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Variations in Investment Advice Provision: A Study of Financial Advisors of Millionaire Investors

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Abstract: Vignette methodology is used to examine how the personal characteristics of investors and financial advisors contribute to portfolio recommendations, and the judgements that advisors make about investment knowledge and control of prospective millionaire UK clients. We find that advisors use investor characteristics to make recommendations broadly in line with economic theory and regulatory requirements. However, women are judged less knowledgeable and in control of their investments than equivalent men. They also receive portfolio recommendations with slightly lower risk profiles. Portfolio recommendations vary by advisor, with experienced advisors and those with wealthier clients recommending higher risk portfolios. Unmeasured advisor variables also impact on judgements and recommendations. These findings have relevance to the wealth management industry and regulators, in focusing attention on the conscious and unconscious influences on the judgements advisors make about their clients.

Keywords: : financial advice; investors; risk tolerance; vignette; financial advisors; gender

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1 Introduction

Economic theory asserts and financial markets regulators uphold that certain observable personal characteristics such as age, net worth and prior investment experience determine the suitable risk and return composition in investment portfolios held by individual investors. Based on this premise, in situations where investors engage financial advisors to assist with managing their assets, financial market regulators require that advisors recommend suitable investment portfolios according to the individual characteristics and circumstances of each client (see, for example, Financial Conduct Authority Handbook, 2020[1]). However, regulatory supervision of advisor activities is based on best practice guidelines without precise specification of which investor characteristics to include or a standardised approach for how these should be evaluated. Financial advisors must therefore rely on their own judgement, and often limited client information, when they determine the most suitable investment portfolios for their clients. Further, there is little understanding of how the advisor's own personal characteristics and circumstances may influence how they interpret client needs and formulate recommendations.

To date, the few studies that have investigated how financial advisors make portfolio recommendations focus on mass-affluent investors (Foerster, Linnainmaa, Melzer, and Previtero, 2017; Kramer, 2016). Our current understanding is therefore particularly limited for millionaires, a key demographic for the wealth management industry - one who jointly possess nearly half of global wealth (CreditSuisse, 2019) and whose investment decisions have large societal and economic consequences. Further, despite female personal wealth growth outpacing that of men and hence wealthy women becoming an increasingly important client segment for financial advisors, research on financial advice to wealthy women is sparse.

Motivated by a combination of economic theory and previous empirical evidence, our study

[1] https://www.handbook.fca.org.uk/handbook/COBS/9A/2.html

contributes to extant research by examining the investor and advisor characteristics that financial advisors pay attention to when they interpret the investment needs of millionaires in order to formulate portfolio recommendations. In addition to those characteristics that economic theory asserts should contribute, we draw on social psychology research to investigate whether additional investor and advisor characteristics also contribute to these decisions. Psychological studies show that the way in which different observers judge the same person can vary considerably, depending on both observer and subject variables. Interpersonal judgements are influenced by the observer's personal characteristics, including attitudes and needs (Harvey, Madison, Martinko, Crook, and Crook, 2014; Weiner, 1985), and stereotypical, or implicit, assumptions based on group membership can also determine how observers interpret the needs and preferences of a subject, in this case individual investor clients (Fiske, 1998). For example, implicit gender theories typically result in observers underestimating women's ability and performance relative to that of men (Kray, Howland, Russell, and Jackman, 2017). More specifically, whereas performance success by men is more likely to be attributed to greater knowledge, women are considered less skilful (Martinko, Harvey, and Douglas, 2007) and to have less control over their successes (Heilman and Haynes, 2005; Swim and Sanna, 1996). Self and social perceptions about gender differences in abilities and control are particularly pertinent in quantitative domains (Meece, Glienke, and Burg, 2006), where entrepreneurs are typically judged to have high risk-tolerance, and investors with dependents to be more cautious about spending (Martinko et al., 2007). To date, there has been very little consideration of the potential for financial advisors to make differential judgements of the likely preferences and needs of wealthy male and female clients. However, it is possible that implicit assumptions influence initial judgements that advisors make about their clients.

With little known about how advisors judge the needs of male and female millionaire clients, our study considers two research questions: (1) how does the set of personal characteristics that financial advisors typically collect from millionaire clients contribute to the evaluative judgements advisors make about the investment risk tolerance, knowledge and control of millionaire investors, and (2) how do the personal characteristics of financial advisors contribute to their evaluative judgements of the investment risk tolerance, knowledge and control of millionaire investors?

We investigate these research questions with UK-based financial advisors who work predominantly with millionaire clients, and use vignette methodology to mimic early-stage meetings between financial advisors and prospective millionaire clients. Ten vignettes, each depicting a different millionaire, are presented to 129 financial advisors. Each vignette presents a realistic pen-portrait of an investor using the same characteristics (e.g., age, net worth and prior investment experience) that vary in content across investors (vignettes). We include ten different investor characteristics in each vignette. Each of these relate to a variable that, according to economic theory, contributes to the risk tolerance of an individual investor, and features in investment risk tolerance questionnaires, financial market regulatory suitability requirements, and previous empirical investigations. The panel of financial advisors in our study rate how knowledgeable and in control over their investments they believe each of the ten (fictional) investors is likely to be, and then recommend for each investor one of seven investment portfolios with varied risk profiles. To measure judgements bias in relation to gender, we control for gender by creating two versions of each vignette – one male and one female – that are rated by different advisors.

Our results show that investor characteristics included in the vignettes contribute to portfolio recommendations and advisor judgements in ways that mostly correspond with economic theory and regulatory requirements (Morin and Suarez, 1983; Wärneryd, 1996). For example, older investors are, on average, recommended less risky portfolios, while more experienced and wealthier investors are directed towards more risky portfolios. Investors with more experience are also judged more knowledgeable and in control of their investments.

However, variables included in the vignettes do not sufficiently explain advisor ratings. The riskiness of portfolios recommended for the same investor vary greatly across advisors, driven by measured but mainly unmeasured advisor characteristics. We find that more experienced financial advisors, and those with a wealthier existing 'real life' client base, make riskier recommendations. Indeed, unmeasured advisor characteristics contribute as much to portfolio recommendations as do investor characteristics, confirming findings by Foerster et al. (2017) who investigate advisor recommendations for less wealthy clients in a different setting and using a different methodology.

We find gender differences such that advisors judge female millionaires to have less knowledge and control of their investments compared to male millionaires in identical vignettes. Furthermore, when advisor characteristics are included in the regression, we show that female millionaires are recommended lower risk portfolios than those recommended to equivalent male millionaires. These findings correspond to previous social psychology research that shows gender stereotypes can bias judgements about women's capabilities and needs relative to men in other settings (Heilman and Haynes, 2005; Swim and Sanna, 1996). In a financial advice setting, these gendered assumptions are important, because they could result in more conservative recommendations that disadvantage women millionaires by leading them to invest in portfolios with lower return potential. Nevertheless, the economic magnitudes of these effects are quite small. The effect of changing the vignette gender from male to female, keeping all other information unchaged, is to decrease the risk of the recommended portfolio by just 0.05%. The effect on control is larger, equivalent to a decrease of one-quarter of a standard deviation of the pooled control responses. This is contrary to most of the existing research based on less affluent investors and suggests that gender bias attenuates with rising wealth levels.

We conclude that advisors do not solely evaluate client needs and make portfolio recommendations based on a predefined set of investor characteristics recognised by economic theory and regulators, but are influenced by a range of factors, including extraneous information about investors, their own individual characteristics, and gender. Our findings therefore contribute to a growing literature on financial advice, and are pertinent to financial markets regulators and the wealth management industry.

Our results highlight the need for future financial advice research to consider how financial advisors interpret their clients' investment needs, and how this sensemaking is influenced by investor and advisor characteristics, including the underlying motivations of financial advisors. Our study challenges how the activities of advisors are monitored and regulated today, giving rise to a need for institutions and regulators to increase understanding of potential bias in the financial advice process when they monitor the suitability of the portfolio recommendations that advisors make to their clients.

The remainder of this paper is organized as follows. In section 2 we discuss the literature. In section 3 we present our data set, describe the vignette methodology and the variables included in the study. Our results are presented and discussed in section 4, and we present our summary and conclusions in section 5.

