for a critical literature review of the CAPM], most of the subsequent studies in the behavioural finance literature have focused on retail investors that trade on their own, showing the potential costs associated with excessive trading due to biases such as overconfidence, that is, the tendency to overestimate knowledge or skill (Barber and Odean, 2001). Overconfident investors tend to trade too much, thus lowering the net performance of their investment once transaction costs are considered (Barber and Odean, 2000). Men tend to be more overconfident than women and, on average, they trade more, especially on more aggressive stocks, and thus, perform worse (Barber and Odean, 2001). The illusion of control is a typical cause of overconfidence and partly explains the evidence that past portfolio performances tend to increase individual investors' trading. Individual investors are also net buyers of stocks that grab their attention either through recently recorded extra returns or abnormal volumes, or due to being mentioned in the media (Barber and Odean, 2008).

Moving to advisory, few studies deal with the relationship between investors and advisors, due to the scarcity of available data and their confidentiality. Moreover, these studies mainly focus on mass-market clients, a segment of clients characterised by a high level of standardisation (Hoechle et al., 2014). Thus, there is a relevant gap in the literature to be filled.

We position our paper in these two streams of research – impact of advisory on value creation and on bias mitigation – aiming at filling the above-mentioned gap, with the purpose of focusing on financial advisory related to discretionary mandates, contributing to both literature streams, given our unique proprietary dataset of private high net-worth clients. In order to better identify our research framework and its contribution, it is worth dwelling on the investment alternatives provided by the asset management industry. Asset management portfolios can be made up of investment funds or discretionary mandates. Investment funds are pools of assets with specified risk levels and asset allocations, into which one can buy and redeem shares. A discretionary mandate is a mandate given by a client to an asset manager to manage a portfolio of assets and execute orders in compliance with a predefined set of rules and principles, on a segregated basis and separate from other clients' assets. Asset managers must stick to the terms of the investment objectives agreed with their clients and cannot go beyond this remit (EFAMA, 2014).

We focus on wealthier clients that opt for the private banking advisory service. In this context, advisors may add value by offering tailored asset allocations, based on clients' characteristics, as claimed by the 'interior decoration' hypothesis suggested by Bernstein (1992) and Campbell and Viceira (2002), especially when advisors follow a low number of high-net-worth clients, having a stronger commitment toward them due to the possibility to dedicate more time to each of them.

Our dataset is unique not only because it is proprietary and includes a high number of client-year observations – we analyse the portfolios of over 5,600 clients of a leading European private bank, during the period (2005 to 2013) – but mostly since it contains relevant information about high-net-worth clients' portfolio asset allocation and personal characteristics (age, gender and level of wealth), in contrast with the dataset used in the majority of previous studies, based on mass-market clients.

Our central argument, that differentiates our paper from previous studies in the literature, is focused on advice offered to high-net-worth clients that should be more customised with respect to mass-market advice, in order to better relate to the clients' needs and their dynamics. Our findings, however, show that portfolio asset allocation is quite similar across clients and its risk profile is not related to clients' age. Second, focusing on the dynamic of the strategic asset allocation, during the observation period, we have found overall static portfolios despite the financial market volatility caused by the two financial crises that occurred, the Global Financial Crisis (so-called 'subprime crisis') and the European Sovereign Debt Crisis. Third, focusing on portfolios 'switches', which are changes in the strategic asset allocation driven by changes in risk profile, we have found that bigger switches are characterised by smaller variations in their risk profile and *vice versa*. Moreover, we have not found that significant risk adjusted extra returns after the switches, thus confirming that a conservative approach of advisors can limit the portfolio value creation. Finally, we have found that clients (and/or advisors) are affected by self-attribution bias and by return-chasing behaviour, explained (at least in part) by extrapolation bias, since changes in risk profile are influenced by past performances, both of the client's portfolio and of the stock market.

Our paper contributes to the existing literature on the relationship between advisors and their clients in several ways.

First, we have used a unique dataset from one of the largest European private banks and have analysed the portfolio characteristics of high-net-worth clients. Since each banker handles a limited number of clients, these clients are entitled to a tailored consultancy. This characteristic allows us to differentiate our study from most of the previous ones relying on the mass-market segment characterised by high levels of standardisation.

Secondly, we focus on private banking where advisors are employed by the bank and have a base salary. This means that their compensation schemes are mainly related to the growth of assets under management rather than to the commission profile of the managed product. More specifically, in many European countries, advisors are remunerated through the so-called 'inducements', that is, a percentage of the management fee collected by the advisor. This mechanism can lead to mis-selling because it can lead to recommending investment products that offer bigger commissions, instead of those products which are more suitable for clients. Thus, we differentiate from previous studies that mainly rely on advice based on inducements, thus facing, at least potentially, higher conflicts of interest.

Thirdly, we are able to verify the impact of advice on portfolio strategic asset allocation that should be related to clients' personal characteristics, to clients' risk attitude, as well as to market volatility.

Fourthly, we contribute to the behavioural finance literature, verifying whether advisors are able to overcome the biases related to the influence of past performances on clients' risk attitude, which are self-attribution bias and extrapolation bias, leading to the return-chasing behaviour.

Our findings have relevant managerial and theoretical implications for both practitioners and academics, described in detail in the paper and in the section dedicated to our conclusion and future research suggestions.

The paper is organised as follows: Section 2 provides the theoretical foundations and the literature review; Section 3 presents the methodology; Section 4 describes the sample and the main results. Section 5 sets out the conclusion, underlines potential limitations, proposes areas of future research and highlights theoretical implications for the academic literature, and also the managerial implications for the wealth and asset management industry.

2 Theoretical foundations and literature review

The impact of financial advice on clients' performance is still debated. While the literature on retail investors' behaviours has substantially grown in recent years, few studies have analysed whether financial advisors really convey value to their clients or, at least, reduce the negative effects of behavioural biases. This theme has gained the attention of scholars in the last years, providing insights on the pros and cons of financial advice. While earlier studies claimed that financial advisors create value for clients (Shapira and Venezia, 2001), more recent ones have shown that advisors seem to have a negative impact (Chalmers and Reuter, 2013; Hackethal et al., 2012) or at best, no influence on their clients' performance (Kramer, 2012). While financial advisors seem to induce excessive trading (Hackethal et al., 2011, 2012), they tend to improve portfolio diversification (Chalmers and Reuter, 2013; Kramer, 2012).

These studies suffer from various shortcomings. A key issue concerning many previous studies is that they could not isolate the effect of the financial advisor on the clients' portfolio performances because it is difficult to distinguish whether portfolios are solely managed by advisors or investment decisions are jointly taken with clients. Moreover, the notion of 'advice' itself is not clearly defined because, usually, it is hard to distinguish between clients who completely delegate investment decisions to their advisors and others who mainly trade alone and only partly rely on advisors' advice.

Typically, both kinds of clients are considered advised, but this is often true only for a few cases. Another important issue is related to the so-called selection bias. On the one hand, individual investors with a low level of financial education or poor investment skills may be the ones more likely to hire a financial advisor. On the other hand, Gentile et al. (2016) find that less financially educated investors rely on informal advice, such as advice received from friends, instead of looking for professional advice. This may be because investors with a higher level of financial literacy understand the need to be guided by professional financial advisors.

Bernstein (1992) points out that many financial planners and advisors justify their fees by emphasising the need for each investor to build a portfolio reflecting his or her unique personal situation. Campbell and Viceira (2002) highlight the fact that financial planners follow some systematic patters such as the tendency to encourage young investors to take more risks than older investors. However, the relationship between 'risky share' (i.e., the percentage of equity in the portfolio) and investor age is not clearly defined. Poterba and Samwick (2001) find that the risky share increases with age, and Guiso et al. (2002) demonstrate that while the age profile for ownership of risky assets is hump-shaped, conditional on participation, the share of risky assets tends to be flat. Fagereng et al. (2013) underline that the hump-shaped pattern peaks around retirement. In contrast, Foerster et al. (2017) find that the risky share declines with age, peaking around the age of 40 years, and declining as retirement approaches. Generally, the authors test whether financial advisors adjust portfolios depending on clients' risk tolerance (see also Chhatoi and Mohanty, 2022) by studying variations in the risky share and find that advisors provide little customisation to their clients and tend to propose similar portfolios irrespective of the customers' personal characteristics. Advisors' characteristics, instead, explain variations in portfolio risk more than clients' personal attributes such as risk tolerance, age, and level of financial literacy. Even though advised portfolios cost the clients an average of 2.6% per year, advisors' personal asset allocation predicts what they propose to their clients, and this explains the limited customisation offered to their clients. The authors claim that advisors may still add value to clients through financial planning, helping them reaching their retirement goals (Lusardi and Mitchell, 2011), creating tax-efficient asset allocations (Bergstresser and Poterba, 2004; Amromin, 2008), or encouraging risk-taking where needed (Gennaioli et al., 2015).

Regardless of the effect on clients' performances, evidence on whether advisors have any effect in helping their clients overcome behavioural biases is mixed, and the debate continues.

Advisors can also deliver value to clients by helping them overcome behavioural bias. Extensive literature has devoted attention to the behaviours of individual investors and has shown several mistakes they make when investing. Apart from the above-mentioned studies on the effects of overconfidence on trading performances, self-attribution bias leads investors to think that good past performances are due to their skills, and not luck or a positive market trend. Extrapolation bias causes investors to extrapolate past market returns into the future or at least chase returns (Brown and Cliff, 2004), despite the evidence of an eventual reversal (Zaremba et al., 2020), explaining why past market returns positively affect individuals' trading (Glaser and Weber, 2009). Regarding how individuals choose their stocks, several studies show how the 'home bias' – that is the tendency to mainly investing in domestic or even local, thus more familiar stocks – can harm investors' performance (Mishra, 2015). In this respect, financial advisors seem to reduce home bias in their clients' portfolios (Kramer, 2012).

While excessive trading may potentially harm net performance due to transaction costs, the reduction of behavioural biases may improve it. Overall, the evidence on individual investors' behavioural biases underlines the dangers of self-investing and advocates the need to hire a professional financial advisor. Further, advisors may help their clients choose a better market timing with respect to individual investors' typical actions: on average, individual investors tend to increase their equity holding when markets are high and decrease their holdings when markets are low. Errors in market timing usually worsen investors' portfolio performances. However, the opposite behaviour, that is, return-chasing, may characterise advisor-directed investments. Mullainathan et al. (2012) find that advisors tend to encourage their clients to chase past returns, purchasing actively managed mutual funds instead of passively managed ones, or exchange traded funds (ETFs). Guiso et al. (2008) show that advisors may elicit feelings of trust, while Gennaioli et al. (2015) claim that having a financial advisor may reduce clients' anxiety. In general, analysing the behaviour of clients and advisors is quite complex due to the unavailability of reliable datasets. Additionally, ascertaining whether a dataset used for the analysis includes clients' investment account or their 'gambling account', that is, the account used to enjoy trading, which typically uses only a limited amount of the client's funds, is difficult (Goetzmann and Kumar, 2008). Some studies analyse the data of discount brokers (e.g., Hackethal et al., 2012), which is a typical example of gambling accounts. The 'gambling effect' however tends to increase trading and causes 'gambler' investors to prefer lottery-like stocks, while risk-averse investors usually tend to choose lower-volatility stocks (Dorn and Huberman, 2010). Hoechle et al. (2014) use a large Swiss retail bank's dataset to discern whether financial advisors can improve their clients' performance or least help them in de-biasing. Their database allows the authors to classify individual trades as either advised or independent. Thus, the study is neither affected by the selection bias, nor by endogeneity issues. They find that financial advisors hurt their clients' performance, and that they do not help clients in reducing behavioural biases. However, we underline that in their sample, each financial advisor handles several retail clients (800 on average), thus they probably propose standardised (not tailored) advice to their clients. This may be one of the reasons of not creating value for clients or even damaging performances.

Our study contributes to the above-mentioned literature on financial advisors in the asset and wealth management industry, with particular regard to private banking, both analysing the relationship between advice and value creation and studying the role of advisors in mitigating investors' behavioural biases.

3 Methodology

In our private banking context, clients sign a so-called discretionary portfolio investment management agreement (or investment mandate), that is, the authorisation to invest and manage their portfolio. The private banker provides a broad coverage of the portfolios risk spectrum through a blend across equity and fixed income. Thus, the investment mandates are multi-assets, that is, the bank offers several 'investment options', each characterised by a different risk profile and a relative benchmark.[1] During the investment mandate, clients can modify their portfolio risk profile (i.e., changes in asset allocation) through a so-called 'switch' from the chosen investment option to another. The switch requires a formal authorisation, and thus, it is a decision that must be shared with the private banker.

Our dataset includes data on both clients' demographic information (age and gender), and their portfolios details that include: the date of the agreement, name of the investment option and related benchmark, portfolio size (on a monthly basis), dates and amounts of subscriptions and redemptions. Moreover, for active clients – defined as those who have switched at least once during the study period – the dataset includes dates, amounts, and denominations of the old and new investment options.

Although our database contained 37 distinct 'investment options'[2], we aggregate them into nine 'risk profiles' because investing in securities implies different degrees of risk. Based on their benchmark composition, we classify risk profiles from the lowest risk (*liquidity*) to the highest risk (*equity*). Based on the risk profile, we associate each investment option to a *risk score* (*RS*), ranging from one (lowest risk) to nine (highest risk), as follows:

1. *Liquidity:* Cash or money market securities.
2. *Bonds:* 100% government bonds.
3. *Corporate and emerging market bonds:* Corporate and emerging markets bonds.
4. *Balanced 10:* At most 10% equity, 90% government bonds.
5. *Balanced 20:* At most 20% equity, 80% government bonds.
6. *Balanced 30:* At most 30% equity, 70% government bonds.
7. *Balanced 50:* At most 50% equity, 50% government bonds.
8. *Balanced 75:* At most 75% equity, 25% government bonds.
9. *Equity:* 100% equity.

Although unsophisticated (i.e., not based on statistical risk measures such as volatility), this rank helps clients to understand the level of risk characterising each risk profile in their portfolio. Assigning a RS to each risk profile also allows to calculate the average RS for each portfolio. This rank represents a sort of risk thermometer, a useful tool for risk comparison. Thus, based on the client's risk attitude, advisors can define a strategic asset allocation that can be implemented by investing in multiple risk profiles among those offered by the bank. This ranking is also important for our analysis since it represents the risk scale offered to clients both when they sign the agreement and when they rebalance their portfolio through switches.

We are not aware of who takes the initiative for the switches, that is, if they are suggested by bankers or if clients request them. However, since switches need a formal authorisation by the private bankers, they have a role in the decision. Irrespective of who has the initiative for the switches, we are interested in analysing the effect of these switches on portfolio performance. This portfolio rebalancing activity may be due to several reasons, but a switch should be justified by the possibility of higher risk-adjusted expected returns (ERs). Not necessarily higher since, in case of a switch towards a lower risk profile, ERs may also be lower. However, adjusting for risk, we should expect higher risk-adjusted ERs that we measure calculating Sharpe ratios (SRs).

Table 1 Definition of variables

Variable	*Definition*
$\Delta Risk_{RS}$	Difference between the risk of the new and old risk profiles in terms of risk score (RS)
$\lvert\Delta Risk\rvert_{RS}$	Absolute value of $\Delta Risk_{RS}$
$\Delta Risk_{SD}$	Difference between the risk of the new and the old risk profiles in terms of standard deviation
$\lvert\Delta Risk\rvert_{SD}$	Absolute value of $\Delta Risk_{SD}$
Age	Clients' age: in the descriptive statistics part of the paper, we take clients' age as of 2005, while in the models analysed thereafter, we consider clients' age at the time of the switch
Gender	Dummy variable: women (0); men (1)
AuM	Asset under management (portfolio size in logarithmic terms)
Weight	Weight is the amount of the switch (i.e., 'switch size') divided by total AuM
Turnover	Sum of overall switches' weights divided by the length of the portfolio management
$ER + 1$	One-month excess return: one-month return 'new' risk profile minus one-month return 'old' risk profile
$ER + 3$	Three-months excess return: three-months return 'new' risk profile minus three months return 'old' risk profile
$ER + 6$	Six months excess return: six months return 'new' risk profile minus six months return 'old' risk profile
$ER\_Ptf + 1$	One-month portfolio excess return: (one-month return 'new' risk profile minus one-month return 'old' risk profile) multiplied by the weight, considering a one-month time horizon
$ER\_Ptf + 3$	Three-months portfolio excess return: (three-months return 'new' risk profile minus three-months return 'old' risk profile) multiplied by the weight, considering three-months' time horizon
$ER\_Ptf + 6$	Six-months portfolio excess return: (six-months return 'new' risk profile minus six-months return 'old' risk profile) multiplied by the weight, considering six-months' time horizon
$\Delta SR + 1$	Difference between the Sharpe ratio of the 'new' risk profile and the SR of the 'old' risk profile, considering a one-month time horizon
$\Delta SR + 3$	Difference between the Sharpe ratio of the 'new' risk profile and the SR of the 'old' risk profile, considering a three-months' time horizon
$\Delta SR + 6$	Difference between the Sharpe ratio of the 'new' risk profile and the SR of the 'old' risk profile, considering a six-months' time horizon
$\Delta SR\_Ptf + 1$	Difference between the Sharpe ratio of the 'new' risk profile and the SR of the 'old' risk profile multiplied by the weight considering one-month time horizon
$\Delta SR\_Ptf + 3$	Difference between the Sharpe ratio of the 'new' risk profile and the SR of the 'old' risk profile multiplied by the weight considering three-months' time horizon
$\Delta SR\_Ptf + 6$	Difference between the Sharpe ratio of the 'new' risk profile and the SR of the 'old' risk profile multiplied by the weight considering six-months' time horizon

Table 1 Definition of variables (continued)

Variable	*Definition*
$R - 1$	Performance of the 'old' risk profile in the month before the switch
$R - 3$	Performance of the 'old' risk profile in the three-months before the switch
$MR - 1$	Market return (Italian Stock Equity Index) in the month before the switch
$MR - 3$	Market return (Italian Stock Equity Index) in the three-months before the switch

For this aim, we first calculate the ERs registered by the switch and compare the performance of the two risk profiles involved in the switch. We define 'old risk profile' as the risk profile chosen by the client before the switch, and 'new risk profile' as the risk profile the client switched to. For example, if a client switches from *bond* to *equity*, we consider *bond* as the 'old risk profile' and *equity* as the 'new risk profile'. The performance of the risk profile is calculated using the price series of the related benchmarks provided by Bloomberg Information Provider. Then, we use the benchmarks' daily returns to calculate the SRs over the same time frames, to account not only for ERs after switches, but also for the different riskiness of the new risk profile compared to the old one, that is, we consider risk-adjusted returns.

We aim to determine whether changes in the portfolio risk profile (switches) can create value for clients by analysing the risk-adjusted returns of the new portfolio with respect to the old one over different time frames. We focus on three distinct time horizons, namely, one month, three months, and six months after the switch date. All the statistical analyses are developed using the R software (R Core Team, 2019). In particular, the linear mixed-effects library lme4 is used for the model estimation (Bates et al., 2015) and the library performance is used for the model evaluation (Lüdecke et al., 2021). Table 1 summarises the variables used in our models.