2 Related Literature

Psychological factors inform investment decisions in ways that can lead to bias in investment decision-making behaviour (Kahneman and Tversky, 1973; Wärneryd, 1996). In order to minimise bias, and maximise the return on invested capital, wealthy individuals often engage professional financial advisors who provide information to help them navigate a complex investment landscape, and recommend how to invest their wealth. They do so with the expectations that the advisor will improve the investment decisions that they would have made in isolation. In these situations, an agency relationship forms where the investor delegates decision-making authority to the agent (the advisor) who is expected to apply rational decision making criteria in order to recommend optimal portfolios for the client's risk tolerance and personal goals.

During the early stages of a new client relationship, and as required by regulators prior to an advisor being able to provide investment recommendations, advisors capture client information using an investment questionnaire. This collates information about a range of client characteristics and personal circumstances that are used to help determine a risk and return profile for a client (Kramer, 2016; Charness, Gneezy, and Imas, 2013). The questionnaire is a means to understand and protect investor interests and provide regulators with evidence that investment recommendations are suitable for a particular client (Hermansson, 2018).

Early client meetings are also important social interactions: they initiate the financial advice relationship and set the context for advisor sensemaking and perceptual judgements about clients that can ultimately increase or decrease the allocation to risky assets in client portfolios (Hong, Kubik, and Stein, 2004). By leveraging their superior experience, expertise and access to information, advisors ought to be predisposed to rational investment decision making to reduce the behavioural biases an investor might exhibit in their own investment decisions (Feng and Seasholes, 2005). Therefore, potentially by encouraging reluctant investors to invest more, advisors ought to improve investment decisions for clients, and increase portfolio returns (Gennaioli, Shleifer, and Vishny, 2015). Advised portfolios can be better diversified (Kaustia, Alho, and Puttonen, 2008), however, evidence shows that advisors may also vary their recommendations to maximise fee income, encourage overtrading, and make unsuitable investment recommendations for clients (Sappington, 1991; Mullainathan, Noeth, and Schoar, 2012; Inderst and Ottaviani, 2012). Advisory portfolios can therefore have a lower return profile relative to self-directed portfolios, and there is currently no agreement as to whether advised portfolios are better diversified or have higher returns than self-directed portfolios (Hackethal, Haliassos, and Jappelli, 2012; Kramer, 2012; Hoechle, Ruenzi, Schaub, and Schmid, 2017).

That advisors' interpretation of client needs also depends on who the advisor is, has been confirmed by Foerster et al. (2017) who analyse transactional data on Canadian mass-affluent investors and find that measured and unmeasured advisor characteristics strongly affect the advice they give; including how advisors make recommendations that are very similar to the mutual funds that they hold in their own portfolios. Likewise, Mullainathan et al. (2012) find that while mass-affluent oriented financial advisors appear to consider client characteristics when formulating advice, they fail to de-bias their clients' portfolios and instead often exacerbate biases in order to further their own interests. Advisors recommending investments that are familiar to them is more congruent with a Keynesian than a Markowitz approach and suggests that that advisors tread carefully when recommending assets that are outside of their competence (Boyle, Garlappi, Uppal, and Wang, 2012). This is disadvantageous to investors because advisors – when making investment decisions for themselves – have been found to exhibit return chasing behaviour, trade too much, buy expensive mutual funds and hold under-diversified portfolios (Linnainmaa, Melzer, and Previtero, 2017).

Extant research on financial advice has focused on mass-affluent investors – typically considered to be those with less than USD100,000 to invest[2] – and their advisors. Our research focuses on millionaire investors and their financial advisors, a powerful, yet understudied and hard-to-reach research population. Our study participants are UK financial advisors working predominantly with millionaire clients. Ranking fourth largest in terms of the number of resident millionaires globally, the UK has a large and reputable wealth management industry, making the UK a relevant market in which to study financial advice to wealthy individuals with relevance to other jurisdictions.[3] However, with 73% of UK millionaires en-

[2]Europe Economics. 2014. Retail Distribution Review Post Implementation Review. http://www.fca.org.uk/static/documents/research/rdr-post-implementation-review-europe-economics.pdf.

[3]The UK wealth management industry manages privately owned offshore and onshore financial assets of USD1.79 trillion, equivalent to 46% of the country's GDP. In size, the offshore wealth management industry ranks second behind Switzerland

gaging financial advisors to assist in managing their assets, compared to only 9% of the adult UK population as a whole, financial advisors service primarily wealthy individuals (Credit-Suisse, 2019; FinancialConductAuthority, 2018). Researchers have associated the persistent wealth inequality to how the return on invested capital, i.e., capital that advisors facilitate millionaires to grow, exceeds the return of the economy as a whole (Piketty, 2015). Financial advisors therefore have the potential to influence the investment behaviour of a powerful, yet understudied, demographic whose investment behaviour has wide ranging economic and societal impact (Bhattacharya, Hackethal, Kaesler, Loos, and Meyer, 2012). Furthermore, the credibility and success of the UK wealth management industry is dependent on the ability of advisors to accurately understand and service the individual needs of these clients, which motivates the need to increase understanding of how financial advice is provided to millionaires.

The advisors who participate in our study look after 71 clients on average and manage assets in excess of USD450 million each. Advisors catering to the mass-affluent market typically have many more clients, but much lower levels of assets under management. For example, those examined in Foerster et al. (2017) have as many as 200 clients but only manage assets averaging CAD5.2m (USD4m) each.[4] Another important difference is that whilst most research examines advisors who are likely to be as wealthy as their clients, we study advisors whose personal wealth characteristics are very different to those of their clients.[5] Consequently, whilst advisors might recommend their mass-affluent investors to hold portfolios comprised of mutual funds that are also accessible to, and often held by, the advisors themselves (Foerster et al., 2017; Linnainmaa et al., 2017), advice to millionaires

and ahead of the US. See: https://www2.deloitte.com/content/dam/Deloitte/ch/Documents/financial-services/ch-fs-1800914_Deloitte-wealth-managemnet-Ranking-2018.pdf and https://www.theglobalcity.uk/PositiveWebsite/media/Research-reports/CoL-Global-City-Factsheets-Wealth-management-digital.pdf

[4]The largest advisor in their sample manages CAD14.6m (USD11m).

[5]Financial advisors earn on average USD90,000 annually (see U.S. New Money, 2018, "How Much do Financial Advisors Make?" https://money.usnews.com/careers/best-jobs/financial-advisor/salary

is more bespoke. With investment commitments frequently ranging from USD100,000 to several millions, the investment options available to the millionaire investors portrayed in our vignettes are ordinarily out of reach for their much less wealthy advisors. Relative to mass-affluent investors, millionaires have far less need to secure their future, and are more likely to have diverse investment goals including the acquisition of luxury assets, wealth transfer to future generations or philanthropic endeavours. This, combined with the cross-sectional variation in risk preferences and decreasing relative risk aversion with wealth demonstrated by Paravisini, Rappoport, and Ravina (2016), motivate our argument that financial advisors and their millionaire clients are likely to differ from those investigated previously, making it unwise simply to extrapolate findings from studies about financial advice to mass-affluent investors.

Evidence that advisors deviate from rational decision-making and investment metrics is problematic, but perhaps not surprising given that advisors make subjective interpretations of clients' needs and preferences, using information beyond that advocated by economic theory and financial markets regulators. Yet with very little known about how advisors make sense of client needs, nor what influences their perceptions, this study aims to address an important gap. We do so by investigating how advisors make use of investor and advisor characteristics for making portfolio recommendations and when evaluating the investment knowledge and control of millionaire clients.

3 Methodology

3.1 Vignette Methodology

Vignettes are meticulously constructed pen-portraits that describe hypothetical, yet lifelike, situations or specific characters. In the present study we follow accepted best practice in quantitative research, combining vignettes portraying individual millionaire investors with traditional survey questions on decision-making to examine the dependent variables (Aguinis and Bradley, 2014). Our vignettes include a range of investor characteristics and other contextual detail to ensure that the vignette narratives are realistic. Additional participant information is used as covariates for analysis and interpreting results (Atzmüller and Steiner, 2010). This process allows us to investigate how included characteristics contribute to advisor recommendations, and how advisor perceptions and judgements may be influenced by bias whilst ensuring good internal and external validity (Schoenberg and Ravdal, 2000).