In particular, $\Delta Risk_{RS}$ is the difference, in case of a switch, between the RS of the new and old risk profiles. We also consider the variation of the RS in absolute terms ($|\Delta Risk_{RS}|$) to analyse the risk change, regardless of its direction (more risk vs. less risk). Similarly, $\Delta Risk_{SD}$ (and its absolute value $|\Delta Risk_{SD}|$) is the difference between the SD of the new and old risk profiles. *Age* is the clients' age at the date of the switch. *Gender* is a dummy variable equal to one if the client is a man, and zero otherwise. *AuM* measures the assets under management (in logarithmic terms). In case of multiple managed portfolios, we consider the overall wealth asset allocation. *Weight* is the amount of the switch divided by AuM, and it is used to account for the different relevance of each observation, to give more importance to larger changes in the RS of the overall portfolio. Each switch is then weighted in the computation of the objective function (simple sum of squared residuals – for OLS estimates, or more complex likelihood functions – estimating random effects models) used to estimate the model parameters. *Turnover* is the sum of weights of the clients' switches divided by the length of the investment period on an annual basis. $ER + 1$, $ER + 3$, and $ER + 6$ are the differences between the returns of the new and old risk profiles over the three distinct time horizons, namely, one month, three months, and six months, respectively. Moreover, considering the same time horizon, $ER\_Ptf + 1$, $ER\_Ptf + 3$, and $ER\_Ptf + 6$ are the ERs of the new overall portfolio with respect to the old one, accounting for the size (*weight*) of the switches. $\Delta SR + 1$, $\Delta SR + 3$, and $\Delta SR + 6$ are the differences between the SRs of the new and old risk profiles; $\Delta SR\_Ptf + 1$, $\Delta SR\_Ptf + 3$, and $\Delta SR\_Ptf + 6$ are the differences between the SRs that consider the size (*weight*) of the switches. $R - 1$ is the benchmark performance associated with the old risk profile in the month before the switch, while $R - 3$ refers to the three months before the switch. $MR - 1$ is the performance of the FTSE Mib Index registered one month before the switch, while $MR - 3$ refers to the that of three months before the switch. We use this variable to verify if clients, supported by their advisors, tend to suffer from extrapolation bias, that is, if they tend to extrapolate past trends into the future, thus basing investment decisions on recent market performance. We consider the Italian Stock Market since we analyse Italian investors and assume that they are affected by home bias, and thus pay more attention to the domestic stock market exchange.

Our dataset, used for model estimation, presents repeated measures for the same individual (client) during the observation period. The analysis includes all the clients the bank (i.e., the entire population), considering the clients who decided to redeem their investments as well. For this reason, we use unbalanced panel regressions. Moreover, in a single year, we observe multiple switches for each investment option and client. Thus, we cannot claim that the data present a pure panel structure. Notwithstanding, the presence of repeated observations for clients in our sample suggests the opportunity to include an individual (random) effect in the model specification. Thus, all models are defined by considering the hierarchical structure of the dataset. The specification follows a fixed-effect approach and random-effects approach for the time-specific and the individual (clients)-specific effects, respectively. The model specification is:

$$y_{it} = \alpha_i + \beta_t + f(x_{it}) + \epsilon_{it}$$

where x_{it} comprises the explicative variables and some specific control variables (for instance, the risk profiles). As the dataset presents a hierarchical structure in which investors are observed over time, the model specification is developed using a random-effect approach to consider the unobservable characteristics of clients.

The choice of the random effect is justified since the observed statistical units do not represent the entire population and new investors continuously enter the sample. Since the observations are not regularly collected over time, the classical solutions to panel data analysis cannot be directly adopted.

Thus, including the individual random error term in the model specification is the only solution that may account for the correlation over the time span. The effect of market condition over time is then included in the model by considering some time-dependent explicative variables. The dataset comprises all the observed switches. We weighted the observations through their relevance on the total available amount of capital. Considering a fixed variance function in the model estimation, we have naturally accounted for the individual heteroscedasticity due to the phenomenon size.

We have performed several regression models.

Model (1) verifies the effect of potential explanatory variables on the changes in RSs in absolute terms $|\Delta Risk_{RS}|$:

$$\left|\Delta Risk_{RS}\right|_{it} = b_{0i} + b_1 Age_t + b_2 Gender_t + b_3 AuM_{it} + b_4 Turnover_{it} + \varepsilon_{it} \tag{1}$$

As noted in previous studies (e.g., Barber and Odean, 2001), *age* and *gender* are important explanatory variables affecting risk attitudes. Furthermore, *turnover* may proxy for investors' (and advisors') propensity to vary the portfolio risk profile.

Model (2) tests the variable $\Delta Risk_{RS}$ to discern the direction of the risk change due to the switch, that is, if the switch determines an increase or decrease of risk:

$$\Delta Risk_{RSit} = b_{0i} + b_1 Age_i + b_2 Gender_i + b_3 AuM_{it} + b_4 Turnover_{it} + \varepsilon_{it} \tag{2}$$

To test the alternative metric of risk based on SD, we further perform two regressions using $|\Delta Risk_{SD}|$ and $\Delta Risk_{SD}$ [models (1bis) and (2bis)]:

$$\left|\Delta Risk_{SD}\right|_{it} = b_{0i} + b_1 Age_i + b_2 Gender_i + b_3 AuM_{it} + b_4 Turnover_{it} + \varepsilon_{it} \tag{1bis}$$

$$\Delta Risk_{SDit} = b_{0i} + b_1 Age_i + b_2 Gender_i + b_3 AuM_{it} + b_4 Turnover_{it} + \varepsilon_{it} \tag{2bis}$$

Regarding performance, we analyse the portfolio ERs (*ER_Ptf*) over the three distinct above-mentioned time frames. The aim is to test whether the ER is different based on the clients' or their portfolio characteristics. We use weighted ERs in the regression model specifications. Furthermore, using the weighted variation of risk, the assumption regarding the Gaussian of the model residuals can be considered more reliable. Thus, models (3), (4), and (5) are as follows:

$$ER\_Ptf + 1_{it} = b_{0i} + b_1 Age_i + b_2 Gender_i + b_3 AuM_{it} + b_4 Turnover_{it} + \varepsilon \tag{3}$$

$$ER\_Ptf + 3_{it} = b_{0i} + b_1 Age_i + b_2 Gender_i + b_3 AuM_{it} + b_4 Turnover_{it} + \varepsilon \tag{4}$$

$$ER\_Ptf + 6_{it} = b_{0i} + b_1 Age_i + b_2 Gender_i + b_3 AuM_{it} + b_4 Turnover_{it} + \varepsilon \tag{5}$$

To analyse the portfolio risk-return profile, we test the difference of the portfolios' SRs (*SR_Ptf*) calculated over one, three, and six months respectively, after the switch. Thus, models (6), (7), and (8) are as follows:

$$\Delta SR\_Ptf + 1_{it} = b_{0i} + b_1 Age_i + b_2 Gender_i + b_3 AuM_{it} + b_4 Turnover_{it} + \varepsilon_{it} \tag{6}$$

$$\Delta SR\_Ptf + 3_{it} = b_{0i} + b_1 Age_i + b_2 Gender_i + b_3 AuM_{it} + b_4 Turnover_{it} + \varepsilon_{it} \tag{7}$$

$$\Delta SR\_Ptf + 6_{it} = b_{0i} + b_1 Age_i + b_2 Gender_i + b_3 AuM_{it} + b_4 Turnover_{it} + \varepsilon_{it} \tag{8}$$

Finally, we aim to verify whether prior performance affects changes in clients' risk attitude. In particular, models (9) and (10) focus on the one-month – (R – 1) and three-months – (R – 3) prior performance of the portfolio held by the client, respectively.

$$\Delta Risk_{RSit} = b_{0i} + b_1 R - 1_{it} + \varepsilon_{it} \tag{9}$$

$$\Delta Risk_{RSit} = b_{0i} + b_1 R - 3_{it} + \varepsilon_{it} \tag{10}$$

We consider the variation in risk (delta risk), not in absolute terms, to identify the direction of the change in risk profile after the switch, that is, to discern whether (recent) past performance influences the decision to increase or decrease the riskiness of clients' investments.

Previous studies (e.g., Foerster et al., 2017) show that positive recent market returns seem to increase individual investors' risk appetite, while poor past market performance decreases it, displaying a return-chasing attitude based on extrapolation bias, that is, the tendency that some investors have to extrapolate past returns into the future. To evaluate whether clients (or advisors, or both) suffer from this bias and thus tend to chase returns, we test models (11) and (12), wherein the explanatory variable is the equity market performance of one (M – 1) or three months (M – 3) before the switch, respectively:

$$\Delta Risk_{RSit} = b_{0i} + b_1 MR - 1_{it} + \varepsilon_{it} \quad (11)$$

$$\Delta Risk_{RSit} = b_{0i} + b_1 MR - 3_{it} + \varepsilon_{it} \quad (12)$$

Furthermore, to test the variation in the portfolio risk profile using $\Delta Risk_{SD}$ instead of $\Delta Risk_{RS}$, we run the following regression models [models (9bis), (10bis), (11bis) and (12bis)]:

$$\Delta Risk_{SDit} = b_{0i} + b_1 R - 1_{it} + \varepsilon_{it} \quad (9bis)$$

$$\Delta Risk_{SDit} = b_{0i} + b_1 R - 3_{it} + \varepsilon_{it} \quad (10bis)$$

$$\Delta Risk_{SDit} = b_{0i} + b_1 MR - 1_{it} + \varepsilon_{it} \quad (11bis)$$

$$\Delta Risk_{SDit} = b_{0i} + b_1 MR - 3_{it} + \varepsilon_{it} \quad (12bis)$$

4 Results

4.1 Descriptive statistics

Our dataset makes it possible to overcome many of the previous studies' shortcomings for the following reasons:

1 it comprises the entire set of clients of the private bank and not just a sample provided by the bank itself, allowing us to avoid the above-mentioned sample selection problem

2 private bankers are not affected by conflicts of interest as they receive a fixed salary from the bank; their bonus is based on the net inflows rather than on the management fees charged, meaning that the choice of the portfolio's asset allocations are not affected by advisors' own interests[3]

3 investment mandates are characterised by a medium-long term time horizon, meaning that these portfolios are not intended for trading/gambling activities

4 changes in strategic asset allocation (i.e., switches) require the support of the private banker, which means that even when the portfolio choices are at the initiative of the clients, these must be always shared with the consultant

5 private banking is conceived as a tailor-made service, which means that consultancy plays a decisive role in the relationship with the client.

Our study is based on an unbalanced panel of 5,627 wealthy Italian clients of a leading European private bank (the 'bank' from now on) over a nine-year period (from January 2005 to December 2013). This time frame allows analysis of the portfolio dynamics during the Global Financial Crisis (i.e., subprime crisis) and the European Sovereign Debt Crisis. As mentioned in the previous section dedicated to the description of the methodology, we focus our attention on the dynamic of portfolio management, focusing on portfolio rebalancing using switches of risk profiles.

We analyse 7,691 switches in the portfolios of 1,783 'active clients'.[4] Table 2 presents the descriptive statistics of our sample.

First, we split clients by gender, and then, by age (registered at the beginning of the observation period). We group ages into four categories: under 40; 40–55; 56–70; and over 70. The largest age group (37% of clients) is 56–70. This age group also shows the largest gender difference: the number of men is twice that of women, that is, 25% vs. 12% of the total. In the overall sample, men (62% of clients) consistently outnumber women. The smallest age group (11%) is under 40, as we could expect since wealthy clients are typically older. The average AuM is around €1,000,000 (€995,124 for women; €1,191,861 for men), but we distinguish portfolio size (in Euros) in three classes: below 200,000; [200,000–1,000,000] and > 1,000,000.[5] While among women, the average AuM is similar between age groups, among men, the wealthier clients are over 70 years, showing wealth almost double that of the other age groups. Clients' own portfolios were invested in more than one investment option (on average, 1.28 for women and 1.36 for men). Surprisingly, the average portfolio RS is in the middle of the risk scale presented in Section 3 and appears similar across all age groups of clients. This first evidence contrasts with the well-known inverse relation between age and risk tolerance. Conversely, in line with the prevailing literature, the risk profile is slightly higher for men (5.09) than for women (4.73), confirming that, on average, women are more risk-averse than men (Barber and Odean, 2001).

Table 2 Sample descriptive statistics

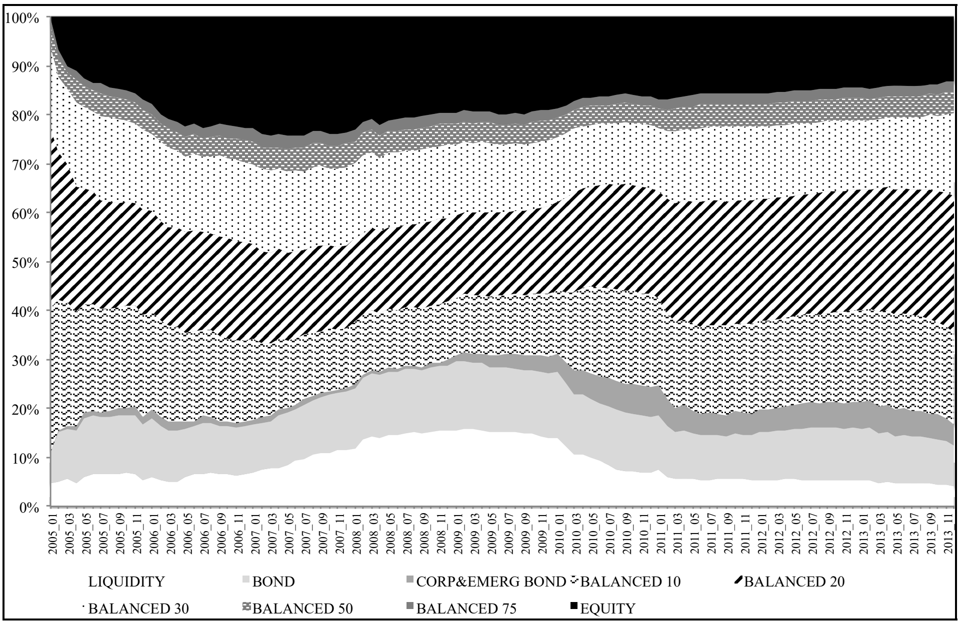
	Clients		*AuM (in Euros)*			*Average risk score*	*Average number of risk profiles held by client*
	Number	*%*	*Average*	*Min*	*Max*		
Women	2,126	38%	995,124	21,280	26,511,499	4.73	1.28
<40	296	5%	1,021,884	49,264	13,497,989	5.03	1.25
40–55	707	13%	982,264	50,000	26,511,499	5.10	1.29
56–70	699	12%	985,926	21,280	19,559,452	4.70	1.29
>70	424	8%	1,013,051	31,419	11,031,394	4.47	1.30
Men	3,501	62%	1,191,861	18,260	237,358,504	5.09	1.36
<40	333	6%	856,013	46,194	13,009,416	5.29	1.18
40–55	1,208	21%	1,087,070	30,039	39,854,529	5.10	1.37
56–70	1,428	25%	1,070,759	18,260	17,718,039	5.12	1.37
>70	532	9%	1,965,095	49,944	237,358,504	4.94	1.40
Total	5,627	100%	1,117,530	18,260*	237,358,504	4.96	1.33

Notes: Clients are classified by age groups (as of 2005) and gender, assets under management (AuM), average RS, and average number of investment options held. RSs range from 1 (lowest risk = *liquidity*) to 9 (highest risk = *equity*). *we included the portfolios of all the clients, also the ones that were about to close their investment mandates with the bank. Thus, minimum amounts are low since they represent portfolios that clients were closing.

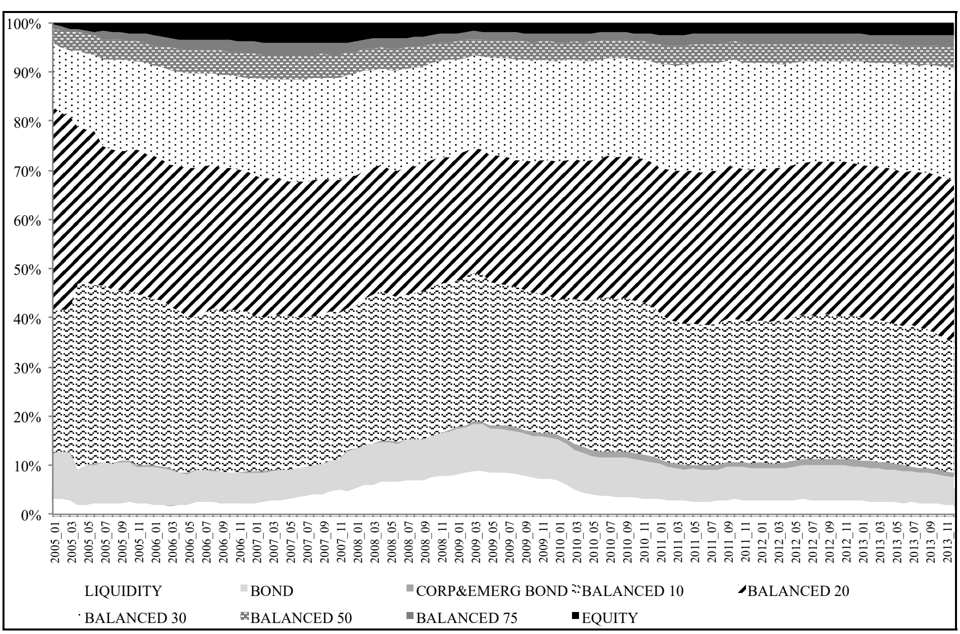
We proceed with a more in-depth analysis of the strategic asset allocation chosen by clients, observing the percentage of portfolios associated with each of the risk profile. Figure 1(a) shows that the clients' preferred risk profiles are *bond*, *balanced 10*, *balanced*

20, and *balanced 30*, representing, in aggregate, nearly 75% of the overall portfolios, belonging the lowest levels of equity.

Figure 1 (a) Dynamic of clients' portfolios distribution allocated among investment options over time (based on number of clients) (b) Dynamic of clients' portfolios distribution allocated among investment options over time (based on AuM)

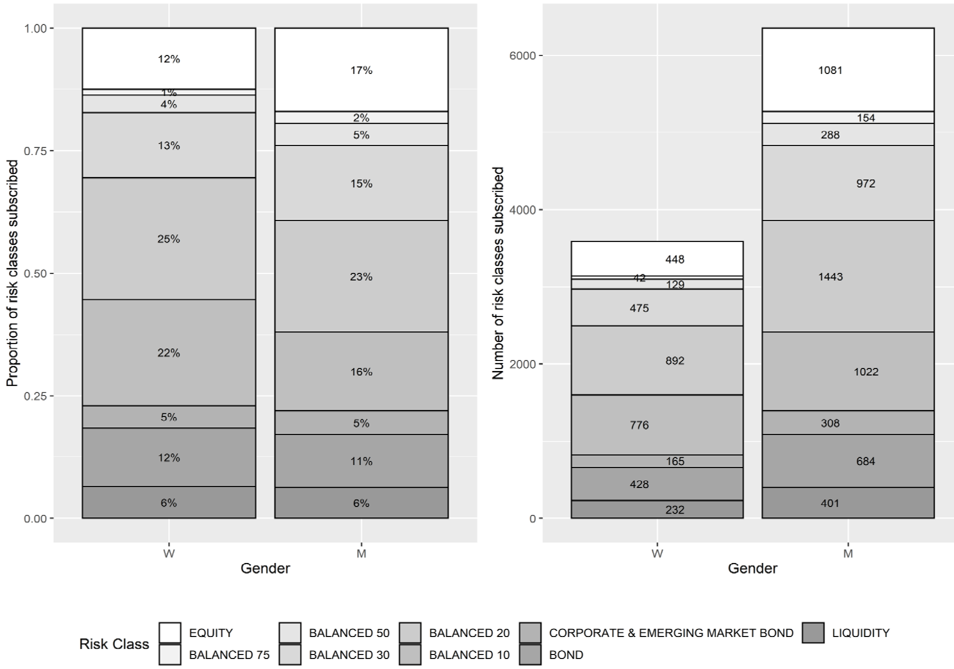


(a)

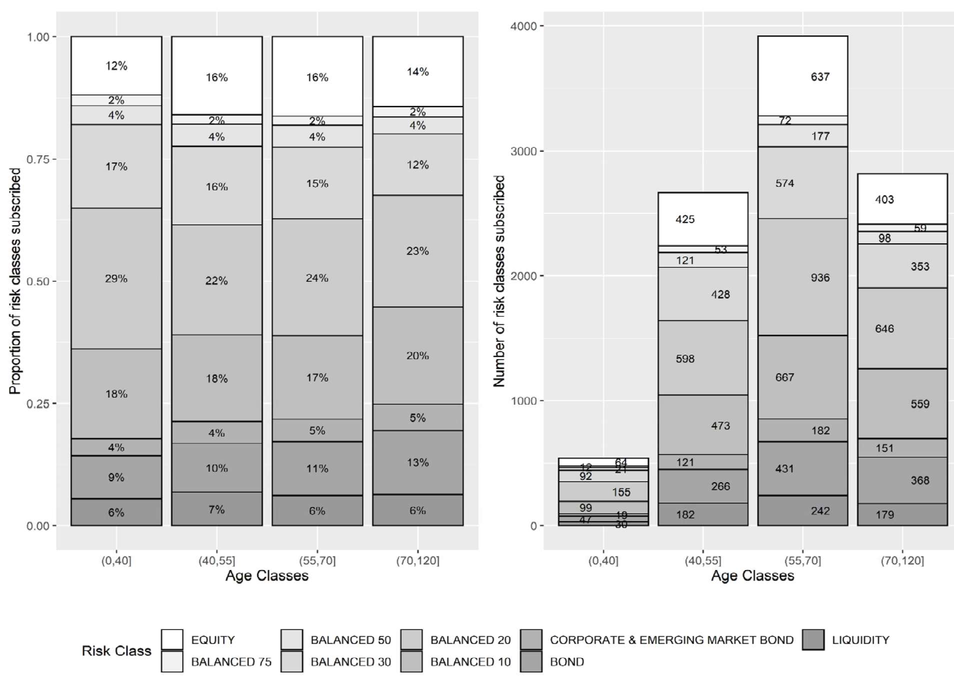


(b)