Vignette methodology is commonplace in social science (Wallander, 2009). Aguinis and Bradley (2014) report that it has featured in more than 300 studies published in management journals, and has been used to investigate a diverse range of topics, including evaluative judgements about employee performance ratings (Skarlicki and Turner, 2014), institutional complexity (Raaijmakers, Vermeulen, Meeus, and Zietsma, 2015), business ethics (Hyman and Steiner, 1996), medical treatment (Ludwick and Zeller, 2001) and family obligations (Finch, 1987).

Despite its use in organizational behaviour, human resource management and psychology, the potential for using vignette methodology to examine decision making in financial advice settings has yet to be realised. However, recent economics research (Ambuehl and Ockenfels, 2017) has used vignettes to investigate ethical judgements about financial compensation for human egg donation, with participants rating vignettes that contain varying subject characteristics such as cognitive ability, education and financial situation. Kübler, Schmid, and Stüber (2018) use vignettes to investigate gender hiring discrimination in apprenticeship applications; by controlling for all applicant characteristics and varying gender, they found that male vignettes received significantly more positive evaluations from hiring managers than equivalent female vignettes.

Whilst this methodology tends have good internal validity, generalisability of vignettes to judgements or decision making in real scenarios is more challenging because, for example, satisficing render respondents to over or undervalue the fictional portraits relative to real scenarios (Stolte, 1994; Gould, 1996). Subsequently advisors in the present study may under or overestimate the relevance of the variables contained within the vignettes. The methodology can reduce the risk that advisors pander to their clients' preferences (Gennaioli et al., 2015), but the design may instead induce advisors to pander to the experimenter by behaving according to what they believe is expected of them (De Quidt, Haushofer, and Roth, 2018). However, Hainmueller, Hangartner, and Yamamoto (2015) compare the judgements made about the naturalization applications of hypothetical immigrants described in vignettes with real life decision making and identify high levels of similarity, providing comfort about the external validity of the present study.

Meetings between financial advisors and clients are difficult to access and observe for confidentiality reasons. Moreover, if observation was to occur, this could itself influence the way in which the two parties interact and behave. Semi-structured interviews with financial advisors can provide insights into the social judgements they make of their existing clients, but interviews may be contaminated by noise or non-verbal factors such as body language, personal appearance and casual conversation. Previous financial advice research has used historic transaction data records of retail accounts (Foerster et al., 2017; Hoechle et al., 2017) to analyse patterns of trading activity, return and diversification differentiation for advised accounts. However, database methodologies often lack information about the interactions between investors and advisors or how the social cognitive judgements that advisors make of investors impact on trading decisions, analyses made possible in this paper through the application of vignettes. Furthermore, unlike previous methodologies which limit the investigations to the recommendations made by one specific advisor to a specific investor, we investigate the recommendations that a panel of advisors make to the same set of ten investors.

Our method therefore makes it possible to evaluate the perceptual or biased judgements made by advisors as well as their advising behaviour in a test that replicates real scenarios in a situation where it is difficult to observe real life interactions, and in a more realistic way than asking a range of non-contextualised survey questions (Finch, 1987).

3.2 Dependent Variables

We investigate the judgements that advisors make in relation to three variables: portfolio recommendations (risk tolerance), investment knowledge and investment control.

3.2.1 Portfolio Recommendations

Portfolio theory assumes that investors are concerned with the risk and return of their overall investment portfolio. Therefore, it is commonplace for wealth management institutions to design a range of model portfolios with varied asset allocation and different expected risk and return profiles. This method follows the mean variance portfolio theory formulated by Markowitz (1952).

Advisors, or the institutions where they work, may have different views on what the portfolio asset allocation and internally developed model portfolios vary by institution, but the common strategy is to map a model portfolio to each clients' risk profile, derived using in house investment questionnaires. Following this methodology, each investor risk profile, and therefore each client, has a suitable model portfolio that advisor can recommend to them and which also corresponds to regulatory expectations. These model portfolios can be considered as the core investment offering by the institution, and by recommending them advisors help their clients to allocate wealth among a diverse collection of assets that the institution attempt to optimise using in-house financial modelling tools.

To have a controlled and familiar measure for how advisors make investment recommendations that reflect the evaluations that they make about clients' risk tolerance judgements we therefore create seven investment portfolios with varied asset allocations reflecting levels of risk. After reading each vignette we ask advisors: 'Which of the following portfolios would you recommend to this client?' Seven alternative investment portfolios were offered using varied asset allocations reflecting differing levels of risk ranging from 1 (very low) to 7 (very high). This follows methodology used in previous research, e.g., (Bhattacharya et al., 2012; De Bondt, 1998) and FCA approved advisor qualification training.[6] This method allows us to have a controlled measure of portfolios with varied asset allocation and different levels of return and risk expectations. Table I shows the asset allocation of the seven portfolios.

Four of the seven portfolios used in our study are the Wealth Management Association's benchmark portfolios prevailing at the time the survey was conducted. These are denoted with the titles "Conservative", "Income", "Balanced" and "Growth" in the headings of Table I. The Wealth Management Association[7] represents member firms within the private wealth management investment community in the UK. As such, these four portfolios are each familiar to the advisors we survey, and representative of the benchmark portfolios offered to private wealth management clients at the time. The portfolios without headings are interpolated/extrapolated from these benchmarks to provide a full range of alternatives with approximately equal difference in risk between each adjacent pair of portfolio as discussed further below.

Each portfolio includes a mix of investments, including stocks, bonds and other assets. The asset mix varies so that each portfolio has different risk as measured by the standard deviation of the return distribution of the asset portfolio. For example, portfolio one contains

[6] See for example the Financial Conduct Authority approved Chartered Wealth Manager Qualification: https://www.cisi.org/cisiweb2/cisi-website/study-with-us/wealth-retail/chartered-wealth-manager-qualification

[7] Since renamed the Personal Investment Management and Financial Advice Association.

51% bonds and 19% equities, whilst portfolio seven contains 3% bonds and 86% equities. Following their creation, a large UK bank helped in assessing the portfolios as representative for varied investor risk profiles and for their familiarity to advisors. During the pilot study, advisors and lay people were asked to rank the portfolios in order of risk, a task which they completed without any difficulty and portfolios were consistently ranked in the same order as they were designed. Hence, we are confident that professional advisors, when choosing portfolios, can assess the risk levels of each portfolio appropriately.

The final row of Table I gives an estimate of the volatility of the portfolio returns using recent historical data from the time the portfolios were constructed. Designed to be indicative of the level of risk each portfolio is expected to have, these values are not distributed with the portfolios and are merely presented here for information. However, by construction, the risk levels of the portfolios increase monotonically and almost linearly. In the statistical analysis below, we will use the portfolio number as the Recommended Portfolio (Rec. Port.) dependent variable in the analysis. Recognising that this is an ordinal ranking we will report results from ordered probit regressions. However, OLS results are very similar and given that a simple estimate of the portfolios' risks are closely and almost linearly related with the portfolio numbers, the portfolio numbers are also close to being cardinal. In the discussions below we deliberate the effect of explanatory variables in terms of how many portfolio units they alter the dependent variable (Rec. Port.). A one portfolio unit increase would be a move from portfolio 3 to 4 (or from 1 to 2, or from 6 to 7). Based on our computed standard deviations reported at the foot of Table I, the average change in portfolio risk in moving between adjacent portfolios is fairly consistent at 0.7. Therefore, a one portfolio unit increase also corresponds to an approximate 0.7 increase in risk. Thus, our results can also be interpreted in terms of portfolio risk whereby portfolio 1 has an annualised standard deviation of 6.31 and portfolio 7 has an annualised standard deviation of 10.60. This variation is comparable with other private investor indices, e.g., the MSCI PIMFA Private Investor

Indices where the five-year annualised standard deviation is 6.31 for the conservative index and 9.95 for the growth index.

3.2.2 Investment Knowledge

Our second dependent variable is investment knowledge. We ask advisors: 'On a scale from 1 to 10 how knowledgeable would you rate this client to be about investments?' (where 1 = not at all knowledgeable, 10 = extremely knowledgeable). Our measure follows that used by Lusardi and Mitchell (2014) whereby we elicit the advisor judgements using an assessment type question. This method is further closely aligned to the real role of the advisor who is faced with making a subjective assessment of their clients' investment knowledge.

Investment knowledge is found to predict both how confident investors are and how much risk they adopt in their investment portfolios. Conservative investment behaviour is often explained by lower levels of knowledge and confidence about making investment decisions, with notable gender differences (Charness and Gneezy, 2012; Eckel and Füllbrunn, 2015). In a review, Stolper and Walter (2017) demonstrate how the lack of financial knowledge and the ability to apply such knowledge to investment decision making are linked to suboptimal investment behaviour. Conversely, Bellofatto, D'Hondt, and De Winne (2018) show that knowledgeable investors make better investment decision, and hold diversified portfolios with higher returns.

Individuals with lower self-rated financial knowledge who are less confident about their investment abilities are found more likely to seek financial advice compared to those who consider themselves highly competent (Kramer, 2016). Investment knowledge has also been linked to how investors act in the relationship with their financial advisors. Those with higher confidence in their abilities are found monitor advisor activities more and seek second opinions (Calcagno, Giofré, and Urzì-Brancati, 2017). The tendency to overconfidently assess one's investment knowledge is more prevalent among male that female investors (Agnew and Szykman, 2005; Barber and Odean, 2001). This is recognised by financial markets regulators who include investment experience in their suitability requirements with clients' experience and knowledge important determinants for their abilities to understand investment risk and ability to adopt risk in their portfolios. Investment knowledge is therefore of economic importance for individuals and an important determinant for what portfolio recommendations advisors can make to their clients.

3.2.3 Investment Control

Our third dependent variable measures perceived investor control over investments. Advisors were asked to rate each vignette: 'Relative to the average investor, how much control do you think this client is likely to have over their investments?' (where 1 = a lot less than the average investor and 5 = a lot more than the average investor).

The psychological concept of *perceived control* has generated a substantial body of research. Broadly concerned with an individual's belief about the control that they and/or others have over their environment, it is also central to several important psychological theories, including social learning theory (Rotter, 1966), self-efficacy (Bandura, 1997), the theory of planned behaviour (Ajzen, 2002) and attribution theory (Weiner, 2018; Seligman, 1975). When comparing individuals with equal abilities, those who perceive themselves to have greater control over their abilities are found to act in a goal-oriented manner, compared to those who perceive themselves to have less control (Hsu and Chiu, 2004). An individual's ability to exert control can be influenced by the perceptions and expectations held by others, and there is considerable evidence that observers' judgements of the relative control men and women exert over equivalent outcomes are driven by stereotypical assumptions about male and female ability or preferences (Alan, Ertac, and Mumcu, 2018; Bordalo, Coffman, Gennaioli, and Shleifer, 2016; Carlana, 2019; Coffman, 2014; Milkman, Akinola, Chugh, Cachon, Caruso, and Fernandez, 2014). For example, observers are more likely to attribute the performance of women to luck (i.e., low control), and the performance of men to ability because of their assumed high levels of control (Deaux and Emswiller, 1974; Dweck, Davidson, Nelson, and Enna, 1978; Försterling, Preikschas, and Agthe, 2007). More recent studies in economic contexts have found similar gendered differences in how observers assess outcomes for male and female actors (Fenske, Castagnetti, Sharma, et al., 2020), including executive pay in the finance sector (Selody, 2010), firing of corporate executives (Landsman, 2018), and punishment for misconduct (Egan, Matvos, and Seru, 2017). Hajli and Lin (2016) propose that bias is more likely to emerge naturally in real-world settings where gender is more salient. Thus, in the case of financial advice, and when there is an absence of more detailed information about clients (e.g., when encountering a client for the first time), advisors' judgements may be more prone to influence from stereotypes based on distinctive group features, such as gender, as a basis – albeit potentially erroneous – for differentiating client needs (Hilton and Von Hippel, 1996). Consequently, financial advisors may assume that wealthy women clients will seek less control over investment decisions and have less knowledge of investing compared to equivalent wealthy male clients. In our study we investigate this possibility.

3.3 Vignette Variables

We include the same ten investor characteristics (i.e., 'vignette variables') in each of our ten vignettes, but vary the content for each client (i.e., 'vignette'). Vignette variables were selected based on previous empirical studies about financial advice and individual investors (Cooper, Kingyens, and Paradi, 2014; Foerster et al., 2017; Kramer, 2016), normative explanations of investor behaviour in economic theory (Campbell, Viceira, and Viceira, 2002) and variables included in investment risk tolerance questionnaires (Kramer, 2016), and which meet with the suitability requirements of financial market regulators. Whilst not intended as an exhaustive set, our variables are those that are typically collected by advisors of millionaire investors and those that financial advisors should pay attention to when making portfolio recommendations to their clients.

A major UK private bank assisted in assessing the vignette characteristics during the design and pilot process to verify that they include realistic variables from which advisors are able to derive risk tolerance and recommend portfolios. To ensure that the information about the variables in the vignettes was realistic and sufficient for advisors to make portfolio recommendations and rate the investment knowledge and control of the fictional investors, all vignettes and the portfolios advisors could select were initially tested with a small group of wealth management professionals and laypeople. This process provided confirmation that the information contained in the vignettes were credible in their description of millionaire investors about whom a judgement about investment risk tolerance, knowledge and control could be made. Following some minor amendments, and before the survey was distributed to respondents, it was piloted in its entirety with ten advisors who did not report any complications.

We have two aims in analysing the relations between vignette variables and our three explanatory variables. First, while our experience of the wealth management industry, the literature we discuss below and the views of the professionals who helped in designing the vignettes all suggest that these characteristics ought to be important in determining how advisors assess investors, we can test the relevance of individual characteristics in a controlled setting, concentrating on millionaire investors and advisors experienced in working with such clients. For many of the characteristics we have reasonably precise priors on the signs and sometimes even the magnitudes of their relation with risk tolerance. The focus here is whether there is a material difference between what we know from prior research based on less afluent investors and what we find in our analysis of millionaires. We have far weaker priors when we examine the perceived investment knowledge and control of investors and here our analysis is much more exploratory.

We pay particular attention to gender. Gender is not a personal characteristic that, according to the regulator or economic theory, ought to contribute to variations in risk tolerance. Notwithstanding this, male gender is associated with being more overconfident (Barber and Odean, 2001; Estes and Hosseini, 1988; Grinblatt and Keloharju, 2009), having higher levels of financial knowledge (Lusardi and Mitchell, 2007) and taking more investment risk (Charness and Gneezy, 2012; Dohmen, Falk, Huffman, Sunde, Schupp, and Wagner, 2011) compared to the female gender. Further, women are much less likely to hold a pension and, when they do, tend to make a lower allocation to risky assets compared to men (Agnew, Anderson, Gerlach, and Szykman, 2008). Recent studies demonstrate how other personal characteristics such as age or employment do not shift female conservative investment behaviour, but that investment experience and financial advice are related to women altering their risk-taking attitudes and allocating higher risk assets in their portfolios (Brooks, Sangiorgi, Hillenbrand, and Money, 2019). As explained below, the vignette methodology is particularly helpful in isolating the effect of gender on advisor responses.

Our second aim is to test how well the entirety of the information given in each vignette explains the recommendations and judgements of the advisors. This is more closely related to our first research question of how the set of personal characteristics that financial advisors typically collect from millionaire clients contributes to the evaluative judgements advisors make about the investment risk tolerance, knowledge and control of millionaire investors. Given that the vignette methodology gives us complete control over the information set received by advisors pertaining to each investor, we can test how well the information set explains advisor responses. Anticipating our results, we find that the joint explanatory power of the full set of vignette variables measured by pseudo-R squared regression statistics is quite low ($< 0.12\%$) for all three dependent variables and particularly low ($< 7\%$) for the portfolio recommendation. This motivates our subsequent analysis and second research question of how much advisor characteristics contribute to their recommendations and judgements.

The vignette variables are detailed in Table II and the ten vignettes are available in the Internet Appendix.

(1) Age (2) Years to Retirement: Younger investors with longer investment time horizons are able to allocate more wealth to risky assets, whereas risk tolerance is usually lower as investors age. Spaenjers and Spira (2015) find that the allocation to equities decreases by 0.07 percentage points for each year that investors near their retirement. It would therefore be reasonable to expect that financial advisors will assume that individuals accumulate risky assets during their younger years, and lead them to decrease the riskiness recommendations for older clients (Benartzi and Thaler, 2007).