Figure 2 (a) (b) Distribution of the investment options by gender (c) (d) Distribution of the investment options by age groups (e) (f) Distribution of the investment options by asset under management (AuM)

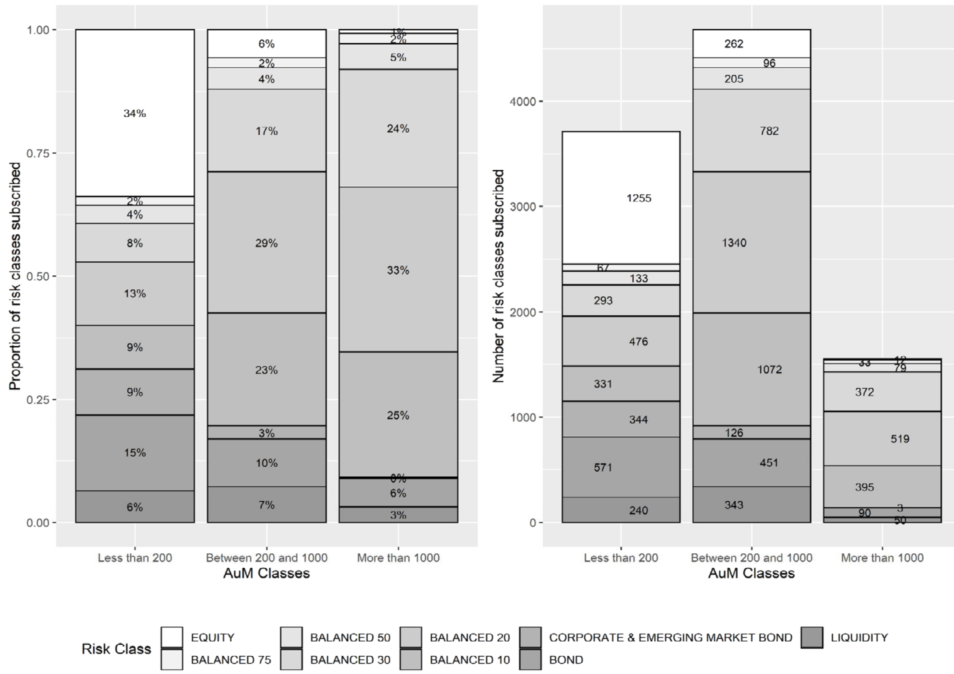


(a) (b)



(c) (d)

Figure 2 (a) (b) Distribution of the investment options by gender (c) (d) Distribution of the investment options by age groups (e) (f) Distribution of the investment options by asset under management (AuM) (continued)



(e) (f)

This statistic suggests a significant overall clients' risk aversion. However, the number of clients that moved into the equity markets increases from 2005 until mid-2007. The reason can be ascribed to the positive equity market performance: bullish markets tend to excite investors (Taffler and Tuckett, 2012; Tuckett, 2011), explaining, at least partly, the increasing number of clients raising their equity stake in that period. Moreover, from mid-2007 to March 2009, that is, during the peak of the Global Financial Crisis, the weight of *liquidity* increases considerably, while *equity* follows a diametrically opposite pattern, suggesting a higher risk aversion. The weight of *bond* remains almost unchanged during the period, while the choice of investing in *corporate and emerging market bonds* is more pronounced from the end of 2008 onward, following the drop of interest rates in the Euro area that stimulated the search for higher returns within the fixed income area. Figure 1(b) shows the same statistics, but based on AuM, instead of number of clients.

The overall AuM increases significantly during the period: in 2005, AuM is €670,000,000, while in 2013 AuM is equal to €7,400,000,000. This strong AuM growth is due to the increase in the number of customers from 982 in 2005 to 5,502 in 2013.[6] In percentage, the investments in the lower risk balanced profiles (i.e., *balanced 10*, *balanced 20* and *balanced 30*) outweigh the sum of the more aggressive and defensive risk profiles, which instead show a residual weight. It is notable that the weight of *equity*, in terms of AuM, is lower than its weight in terms of number of clients [Figure 1(a)], meaning that an increase in the number of equity portfolios does not correspond to a proportional increase of the overall AuM invested in the stock market. This evidence confirms that, on average, clients allocate lower percentages of wealth to equity markets than other asset classes.

Figures 2(a) and 2(b) present the percentage and the number of portfolios associated to each risk profile, split by gender.

While the percentages of more conservative portfolios (i.e., *liquidity*, *bond*, *corporate bond* and *emerging market bond*) are quite similar, on average, women invest more in lower risk balanced portfolios (i.e., *balance 10* and *balance 20*) as compared to men, and *vice versa* regarding the higher risk balanced portfolios (i.e., *balance 30*, *balance 50*, *balance 75* and *equity*). The largest differences are registered in case of *balance 10* (22% women vs. 16% men) and *equity* (12% women vs. 17% men). Thus, these statistics confirm that, on average, women are more risk-averse than men during the entire observation period; the difference in the risk attitude was statistically significant as verified through a Pearson's chi-squared test (not reported here in the interest of brevity).

Figures 2(c) and 2(d) present the percentage and the number of portfolios associated to each risk profile, split by age category.

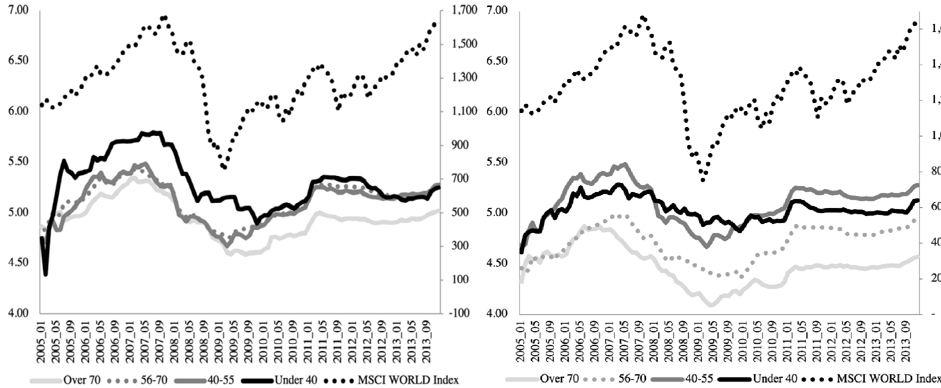
While the percentage of the *liquidity* portfolios is similar among age groups, the percentage of *bonds*, instead, increases for older clients, from 8.7% for clients under 40 to 13.1% for clients over 70. Moreover, there is not much variability either for *corporate bond and emerging market bonds* or for *balance 10* portfolios (slightly higher for the over 70), while the percentage of *balance 20* portfolios is higher for clients under 40 as compared to the older clients. The percentages of *balance 30* and *balance 50* portfolios decrease as age increases, while the percentage of *balance 75* portfolios is stable across age groups. Finally, the highest percentage of *equity* portfolios is concentrated in the two middle age categories. Surprisingly, the youngest clients own the lowest percentage of *equity*. Pearson's chi-squared test confirms the statistical significance of these differences; thus, risk aversion varies depending on age.

Figures 2(e) and 2(f) present the percentage and the number of portfolios associated to each risk profile, split by AuM.

The most striking result is that the average weight of *equity* decreases as the portfolio size increases. In particular, portfolios below €200,000 indicate, on average, 33.8% of *equity* portfolios, which is significantly higher than that of the other two ranges of AuM, equal to 5.6% (€200,000–€1,000,000) and 0.8% (above €1,000,000), respectively. Figures 3(a) and 3(b) show the pattern of the average portfolios' RSs during the observation period of men and women. We compare these patterns with the dynamic of the most popular equity market index of developed countries, namely the MSCI World Index.

It is notable that, since the average RSs are weighted by AuM, their pattern is influenced by the stock market dynamics. Among men [Figure 3(a)], clients under 40 present the highest average risk profile, equal to 5.29, as well as the more volatile pattern. Moreover, the portfolio risk dynamic of the age categories 40–55 and 56–70 almost perfectly overlap for the entire period. Finally, clients over 70 show a risk profile in line with that of the younger clients during the first part of the period; however, during the second part, the average RS for older clients increases less than it did for the others. For women, the graph [Figure 3(b)] shows that the average score decreases with age, presenting a quite stable difference over the period. Moreover, the portfolio risk pattern of the under 40 is less volatile than that of the others.

Figure 3 Dynamic of the portfolios' RS by age group, (a) dynamic of the portfolios' RS (men) (b) dynamic of the portfolios' RS (women)



(a) (b)

To sum up these findings, our analyses based on the portfolios strategic asset allocation show that:

1 The average level of risk is similar across clients and, overall, it is not related to the clients' age.

2 On average, the portfolio risk profile is slightly higher for men than for women.

3 Focusing on each investment option, we have found that the youngest clients own portfolios presenting the lowest percentage of equity

4 Observing the dynamic of portfolio risk profiles during the overall observation period, in the case of men, we have not found a significant difference between the risk profile of clients of different ages.

Instead, we have found a grading of the risk based on age, focusing on the sample of women.

4.2 Risk-return portfolio profiles

In Table 3, we present the net performance registered by clients annually, split by gender, age group, and AuM.