(3) Net Worth (4) Income (5) Investment Amount (6) Outgoings: Higher levels of financial wealth and income can allow investors to invest larger amounts, and take more risk with their personal investments, because they can afford to incur more loss. An increased allocation to risky assets and increased capacity for investment risk among the wealthy is well documented in the literature (Bernheim, Skinner, and Weinberg, 2001; Calvet, Campbell, and Sodini, 2007; Carroll and Samwick, 1997). Consequently we anticipate that financial advisors will recommend riskier portfolios to vignettes where investors have higher levels of net worth, income and investment amounts, and lower risk recommendations for investors with less wealth and greater outgoings.

(7) Marital Status (8) Dependents: Empirical findings related to marital status are mixed with researchers identifying lower (Kannadhasan, 2015) and higher (Grable, 2000) financial risk tolerance among married investors, attributing variability to different financial responsibilities compared to single, and dependent-free investors (Snelbecker, Roszkowski, and Cutler, 1990). Spaenjers and Spira (2015), for example, identify lower levels of risk tolerance

among investors with children. Consequently, we make a tentative prediction that advisors are more likely to make lower risk recommendations to investors with dependents.

(9) Investment Experience: Prior investment experience has been shown to increase investors' ability to evaluate and understand investment options, and the risk associated with these (Agarwal and Mazumder, 2013; Haliassos and Bertaut, 1995). Investment experience is also identified by regulators as an important determinant for individual risk tolerance, with risk tolerance increasing both with investment experience and financial knowledge (Bellofatto et al., 2018; Feng and Seasholes, 2005; List, 2011). It is therefore reasonable to expect that financial advisors will offer riskier portfolios to more experienced investors.

(10) Entrepreneur: There is less evidence of an association between an investor's profession and their risk tolerance, knowledge or desired control in investing, however entrepreneurs characteristically experience greater unpredictability in their income, and may therefore benefit from greater risk diversification. Yet, entrepreneurs are found to have higher risk tolerance than managers with more stable incomes (Stewart Jr and Roth, 2001), and their risk-taking attributes have been linked both to overconfidence, and a higher level of equity market participation (Hvide and Panos, 2014). However, evidence from other research indicates that those in high-risk professions are less likely to participate in the stock market (Haliassos and Bertaut, 1995). Thus, professional advisors may either identify how lower risk investments may be suitable for entrepreneurs with income uncertainty or be tempted to try to match the high self-perceived risk tolerance levels generally associated with entrepreneurs.

Our vignettes are not designed to be representative of the full distribution of potential clients. Ten vignettes are simply too few to capture a distribution, but in pilot testing was judged the maximum number of vignettes that could be considered in a voluntary survey. Rather, the vignettes are supposed to be plausible potential clients with varying characteristics, allowing us to test our research questions. Advisors were informed that the investors were fictional.

Therefore, unlike the study by Mullainathan et al. (2012), where advisors were faced with actors presenting as real prospective clients, this design avoids selection biases relating to advisors making recommendations that they believe pander to clients' preferences in order to gain their trust (Gennaioli et al., 2015).

Our vignettes allow for a controlled experiment where each advisor judges and recommends portfolios to an identical set of ten investors. Since there are no other factors apart from the included variables that can obscure advisors' judgements, the methodology allows for isolation of the effects of investor variables contained in the vignettes. With a particular interest in the subjective judgements and gender bias applied by advisors, this method allows us to analyse the particular aspects within the vignettes that triggered advisors' judgements in our response interpretation. In this context it allows the testing of how the same investor is perceived by 129 different advisors and the portfolios the advisors recommend, something not previously attempted by financial advice researchers.

Another distinct advantage of the vignette methodology is that it is particularly conducive to examining the effect of gender. Congruent with Kübler et al. (2018), who – to measure gender bias in the evaluations of apprenticeship candidates – designed vignettes with equal characteristics in expectation terms, we exactly control for gender. However, unlike Kübler et al. (2018) we vary the gender within each of the ten vignettes to allow us to elicit the judgements made about equivalent male and female millionaires. Two versions of the survey were sent out. In one, the vignette characters' names followed an alternating female/male pattern such that the survey respondents were confronted by, e.g., 'Lucy' then 'Andy' then 'Sarah'. In the second variant, the names alternated male/female: e.g., 'Adam' then 'Stella' then 'Edward'. No other vignette characteristics were altered. This allows us to compare responses by advisors across otherwise perfectly matched male and female vignettes.[8] The

[8]We selected the various names used in the vignette such that they did not convey differences in ethnicity. The vignette approach could be adapted to study this phenomenon but we leave this for subsequent research.

respondents did not know that gender was a focus of our analysis or that vignette names were swapped across alternative versions of the survey.

3.4 Context and Participants

Data for the study were collected directly from financial advisors, employed by approximately ten different private wealth management institutions in the UK. With its long established and large wealth management industry for offshore and onshore assets the UK is a useful venue in which to study financial advice to millionaires with relevance to other jurisdictions.[9] A prerequisite was for participants to work for FCA regulated institutions that specialise in providing financial advice to high net worth individuals and mostly with clients who have at least USD1 million available to invest such as those described in the vignettes.[10]

The advisors in our sample have existing client bases who have assets exceeding USD7 million on average, compared to the average net worth of USD11.9 million in the ten vignettes. This hard to reach population was accessible due to one of the researcher's previous industry experience.

The FCA regulated status further ensures that advisors have obtained, and continue to main-

[9] The UK wealth management industry manages privately owned offshore and onshore financial assets of USD1.79 trillion, equivalent to 46% of the country's GDP. In size, the offshore wealth management industry ranks second behind Switzerland and ahead of the US. See: https://www2.deloitte.com/content/dam/Deloitte/ch/Documents/financial-services/ch-fs-1800914_Deloitte-wealth-managemnet-Ranking-2018.pdf and https://www.theglobalcity.uk/PositiveWebsite/media/Research-reports/CoL-Global-City-Factsheets-Wealth-management-digital.pdf

[10] The UK is of interest due to hosting a high proportion of the world's millionaires (7%), who control 24% of UK household wealth and its prominence in the global wealth management sector (Credit Suisse Global Wealth Databook, 2016, https://www.credit-suisse.com/uk/en/about-us/research/research-institute/news-and-videos/articles/news-and-expertise/2016/12/en/the-global-wealth-pyramid-2016.html). In addition, changes in the regulatory environment following the credit crisis have increased the focus on advisor activities with more stringent regulations that protect consumers and raised requirements of advisor qualifications (Financial Services Authority, 2011, https://www.fca.org.uk/publication/finalised-guidance/fsa-fg11-05.pdf).

tain, their knowledge about evaluating clients' risk tolerances based on the variables captured in investment questionnaires before recommending suitable investment portfolios.

The questionnaire was distributed on-line to approximately 400 financial advisors in 2014 whose responses were recorded anonymously. This resulted in 129 respondents representing approximatively ten wealth management institutions. Whilst the 32% response rate is below the average of 35.7% in organizational research it is within the standard deviation of 18.8 (Baruch and Holtom, 2008). The advisor demographics are summarised in Table III and plots of the distributions of the data are provided in the Online Appendix.

The 129 respondents yielded 1,147 vignette/advisor responses. Participants were on average 42 years old with nearly 13 years' experience of giving financial advice to client bases predominantly made up of millionaires. More specifically, on average 77% of the client base of the participating advisors are millionaires and, of these, 23% have investable assets in excess of USD30 million. Reflecting the relative wealth of their clients, advisors only have 71 clients on their books, on average, compared with advisors catering to the mass-affluent sector who often client bases of up to 250 investors. Our advisors therefore have an average of USD469 million in assets under advisement each. Only 27 of the 129 respondents are female, similar to the demographics of the male dominated advisor profession as a whole.

In the absence of demographic data from non-respondents we compare the demographics of our respondents to advisors who participated in continuing professional training organised by one of the authors during 2019. This training was delivered to 131 advisors who are employed at a large UK wealth management institution.[11] We compare the demographic data of our respondents to this "Institution sample" as a benchmark measure of the representativeness of our sample to the population of advisors at this large institution.

Comfortingly we find that our respondents share similar characteristics to the Institution

[11] Since this training was mandatory for advisors to attend, the 131 advisors represent nearly all advisors employed by the institution at the time it was delivered. The institution wishes to remain anonymous.

sample. The average age of advisors in our data is 41.7, somewhat higher than the Institution sample average of 38.3. Our respondents have almost two years more experience as financial advisors (12.8 vs 10.9), although unlike the age gap this difference is not statistically significant. The proportion of female respondents of 20.9% in our sample is in line with the 22.1% in the Institution sample. Advisors in both samples have mostly millionaire clients in their existing client bases, although the proportion of millionaire clients in the Institution sample is significantly higher (92%) compared to 77% in our sample. Not surprisingly the Institution sample advisors therefore only have 42 clients on average compared to 71 in our sample. As such, both samples fit the criteria of looking after mostly millionaire clients and therefore significantly fewer and wealthier clients than advisors examined in previous studies.

That we identify some differences between the two samples is not surprising since our advisors represents approximately ten wealth management institutions and are therefore perhaps more representative of the advisor population as a whole. With a substantial market share in the UK, the large institution naturally has a high proportion of wealthy clients and a long established training programme for graduate and inexperienced advisors who gain early access to wealthy clients.

4 Results

4.1 Data Analysis

Tables IV and V give correlations between the dependent variables we use and vignette and advisor characteristics, respectively.

The upper-left portion of Table IV shows a strong positive rank correlation between the knowledge and control ratings (significant at the 1% level), but no significant correlation between the recommended portfolio and either knowledge or control. Focusing on the strongest correlations, age, wealth and investment amount relate negatively to the mean investment portfolio recommendation, while evidence of investment and entrepreneurial experience relate positively. The correlation between gender and the portfolio recommendation is not significant.

Higher levels of income and investment experience relate positively to mean knowledge and control ratings, while gender is negatively correlated with the mean control rating (as is the presence of dependents). These correlations suggest that investor characteristics explicit in the vignettes relate to advisors' judgements of other investor characteristics (namely, their knowledge and control).

Conversely, Table V reveals no strong correlation between the dependent variable and advisor characteristics, though there are strong correlations between advisor characteristics.

4.2 Distributions of Ratings

Table VI shows summary statistics of the ratings across the vignettes for each of the three questions. The first point to note is that there is significant heterogeneity across vignettes. For example, Vignettes 8 and 3 are, on average, regarded as requiring low risk portfolios with mean portfolio recommendations of 2.7 and 2.8 (corresponding approximately to expected volatility levels of around 7.7%). Conversely, Vignettes 4, 5 and 10 are viewed as more risk-tolerant and are given mean portfolio recommendations of 4.5 or more (or volatility levels of over 9%). Similarly, advisors' judgements of knowledge and control vary across vignettes.

The second point to emerge from Table VI is that there is considerable within vignette disagreement among advisors. It is particularly noteworthy that for nine of the ten vignettes, every one of the seven alternative portfolios are recommended by at least one advisor. That is, for each vignette, some advisors made extremely conservative recommendations while others recommended extremely aggressive investment portfolios, despite the fact that because of the research design all advisors received exactly the same information set.[12] This suggests that factors beyond vignette characteristics are important in determining the recommendations and judgements, though as noted, there are no significant correlations between measured advisor characteristics and our dependent variables in Table V.

There is attrition in the sample such that while all 129 respondents rate the first vignette, only 109 respond to the final four vignettes. While the attrition rate does correlate with respondent characteristics such that older respondents and those with a larger proportion of millionaire clients are more likely to complete the survey, attrition does not affect our findings materially. All of our main conclusions remain valid if we instead only use the 109 sets of complete responses.

4.3 Vignette Heterogeneity

In this section, we investigate how investor characteristics drive differences in portfolio recommendations and knowledge and control judgements across the ten vignettes. Regressions of the following form are performed:

$$\begin{aligned} Y_{ij} =& \alpha + \beta_1 Age_i + \beta_2 Gender_i + \beta_3 Depend_i + \beta_4 Experience_i + \beta_5 Entre_i + \\ & \beta_6 NW_i + \beta_7 InvAmount_i + \beta_8 Income_i + \epsilon_{ij} \end{aligned} \tag{1}$$

The dependent variable (Yij) is the number of the portfolio recommended for vignette i by advisor j, or the judgements that advisor j makes of the investment knowledge of vignette

[12] Advisors do receive vignettes with different genders but, as discussed below, this does not have a material impact on portfolio recommendations.

i or the control that vignette i has over their investments. The explanatory variables are derived from the information contained within each vignette (see Table II). They include the age of the investor (Age_i), an indicator variable taking the value one if the investor is female and zero otherwise ($Gender_i$), an indicator variable taking the value one if the investor has dependents and zero otherwise ($Depend_i$), an indicator variable taking the value one if the investor has a high level of prior investment experience and zero otherwise ($Experience_i$), an indicator variable taking a value of one if the investor in an entrepreneur and zero otherwise ($Entre_i$), the investor's net worth in USD (NW_i), the intended investment amount ($Invamt_i$), and finally their annual income ($Income_i$).[13]

Recognising that the dependent variables are both discrete and ordered, all regressions are estimated using the ordered probit method (Liddell and Kruschke, 2018). Results are very similar if we use ordinary least squares instead (available on request). Advisor fixed effects are included to control for the considerable heterogeneity across the financial advisors, and we further justify this decision in the following section.[14] We report robust standard errors clustered by vignette.

The first three columns of Table VII report results with the recommended portfolio, investment knowledge and investment control as dependent variable, respectively. Encouragingly, we find that advisors make use of investor characteristics when making portfolio recommendations and judgements about investors, mostly in ways that are straightforward to interpret

[13]Note that the regression excludes three variables. The 'number of years until retirement' variable is excluded because it correlates nearly perfectly and negatively with age (Pearson's r = -0.98). The 'marital status/single' variable is excluded as nearly all vignettes portray investors with partners, and with the 'dependents' variable being more important for risk taking. 'Outgoings' is excluded since it only makes use of an average of 2.53% of the net worth of the investors. Including these variables in the regression does not have an effect on our conclusions.

[14]The use or ordered probit models with fixed effects means we have to consider the incidental parameters problem carefully. We compare results from ordered probit regressions including fixed effects to ordered probit results without fixed effects and to OLS results both with and without fixed effects. While precise coefficient estimates vary across estimations no key parameters change in unexpected ways under ordered probit with fixed effects. We are confident that our inferences are robust.

and that correspond with economic theory.

Older investors, who have shorter investment time horizons, are recommended lower risk portfolios (and are deemed to be more knowledgeable). The impact of age on the recommendation is economically large with a ten-year increase in age being associated with a 0.7-0.94 unit decrease in recommended portfolio (or a 0.5-0.7% drop in risk given the approximate 0.7% change in risk per portfolio number). This finding is robust to alternative specifications such as using log of age or indicator dummies capturing 'young', 'middle-aged' or 'old' investors. This contrasts with the findings of Mullainathan et al. (2012). In their setting, while showing that some client characteristics did appear to influence recommendations, advisors of mass-affluent investors did not tailor portfolio advice with client age.

Consistent with how individuals with higher levels of investment knowledge or experience are more skilled at evaluating investment options (Agarwal and Mazumder, 2013) and thus have a higher capacity for financial risk taking (List, 2011), we show how investors with investment experience receive more risky portfolio recommendations. The magnitudes of these effects are economically significant. A vignette with a high level of investment experience sees half a unit increase in their recommended portfolio. An indicator dummy capturing vignettes with low levels of investment experience is not significant when used instead of the high experience indicator, suggesting that advisors are only willing to boost risk levels for investors with higher than average levels of experience, but do not cut risk even for the least experienced.

While the amount available to be invested increases portfolio risk recommendations, net worth has a decreasing effect, contrary to conventional economic theory which argues that investors with higher net worth can withstand more volatility and thus have an increased capacity for investment risk. The negative net worth effect, though statistically significant, is economically quite small. This contrasts with (Foerster et al., 2017) who note positive income and wealth effects on portfolio recommendations. Our findings suggest that advisors of millionaires make different judgements about the risk tolerance of their clients than do advisors of mass-affluent investors. In particular, they appear to consider that their clients, whilst having a high capacity to take risks, do not necessarily need to invest as much as less wealthy investors since their financial resources are already plentiful. This interpretation is supported by the finding that advisors recommend investors with dependents to hold portfolios with a higher allocation to risky assets than dependent-free investors. This is despite judging investors with dependents to be less knowledgeable and to have less control over their investment. The effect of dependents is large and investors with dependents are recommended portfolios that are nearly one unit more risky than dependent-free investors. Millionaires are different since they do not need to invest to secure their own future. However millionaires with dependents may be concerned with wealth transfer to future generations, and so their advisors recommend more risky portfolios.