The average performance of the managed portfolios is about 0.23% for both women and men, and the slight difference is not statistically different. Clients over 70 register the highest performance (0.247%), followed by under 40 (0.231%), 56–70 (0.224%), and 40–55 (0.207%). Specifically, in the case of women, the highest performance is registered by those over 70 (0.251%); in the case of men, the highest performance is 0.245%, registered by both the oldest and the youngest clients. Interestingly, the main difference in performance is related to the portfolio size. Portfolios greater than €1,000,000 register an average performance equal to 0.313%, while the average performance of portfolios under €200,000 is equal to 0.104%. Additionally, the same difference can be observed by focusing on the size of the portfolio split by gender. This result can be explained by the difference in the risk of differently sized portfolios. As in Figure 2(e), the smallest portfolios present a significantly higher investment in the equity markets as compared to medium-large portfolios. Thus, the difference in performance can be attributed to the difference in asset allocation. Moreover, we focus on the portfolios' risk-return profiles comparing their SRs. Table 4 presents these statistics.

Table 3 Clients' portfolio performance, age, gender and assets under management (AuM)

	Mean	*SD*	*p-values*
Women	0.232	2.35	
Men	0.227	2.62	0.574
<40	0.231	2.28	
40–55	0.207	2.54	
56–70	0.224	2.55	
>70	0.247	2.52	*0.003*
<200,000	0.104	3.35	
200,000–1,000,000	0.294	2.04	
>1,000,000	0.313	1.89	*<0.001*
W <40	0.220	2.37	
W 40–55	0.207	2.34	
W 56–70	0.231	2.35	
W >70	0.251	2.35	*0.070*
W <200,000	0.100	3.19	
W 200,000–1,000,000	0.294	1.86	
W >1,000,000	0.314	1.81	*<0.001*
M <40	0.245	2.15	
M 40–55	0.207	2.65	
M 56–70	0.221	2.64	
M >70	0.245	2.60	*0.048*
M <200,000	0.107	3.42	
M 200,000–1,000,000	0.294	2.14	
M >1,000,000	0.313	1.94	*<0.001*

Notes: The mean comparison tests are conducted on the whole sample first (5,627 clients), considering gender, age class, and assets under management (*AuM*), and then on the sub-samples of women (2,126) and men (3,501) only for the age class and assets under management (*AuM*).

Not surprisingly, the smallest portfolios present significantly lower SRs (1.38, as compared to 3.22 and 2.64 of medium and large portfolios, respectively) due to their previously mentioned lower performance and higher volatility. Furthermore, women present a higher SR as compared to men, which confirms the higher performance registered by their portfolios and lower risk attitude.

Since the portfolio RS is a strategic variable for our analyses, it deserves a more in-depth analysis. As already described, we rank the investment options using nine RSs. While this classification is extremely simplistic (or, perhaps, even naive), it could capture investors' perception of risk. At the same time, we decided to focus also on the portfolio standard deviation (SD) being a more accurate measure of risk. Accordingly, we refine the analysis of the risk profile of the different investment options by comparing the RS of each portfolio with its corresponding SD. The aim is to compare the two measures of risk, namely, the RSs based on client's perception and the SD as a statistical measure. Figure 4 presents the relationship between the portfolios' RS and the SD of each portfolio.

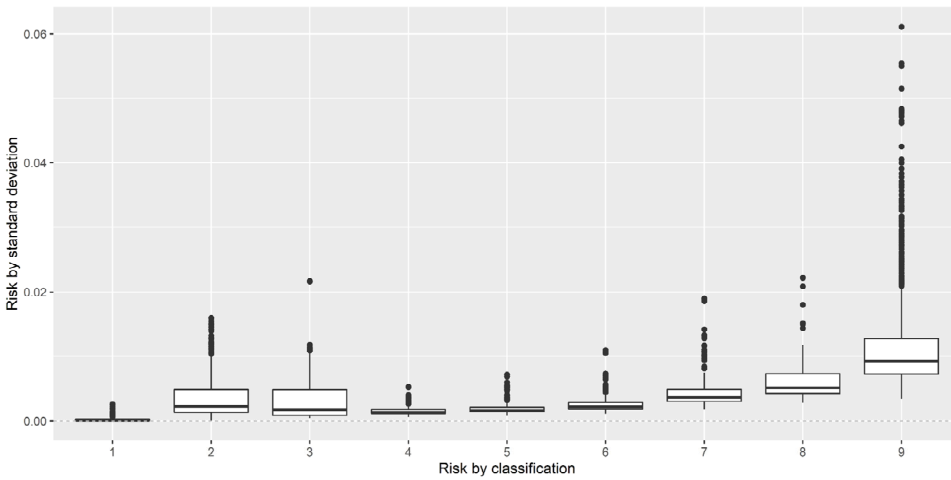
Table 4 Clients' portfolio SR, age, gender and assets under management (AuM)

	Mean	*SD*	*p-values*
Women	2.57	26.4	
Men	2.35	28.1	*0.021*
<40	2.66	21.7	
40–55	2.45	29.4	
56–70	2.46	24.3	
>70	2.34	30.0	0.438
<200,000	1.38	37.6	
200,000–1,000,000	3.22	22.1	
>1,000,000	2.64	15.9	*<0.001*
W <40	2.77	21.9	
W 40–55	2.45	21.7	
W 56–70	2.63	23.8	
W >70	2.54	32.1	0.697
W <200,000	1.61	35.6	
W 200,000–1,000,000	3.21	23.1	
W >1,000,000	2.76	15.6	*<0.001*
M <40	2.53	21.5	
M 40–55	2.45	33.0	
M 56–70	2.38	24.6	
M >70	2.24	28.8	0.466
M <200,000	1.27	38.6	
M 200,000–1,000,000	3.22	21.6	
M >1,000,000	2.57	16.0	*<0.001*

Notes: The mean comparison tests are conducted on the whole sample first (5,627 clients), considering gender, age class, and assets under management (*AuM*), and then on the sub-samples of women (2,126) and men (3,501) only for the age class and assets under management (*AuM*).

As expected, the box-and-whisker plot confirms that risk, measured by SD, generally increases as the RS increases; that is, low SDs are associated with lower RSs. Further, the two metrics are highly correlated, presenting a correlation coefficient of 0.63. Moreover, the dispersion of the SDs is higher for riskier portfolios ($RS > 7$), and the highest for *equity* portfolios ($RS = 9$), which show extreme SDs above the upper whisker. Interestingly, a high dispersion is also registered for portfolios characterised by a low RS (2 and 3 corresponding to *bonds* and *corporate and emerging market bonds*, respectively). This may be due to the high volatility that characterised the bond market during the Sovereign Debt Crisis (2011–2013). Furthermore, regarding the balanced portfolios (characterised by a RS between 4 and 6), *balance 10*, *balance 20* and, to some extent, *balance 30*, we note that the median SDs are lower than the ones associated to the bond portfolios. It is noteworthy that this evidence is attributable to the benefit of financial diversification, which occurs by placing stocks in a bond portfolio.

Figure 4 Relationship between portfolio's RSs ($Risk_{RS}$) and portfolio's SD ($Risk_{SD}$)



These statistics highlight the performance recorded by clients segmented by gender, age and wealth. Our results show low performance for each category examined, which differ by a few basis points, confirming the similarity of the strategic allocations of the portfolios as a whole. At the same time, the period under review was characterised by high volatility, both in the equity market, due to the subprime crisis of 2008, and in bonds, especially in Europe, due to the Sovereign Debt Crisis of 2011–2013.

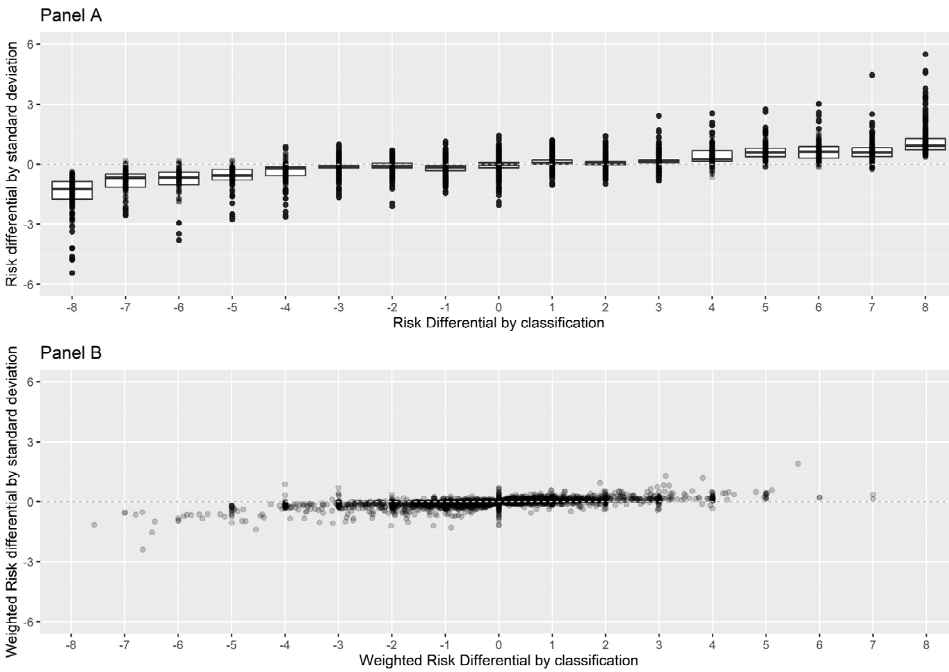
4.3 Changes in strategic asset allocation (switches)

As for the changes in the portfolio risk profile, Figure 5 (panels A and B) shows the relation between the variation in the portfolio RS ($\Delta Risk_{RS}$) and the variation in portfolio SD ($\Delta Risk_{SD}$) following a switch.

In particular, the box-and-whisker graph of *panel A* represents the distribution of the $\Delta Risk_{SD}$ associated to the $\Delta Risk_{RS}$. Since we identified nine risk profiles, potentially, a client can switch up or down at most by eight scores, that is, maximum variation is in the range [–8; +8].[7] The box-and-whisker plot shows that the change of the portfolio SD following a switch is extremely variable.[8] *Panel B*, instead, shows the relation between $\Delta Risk_{RS}$ and $\Delta Risk_{SD}$ multiplied by the *weight* of the switch to emphasise the real effect on the overall clients' portfolio.

We note that the scatter plot is more concentrated in the centre, suggesting that bigger switches are characterised by smaller variations in the risk profile and *vice versa*. In other words, clients favour stronger variations in the portfolio risk profile for a small part of their portfolio. This result confirms the static nature of managed portfolios. In extreme synthesis, few portfolios have been modified in the strategic allocation and these variations have been of modest entity because they have involved small parts of the portfolio.