Entrepreneurs often have high levels of income uncertainty and are frequently identified as having higher risk tolerance relative to employees with stable incomes (Stewart Jr and Roth, 2001). Conversely, a lower allocation to risky assets to diversify from the entrepreneurial risks can be appropriate relative to those with stable incomes (Samuelson, 1989). We find that entrepreneurs are recommended approximately one-half unit lower risk portfolios, on average. Advisors, it seems, deliberate the overall risk exposure of individuals when making lower risk recommendations to entrepreneurs, despite not judging entrepreneurs to have lower financial literacy or control.

Fewer characteristics appear to matter when we focus on the judgements that advisors make about the knowledge and control exhibited by each vignette. Advisors are consistent in judging investors with a high level of prior investment experience to be more knowledgeable and to have more control over their investments (0.2 units on the 10-point scale for knowledge and one unit on the 5-point scale for control). These judgements are in line with portfolio theory, suitability guidelines and previous research which shows that individuals who are financially literate and experienced are more likely to invest in the stock market and have retirement plans (Van Rooij, Lusardi, and Alessie, 2011). The presence of dependents has a similarly large negative effect on both judgements. Higher annual income contributes to increases in the knowledge rating, but its economic impact is slight, while age, net worth, investment amount and whether the vignette portrays an entrepreneur or not are not statistically significant.

The Internet Appendix contains a number of tables of results where we demonstrate the robustness of our conclusions in this section. For each of our dependent variables we first repeat regression (1) using nine of the ten vignettes, sequentially dropping one vignette. Second, we estimate the regression based on the responses of different subsets of advisors. We exclude all young advisors (those less than 36 years old), all old advisors (those older than 47), female advisors, very experienced advisors (more than 17 years), inexperienced advisors (less than 8 years) and advisors who handle relatively few millionaires as a share of all clients (less than 25%). While coefficient estimates vary somewhat and statistical significance is reduced, at least in part due to smaller sample sizes, our main inferences are not affected.

Given the alternating of the names used in the two versions of the study, we have a matched sample with which to test gender effects. Though classical finance theory has little to say on such effects, empirical findings are prevalent. Our findings show that women investors are judged by their advisors to have lower levels of knowledge and control over their investments than identical male investors, consistent with the univariate analysis of gender effects in Baeckström, Silvester, and Pownall (2018). That observers are more likely to underestimate women's abilities relative to men (Heilman and Haynes, 2005) and perceive women to have less control over their successes relative to men (Swim and Sanna, 1996), appears to extend to the judgements that financial advisors make of equivalent male and female millionaires. Nevertheless, the economic significance of this effect is weak, especially for knowledge. Female vignettes receive control ratings which are 0.27 units lower than male vignettes with the effect dropping to just 0.12 units for knowledge. Given the pooled sample standard deviations reported in table VII, the gender effect is 26% of a standard deviation for control and just 5% of a standard deviation for knowledge.

While there is a relatively large body of literature noting important gender effects in finance, these are not fully supported by the judgements that financial advisors make of which portfolios are suitable for equivalent male and female millionaires. Despite advisors rating women as less knowledgeable and less in control of their investments, the statistically significant negative gender effect on the portfolio recommendation is small in magnitude. Changing the vignette gender from male to female while keeping all other information in the vignette unchanged results in a 0.06-unit reduction in the portfolio recommendation, equivalent to a portfolio risk reduction of around 0.05% (of just 0.4% of the pooled standard deviation of Rec. Port.). This is in stark contrast with Foerster et al. (2017) who find women's risky portfolio shares to be nine percentage points below those of men, controlling for other demographic factors in a regression framework, and Mullainathan et al. (2012) who document that female clients are recommended to hold less risky investments than men. Our results suggest that some of the gender bias in terms of investment recommendations attenuates with rising wealth levels, despite the significant differences in knowledge and control assessments.

We argue above that portfolio recommendations might be influenced by how knowledgeable and in control investors are judged to be (but not vice versa). To this end we add Knowledge and Control as explanatory variables in regressions modelling the portfolio recommendation. The results – given in the final column of Table VII – show that advisors make higher risk recommendations to investors who they judge to be more in control of their investments.[15]

[15]Given the high correlation between knowledge and control it is not easy to separate their effects. Knowledge is significant at the ten-percent level when control is not included (and control is highly significant when knowledge is not included), suggesting control is the dominant dimension, though we would not emphasise this distinction strongly.

This can be interpreted as advisors prudently judging the dependence that clients have on them, assuming that those who are more likely to maintain control of their investments can make larger allocations to risky assets. Results in the opposite direction would have been worrying, possibly suggesting that advisors take advantage of clients with high levels of dependence.

We note that the coefficient on vignette gender shrinks and loses all statistical significance in this final column of results. This suggests that the small gender effect on the portfolio recommendation is the indirect result of a social cognitive bias. Female investors are advised (slightly) less risky portfolios than equivalent men and that this relates to women being judged to be less in control of their investments. That observers assume women to have less control over their successes relative to men may therefore extend to financial advisor judgements because, despite how the women described in the vignettes are exactly identical to the men, they are considered by advisors to have less control (Guillén, Mayo, and Karelaia, 2016) over their investments. Advisors may believe that female clients are more dependent on them and are therefore are more cautious with their recommendations in order to manage the possibility of their female clients being anxious about investment risk (Loewenstein, Weber, Hsee, and Welch, 2001). This may indicate that advisor underestimate the competence of their successful female clients to the detriment of their own income and the return potential in the portfolios held by female clients. However our findings also appear congruent with advisors following ethical practices and not 'taking advantage' of individuals with low levels of confidence and high levels of dependence on their recommendations, and in line with the assumption that individuals with little prior investment experience ought to adopt less portfolio risk.

Despite the statistical significance of several variables in the recommended portfolio regressions, the variables included in the vignettes do not sufficiently explain advisor ratings.[16]

[16] Replacing vignette characteristics with vignette fixed effects only very slightly alters explanatory power.

The pseudo-R2 of 16% in column 1 of Table VII falls to just 6.4% if advisor fixed effects are excluded from the regression (see final row of Table VII). This is most apparent for the recommended portfolio but is also true for knowledge and control ratings. Together with the large within-vignette variation noted in section 4.2, this suggests that advisors differ in their views and that recommendations are predicated on other influences. That is, despite each advisor receiving exactly the same information set, the millionaires portrayed in the vignettes receive different portfolio recommendations and are judged differently depending on who the advisor is. We explore the effects of advisor heterogeneity more in the next subsection.

4.4 Advisor Heterogeneity

The impacts of measured advisor variables in determining portfolio recommendations are modelled with regressions of the form:

$$Y_{ij} = \alpha + \beta_1 Age_j + \beta_2 Gender_j + \beta_3 Experience_j + \beta_4 Millionaires_j + \beta_5 NoClients_j + \epsilon_{ij} \quad (2)$$

The dependent variables (Y_{ij}) are the same as those considered in regression (1), namely the portfolio recommendation, knowledge and control. Explanatory variables are the age of the advisor (Age_j), the gender of the advisor, taking the value one if female and zero otherwise ($Gender_j$), the number of years of experience as a financial advisor ($Experience_j$), the total number of clients each advisor has in their real world client base ($NoClients_j$), and the proportion (%) of millionaire clients that each advisors has in their client base, compared to clients with less than USD1 million in investable assets ($Millionaires_j$).

We estimate ordered probit regressions, this time with fixed effects for each vignette. The vignette fixed effects control for the characteristics of each vignette examined above in a parsimonious way.[17] All standard errors are robust and clustered by vignette.