Figure 5 Comparison between the risk change based on RSs and SDs



4.4 Regression analysis results: the impact of switches on performance

With the aim of verifying whether *age*, *gender*, *AuM*, and *turnover* are significant explanatory variables of both the change magnitude of the portfolio risk profile and the excess return derived from the switch, in Table 5 we present the regressions results of models (1)–(4).

The intercept is the value of the observed phenomenon if all the independent variables are null. The intercept, in model (1), is equal to 1.615 and represents the average delta RS in absolute terms. The coefficients associated with the three age categories are not statistically different from zero, suggesting that age does not affect the change in risk attitude. In line with our expectations, *gender* has a positive impact on the absolute delta risk, suggesting that men tend to be more confident in the change of risk attitude as compared to women. However, the coefficient (0.192) suggests that, on average, the difference by gender is relatively small, even if highly significant.

AuM has a negative and highly significant effect, suggesting that the wealthiest clients are less prone to change their risk profile in case of a switch. Thus, larger portfolios are more static than smaller ones. *Turnover* is not statistically significant, suggesting that this variable does not affect changes in risk profile. Model (1bis) confirms the results of model (1), namely, the positive value of the intercept (equal to 0.158 and representing the average delta SD of the portfolio) and that *gender* presents a positive coefficient while *AuM* presents a negative coefficient. Moreover, in contrast with model (1), the coefficient of *turnover* is statistically significant and negative. This result suggests that more active clients change their risk profile less markedly. In models (2) and (2bis), we consider the 'direction' of the variation in risk profile. The results are controversial because the only statistically significant coefficient for both models is *AuM* and it assumes a negative value in model (2) and a positive value in model (2bis). Moreover, in model (2bis), *turnover* presents a positive coefficient, meaning that more active clients assume, on average, more risk when they switch.

Table 5 Changes in clients' portfolio average RS and SD, age, gender, assets under management (AuM) and turnover

Coef.	*Model (1)* $\lvert \Delta Risk_{RS} \rvert$	*Model (1bis)* $\lvert \Delta Risk_{SD} \rvert$	*Model (2)* $\Delta Risk_{RS}$	*Model (2bis)* $\Delta Risk_{SD}$
Intercept	*1.615 (***)*	*0.158 (***)*	0.272	–0.012
	<0.001	<0.001	0.093	0.613
Age class (40, 55)	0.125	–0.004	–0.146	–0.002
	0.427	0.878	0.395	0.939
Age class (56, 70)	0.222	0.018	–0.205	–0.011
	0.154	0.494	0.222	0.644
Age class (over 70)	–0.035	–0.002	–0.138	–0.023
	0.827	0.943	0.416	0.356
Gender (men)	*0.192 (***)*	*0.044 (***)*	–0.032	–0.007
	0.006	<0.001	0.626	0.456
AuM_dem	*–0.168 (***)*	*–0.044 (***)*	*–0.086 (***)*	*0.016 (***)*
	<0.001	<0.001	0.004	<0.001
Turnover_dem	0.000	*–0.046 (***)*	–0.046	*0.021 (**)*
	0.999	0.001	0.517	0.044
σ_a	1.097	0.155	0.000	0.000
σ_e	0.888	0.179	1.643	0.241
Conditional R^2	0.613	0.454	-	-
Marginal R^2	0.023	0.043	0.004	0.006
N. of groups	1,783	1,783	1,783	1,783
N. of observations	7,691	7,691	7,691	7,691

Notes: Some of the estimate variance components are null. The models wherein σ_a is null do not include investors' specific effect, but the estimates are reliable corresponding to a standard regression model specification. The age class reference sub-sample is 40 or less. The gender effect refers to men, as the benchmark level is women. The marginal R^2 is computed considering only the explained variance of the fixed effects component. The conditional R^2, also called Nakagawa's R^2, includes the random effects into the computation of goodness of fit (Lüdecke et al., 2021).

Table 6 presents the results of models (3)–(8), which aimed to verify whether *age*, *gender*, *AuM*, and *turnover* are explanatory variables of the ER and the risk-adjusted ER derived from the switch.

Table 6 Clients' portfolio excess return and changes in SRs after switches, age, gender, assets under management (AuM) and turnover

Coef.	*Model (3) ER_Ptf + 1*	*Model (4) ER_Ptf + 3*	*Model (5) ER_Ptf + 6*	*Model (6) ΔSR_Ptf + 1*	*Model (7) ΔSR_Ptf + 3*	*Model (8) ΔSR_Ptf + 6*
Intercept	0.171	*0.489 (***)*	*0.614 (**)*	0.032	–0.145	0.323
	0.102	0.002	0.012	0.921	0.790	0.727
Age class (40, 55)	–0.144	*–0.684 (***)*	*–0.948 (***)*	0.126	–0.428	–1.000
	0.178	<0.001	<0.001	0.700	0.443	0.294
Age class (56, 70)	–0.108	*–0.447 (***)*	*–0.544 (**)*	0.299	0.154	–0.518
	0.309	0.005	0.028	0.361	0.782	0.584
Age class (over 70)	–0.136	*–0.498 (***)*	*–0.779 (***)*	0.164	0.277	–0.744
	0.209	0.002	0.002	0.621	0.624	0.438
Gender (men)	0.003	0.088	0.158	–0.195	0.171	0.152
	0.953	0.215	0.150	0.181	0.493	0.716
AuM_dem	–0.011	–0.034	*–0.158 (***)*	0.064	0.126	–0.239
	0.584	0.270	0.001	0.308	0.235	0.186
Turnover_dem	0.019	0.085	0.052	–0.107	–0.427	–0.926
	0.740	0.318	0.698	0.546	0.159	0.068
σ_a	0.767	1.095	1.748	2.376	4.093	6.628
σ_e	0.586	0.947	1.401	1.786	2.995	5.405
Conditional R^2	0.633	0.577	0.616	0.640	0.653	0.602
Marginal R^2	0.005	0.012	0.019	0.002	0.005	0.003
N. of groups	1,783	1,783	1,783	1,783	1,783	1,783
N. of observations	7,691	7,691	7,691	7,691	7,691	7,691

Notes: Some of the estimate variance components are null. The models wherein σ_a is null do not include investors' specific effect, but the estimates are reliable corresponding to a standard regression model specification. The age class reference sub-sample is 40 or less. The gender effect refers to men, as the benchmark level is women. The marginal R^2 is computed considering only the explained variance of the fixed effects component. The conditional R^2, also called Nakagawa's R^2, includes the random effects into the computation of goodness of fit (Lüdecke et al., 2021).

Models (3)–(5) focus on the portfolio performance recorded after the switches over three distinct time frames: one month, three months, and six months, respectively. In model (3), neither the intercept nor the explanatory variables are statistically significant, suggesting no ERs after the switches in the shorter horizon (one month). Instead, in model (4), the intercept is positive (equal to 0.489) and highly significant, suggesting that, after the switch, the new portfolio outperforms the old one in the following three months. Here, it is noteworthy that these performances are calculated based on the related benchmark rather than the client's portfolio, and thus, do not consider the transaction costs associated with a portfolio rebalancing. Each coefficient of the dummy variables associated with age categories are negative and statistically significant, suggesting that older clients tend to record lower performances with respect to the clients belonging to the age category of reference, that is, clients under 40. The other variables, instead, are not statistically significant. In model (5), the coefficient of the intercept is positive, statistically significant, and higher in magnitude (0.614 vs. 0.489). Thus, we register an out-performance over six months that is higher in comparison to the three-months' time frame. Moreover, the coefficient of the age categories is negative and statistically significant, confirming that older clients tend to record lower performances. Finally, *AuM* presents a negative and statistically significant coefficient, equal to –0.158, suggesting that bigger portfolios register lower ERs after the switch, *ceteris paribus*. Models (6)–(8) focus on the impact of our explanatory variables on the SR, recorded after the switch. Neither the coefficient associated with the constant term, nor the ones associated with the explanatory variables are significant, suggesting, on the one hand, that, on average, switches do not create extra returns once adjusted for risk and, on the other hand, that there are no differences depending on the clients' individual characteristics.

Finally, Table 7 presents the overall average ERs and SRs, at portfolio level, derived from the client's switches.

Table 7 Clients' portfolio excess returns and changes in SRs after switches

Variables	*Weighted analysis (basis points, bps)*	*p-value*
ER_Ptf + 1	*2.5****	0.009
ER_Ptf + 3	*4.7****	0.002
ER_Ptf + 6	*6.1****	0.008
Δ*SR_Ptf* + 1	0.038	0.169
Δ*SR_Ptf* + 3	0.051	0.278
Δ*SR_Ptf* + 6	*0.141**	0.086

Notes: Statistical significance of the coefficients: *p-value between 0.1 and 0.05, **p-value between 0.05, and 0.01, ***p-value lower than 0.01. Variable definitions are as follows: *ER_Ptf* + 1: one-month portfolio excess return multiplied by the weight (yearly); *ER_Ptf* + 3: three-month portfolio excess return multiplied by weight (yearly); *ER_Ptf* + 6: six-month portfolio excess return multiplied by weight (yearly); Δ*SR_Ptf* +1: difference between the SRs of 'line-in' and 'line-out' multiplied by weight, on one-month time horizon; Δ*SR_Ptf* +3: difference between the SRs of the 'line-in' and 'line-out' multiplied by weight, on three-months' time horizon; Δ*SR_Ptf* +6: difference between the SRs of the 'line-in' and 'line-out' multiplied by the weight considering six-months' time horizon.

ERs are positive and significant but extremely low, equal to 2.5 bps (basis points), 4.7 bps, and 6.1 bps over one, three, and six months, respectively. It is noteworthy that these modest results do not consider the transaction costs associated with portfolio rebalancing. Considering transaction cost may eventually lead to negative performance. Moreover, in the comparison of the SRs (delta SR), we observe positive but statistically insignificant results, except for the six-months' horizon and to a small extent. Overall, our results highlight that switches are not able to create value both in terms of absolute returns and of risk-adjusted returns.

4.5 Regression analysis results: the impact of behavioural biases

Table 8 (*panel A*) presents the results of models (9)–(12), wherein the dependent variable is the delta RSs.

Table 8 Change in risk profile and past performance

Panel A: Risk profile measured by risk score				
Coef.	*Model (9)* $\Delta Risk_{RS}$	*Model (10)* $\Delta Risk_{RS}$	*Model (11)* $\Delta Risk_{RS}$	*Model (12)* $\Delta Risk_{RS}$
Intercept	*0.086*	*0.099*	*0.116*	*0.098*
	0.006	0.002	0.000	0.001
*R*_1	*0.176*	-	-	-
	<0.001	-	-	-
*R*_3	-	*0.062*	-	-
	-	<0.001	-	-
*MR*_1	-	-	*0.073*	-
	-	-	<0.001	-
*MR*_3	-	-	-	*0.050*
	-	-	-	<0.001
σ_a	*0.000*	*0.000*	*0.000*	*0.000*
σ_e	1.628	1.639	1.613	1.607
Conditional R^2	-	-	-	-
Marginal R^2	0.102	0.032	0.098	0.119
N. of groups	1,783	1,783	1,783	1,783
N. of obs.	7,691	7,691	7,691	7,691
Panel B: Risk profile measured by standard deviation				
Coef.	*Model (9bis)* $\Delta Risk_{SD}$	*Model (10bis)* $\Delta Risk_{SD}$	*Model (11bis)* $\Delta Risk_{SD}$	*Model (12bis)* $\Delta Risk_{SD}$
Intercept	*–0.039*	*–0.038*	*–0.032*	*–0.034*
	<0.001	<0.001	<0.001	<0.001
*R*_1	*0.053*	-	-	-
	<0.001	-	-	-
*R*_3	-	*0.030*	-	-
	-	<0.001	-	-
*MR*_1	-	-	*0.009*	-
	-	-	<0.001	-
*MR*_3	-	-	-	*0.005*
	-	-	-	<0.001
σ_a	0.000	0.000	0.000	0.000
σ_e	0.231	0.233	0.238	0.239
Conditional R^2	-	-	-	-
Marginal R^2	0.333	0.276	0.067	0.058
N. of groups	1,783	1,783	1,783	1,783
N. of obs.	7,691	7,691	7,691	7,691

Notes: The estimated variance components corresponding to the investors' effects are null. This means that the models do not include investors' specific effect, but the estimates are reliable corresponding to a standard regression model specification.

Here, the aim is to verify whether the effect of prior performance of the individual portfolio or the equity market can influence a change in the clients' risk attitude. In model (9), the coefficient associated with the one-month-prior portfolio performance (R – 1) is positive (0.176) and statistically significant, suggesting the willingness to increase the portfolio risk profile following a positive recent past performance of the client's own portfolio, and *vice versa* if negative. In other words, for each increase of one percentage point in the performance of the client's own portfolio, the client increases the RS by 0.176 points. This result confirms that clients may suffer from the *self-attribution bias*, increasing their risk attitude after a positive performance of their own investments. Moreover, self-attribution bias may impact both clients and advisors, further reinforcing the tendency to increase risk after positive past performances. This evidence is confirmed by the results of model (10) based on the performance registered three months prior to the switch (R – 3). In this case, the impact is lower (the coefficient is equal to 0.062), suggesting that either the clients or the advisors (or both) are more influenced by the most recent portfolio performance. As for models (11) and (12), based on the prior equity market performance (instead of the own portfolio performance), the results confirm both the positive (and statistically significant) coefficients of the one-month-prior market performance (MR – 1) and three-months-prior market performance (MR – 3), respectively. In this case, the coefficients, 0.073 and 0.050, are lower than those in previous models. These results confirm that clients (and advisors) might suffer from *extrapolation bias*, that is, extrapolating past performances into the future, or at least, *chasing returns*. Table 8 (*panel B*) presents the results of models (9bis)–(12bis), reiterating the same regressions proposed in panel A, but using the SD as risk measure: in line with previous results, the coefficients are positive and highly significant.

These findings suggest that a positive past performance of the client's own portfolio and/or domestic equity market leads clients to add risk to the portfolio. Furthermore, we have found a higher magnitude of the change in the risk profile due to the portfolio past performance, rather than to the equity market performance.

5 Conclusions

Investors rely on financial advisors for their investment choices. However, it is still unclear in the literature whether advisors are able to create value for their clients or at least to reduce the negative effects of clients' behavioural biases. This is a relevant gap in the literature, to which we aim to contribute. We position our paper within the literature on financial advisors, with the purpose of analysing whether private bankers are able to provide customised advisory in terms of strategic asset allocation and create value. Our central argument is that private banking intends to offer more personalised advice than the ones offered to mass-market clients, the latter being already analysed by previous studies. Moreover, we aim to verify whether advisors are able to mitigate typical behavioural biases such as extrapolation bias and self-attribution bias.

We address these issues by analysing the portfolio characteristics of 5,627 clients who signed up for the private banking service of a leading European bank from 2005 to 2013. Our dataset is not only unique because it is proprietary and includes a relevant number of client-year observations, but also because it contains important information on high-net-worth clients' personal characteristics and on their portfolios.

We have found a 'one size fits all' approach in the strategic asset allocation: portfolios are similar and low regardless of the clients' age, particularly in the case of male clients. Younger clients hold the lowest percentage of equity in their portfolios. Women are more risk adverse and more static in their investment choices than men. We have found similar and low performance for each category examined, which differ by a few basis points, confirming the similarity of the strategic allocations of the portfolios as a whole. The number of switches is very low and, moreover, affects only small parts of the portfolio: this evidence depicts a buy and hold investment strategy during a period of high volatility of the equity and bond markets.

5.1 Managerial implications

Our large dataset in terms of the number of clients and the period observed, that includes both two important financial crises, allows us to claim that advisors offer quite similar, low risk portfolios to clients regardless of their age. During the time period observed, where two financial crises occurred, the market volatility of equity and bond markets have been extremely high. We provide evidence that a buy and hold strategy has offered very poor results. In fact, our results reveal a low number of switches, unable to generate significant positive returns.

Thus, even though our sample comprises high-net-worth clients, we have found evidence of neither a greater degree of customisation in the portfolio asset allocation – thus revealing a 'one size fits all' approach in private banking – nor the ability to add value for clients through changes in the portfolio strategic asset allocation.

At the same time, since we have found evidence of self-attribution bias and return-chasing behaviour caused by extrapolation bias, we can claim that advice does not mitigate clients' behavioural biases.

These findings have relevant managerial implications for the wealth and asset management industry. Asset managers should be more proactive to provide higher levels of customising, more focus on the strategic asset allocations and a more dynamic approach to align portfolios and clients' risk profiles. Advisors should consider the personal characteristics of their clients, starting with age, considering the client's lifetime horizon to issue asset allocation recommendations, as well as revision of the strategic asset allocation prompted by market opportunities.

5.2 Theoretical contributions

We provide several theoretical contributions to the literature that have implications for future research in this field.

First, in analysing high-net-worth clients we demonstrate that private bankers do not offer a tailored consultancy, since each banker handles a limited number of clients. Thus, this feature allows us to show evidence that a 'one size fits all' approach also affects private banking.

Second, since in private banking advisors have a base salary and their compensation schemes are mainly related to the growth of assets under management, rather than to the commission profile of the managed product, we provide reliable results because the advice is not subject to conflicts of interest, or at least our findings are less affected by this issue.

Third, we show that bankers suggest few changes in strategic asset allocation and when they do, they are influenced by past performance. This evidence suggests that advisory is not able to overcome self-attribution bias and extrapolation bias, leading to the return-chasing behaviour.

The ability to consider all the above-mentioned issues has implications for future research in this field. Other studies should investigate the quality of financial advice in a context of growing market uncertainty and volatility. The increasingly frequent crises affecting the markets, and investor confidence undermined by sudden shocks or increasingly complex and deregulated products, place a great responsibility on asset managers. The consultants are called upon to put the client's needs at the centre of their operations, or rather to pursue consistency and continuous adherence between the portfolio's and the client's risk profile.

5.3 Limitations and future research

We acknowledge that our paper presents some limitations that may somehow affect the generalisation of our results. The socio-demographic information available on clients are few, only regarding age and gender. As a matter of fact, many individual characteristics are quite sensitive and protected by privacy regulations. Being wealthy, the individuals in our sample may be multi-bank clients, thus we cannot observe their overall asset allocation. Furthermore, we do not possess information on advisors' personal characteristics, neither socio-demographic, nor in terms of expertise, etcetera. Such information may prove to be useful in explaining clients' asset allocation, as suggested by Foerster et al. (2017). The availability of more information both on clients and on private bankers would allow to better distinguish which choice in terms of asset allocation, for example switches, are chosen by the client and which ones instead are an initiative of the advisor. At the same time, it would be helpful to know which clients each advisor works with, to understand who decides to change asset allocation. Future research may address these issues.

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Notes

1 Benchmarks are usually composite indexes, that are, made of more than one index, representative of different asset classes. We use Bloomberg data to analyse the performance of the benchmark for each investment option, considering the return of the exchange rate, in case of local currency indexes (mainly USD).

2 This high number of investment options is due to the M&A activity of the bank, which led to the integration of clients and portfolios previously managed by other asset managers.

3 While the ways in which private bankers are remunerated do not fully exclude potential conflicts of interest, they are at least lower compared to the case in which advisors receive inducements.

4 The number of active clients grew over time as follows: 147 in 2005, 277 in 2006, 295 in 2007, 260 in 2008, 297 in 2009, 484 in 2010, 563 in 2011, 467 in 2012, and 737 in 2013.

5 The threshold, in terms of AuM, for private clients as stated by the bank is €1,000,000, even though investors 'below threshold' with potential for money accumulation may be accepted.

6 In particular, the number of clients grew as follows: 982 (2005), 1,226 (2006), 1,418 (2007), 1,614 (2008), 1,900 (2009), 3,020 (2010), 4,116 (2011), 4,489 (2012), 5,502 (2013). The analysis includes the entire client population, also considering the clients who decided to redeem their investments.

7 For example, a switch from risk score 1 (*liquidity*) to risk score 9 (*equity*) is a variation of +8 risk scores. Vice versa, from *equity* to *liquidity* is a variation of –8 risk scores.

8 In some cases, the level of risk is quite dispersed with respect to its median value, that is, we observe significant outliers. This evidence may be explained by stressed market conditions before the switch, which pushes the standard deviation upward.