Three advisor variables are related to portfolio recommendations (Table VIII, Column (1)).[18] First, the existing client base of advisors affects how they perceive the fictional investors in the vignettes, suggesting that advisors more used to dealing with millionaire clients make higher risk recommendations. Advisors more used to dealing with extremely wealthy clients are aware that such investors can absorb more risk. Conversely, advisors used to less wealthy clients are habitually more conservative. It is possible that these advisors mirror the assumptions they make about the risk tolerances of their usual clients onto the investors portrayed in the vignettes, yet this is in contrast with how portfolio risk recommendations decrease with increased levels of net-worth ascribed to the investors in the vignettes (discussed in section 4.3).

Second, older advisors appear to recommend less risky portfolios while, third, more experienced advisors recommend portfolios with a higher allocation to risky assets and judge investors to be more financially knowledgeable than less experienced advisors. These results appear at odds since one might think that older advisors are likely to be more experienced. To shed more light on this, we replace the continuous Age variable with two indicator variables for 'young' advisors (below 35 years) and 'old' advisors (above 47 years), and we replace advisor experience with indicator variables for 'low' experience (less than eight years) and 'high' experience (more than 17 years).[19] Column (2) of Table VIII gives the results of using these indicator variable and reveals that two off-setting non-linear effects are at play. Advisors younger than 35 tend to advise more risky portfolios but any effect of age on portfolio recommendation disappears once they reach 'middle age'. However, highly experienced

[17]Given the near equivalence of vignette characteristics and vignette fixed effects, it is not surprising that we obtain essentially identical results if we instead use vignette characteristics (results available on request).

[18]The Internet appendix contains a table of results where we repeat this analysis sequentially dropping one vignette at a time to demonstrate the robustness of these results.

[19]These breakpoints correspond to the 25th and 75th percentiles of the age and experience distributions of our respondents.

advisors also make higher risk recommendations, suggesting that advisors who have spent their entire career in the profession recommend more risky portfolios because they are either young or experienced. Conversely, advisors new to the profession initially recommend less risky portfolios and it is only once they build considerable experience that their portfolio recommendations become more risky.

Advisor gender is not strongly related to portfolio recommendations. The point estimates suggest female advisors recommend less risky portfolios, but this effect is quite small and is only weakly significant. Gender does not strongly drive the heterogeneity of portfolio recommendations across advisors.

Advisor gender, age and experience do explain the knowledge judgements that advisors make (Column 3 of Table VIII). Female advisors on average rate investor knowledge one-fifth of a unit lower than male advisors (with marginal significance). Older advisors give significantly lower knowledge scores and again we find that advisor experience has a positive effect on knowledge scores.

Control ratings weakly decline with age, but none of the other observed advisor variables strongly relate to the control judgements advisors make. While the measured advisor characteristics are more successful in explaining portfolio recommendation and knowledge ratings, the pseudo-R2 numbers reported in Table VIII are all quite low, and the vast majority of the explanatory power comes from the vignette fixed effects. In column (1) for example, the pseudo-R2 is just 7.1%. If we remove vignette fixed effects this drops to 0.4%.

The results pertaining to portfolio recommendations, and to a certain extent knowledge and control, suggest that recommendations have an introspective element with advisor age, experience and the make-up of their client base all contributing significantly to the portfolio recommendations that they make. This finding is inconsistent with a metrics-based approach to financial advice, regulatory requirements and economic theory. Advisors, it seems, are not only likely to recommend investments that have a high level of familiarity (Foerster et al., 2017), they also struggle to separate familiar characteristics, both of themselves and of their existing client base, when judging the needs of others. An advisor who have a tendency to regard (all) investors as being less knowledgeable and less in control of their investments also recommends a lower risk portfolio for (all of) them. She may make the same assessment of her own knowledge and control, in which case her own portfolio is also likely to be low risk, but this mechanism is subtly different from simple mirroring. These results suggest that advisors feel that financially literate individuals can withstand more risk than those who are less knowledgeable, in line with Gaudecker (2015) who also find a positive relation between household financial literacy and financial risk taking. An important difference here though is that we find that a large proportion of this subjective judgement about investors' knowledge and control is driven by advisor characteristics. That, in particular older, advisors make more conservative knowledge and control judgements and recommend lower risk portfolios may be an indication that advisors themselves – and in line with economic theory – become more cautious in their own investment behaviour as they age. Advisors bestow this behaviour onto their clients by recommending that they too reduce their equity exposure (Spaenjers and Spira, 2015). Advisor judgements therefore are influenced by their own personal characteristics, attitudes and needs (Harvey et al., 2014; Weiner, 1985).

Replacing advisor characteristics with advisor fixed effects improves the pseudo-R2 numbers for all three dependent variables but especially for the recommended portfolio. If we only include advisor variables in the regressions (i.e., without vignette fixed effects), the pseudo R-squared statistics are all near zero (top row of bottom panel of Table VIII). However, replacing the advisor characteristics with advisor fixed effects, therefore capturing unmeasured advisor characteristics, raises the explanatory power significantly (second row of bottom panel). In fact, we find that advisor fixed effects contribute just as much as investor variables in explaining portfolio recommendations. The final two rows of Table VIII show that the pseudo-R2 for recommended portfolio with just advisor fixed effects is 7.4%, rising to 16.4% when including vignette fixed effects. Since unreported results show that interaction terms and alternative functional forms barely change the explanatory power of advisor characteristics-based regressions, we conclude that unmeasured advisor characteristics are extremely important. These effects are also economically large. Moving from the 25th percentile to the 75th percentile of the distribution of advisor fixed effects increases the portfolio recommendation by 0.77 portfolio units, approximately equivalent to an increase of 0.54% in portfolio volatility. In terms of investor characteristics, such a move is approximately equivalent to a 10 year decrease in the age of the investor, more important than being deemed to have investment experience, but slightly less important than whether the investor has dependents (based on the ordered probit results in Table VII).

The importance of unobserved advisor fixed effects in portfolio recommendations is a key finding of Foerster et al. (2017) who interpret the fixed effects as implying that an advisor with a strong view on future asset performance will recommend that all clients adopt a particular portfolio mix. Naturally, the advisor also adopts the same portfolio. In a mass-affluent setting, that an advisor mirrors their own portfolio in the recommendation they make to clients with similar needs and levels of wealth is plausible and the evidence based on mass-affluent Canadian investors is compelling. In our case, this explanation is less credible given the nature of the investors we consider. Mirroring the advisor's own portfolio in the recommendations made to millionaire clients who have markedly different levels of wealth, investment needs and risk capacities would be particularly inadvisable. The relatively low explanatory power of known advisor characteristics compared to advisor fixed effects, combined with their importance for portfolio recommendations, indicate that in order to fully understand how advisors arrive at their recommendations we need to understand much more about the professionals who provide the advice, perhaps more so than about the clients who they advise.

Unmeasured advisor characteristics also explain a significant proportion of the knowledge and control judgements. Interestingly, the advisor fixed effects estimated (independently) for the three dependent variables are highly correlated. The correlation between the advisor fixed effect coefficients from the portfolio recommendation regression and the advisor fixed effect coefficients from the knowledge (control) regression is 0.41 (0.52). That is, the component of portfolio recommendations originating from advisor characteristics - and hence common to all vignettes - is highly correlated with the (fixed) components of knowledge and control judgements also derived from advisor characteristics.

This implies that an advisor with a tendency to regard (all) investors as being less knowledgeable and less in control of their investments also recommends a lower risk portfolio for (all of) them. This advisor also makes the same assessment of their own knowledge and control, in which case their own portfolio is also likely to be low risk, but this mechanism is subtly different from simple mirroring. The results suggest that advisors feel that financially literate individuals can withstand more risk than those who are less knowledgeable, in line with Gaudecker (2015) who also finds a positive relation between household financial literacy and financial risk taking. An important difference here though is that we find that a large proportion of this subjective judgement about investors' knowledge and control is driven by (unmeasured) advisor characteristics as well as those of the investors.

That the portfolio recommendations made by advisors depend equally on the vignettes and advisor characteristics, with *unobserved* advisor characteristics of particular relevance, is probably the most important finding presented here. Despite reasons to think that millionaires differ in their investment objectives, constraints, risk aversion levels and risk preferences, and that their advisors have different business models to mass-affluent advisors, our results are consistent with findings of Foerster et al. (2017) regarding financial advisors and mass-affluent investors. Economic theory postulates normative explanations to individual risk tolerance based on the personal characteristics of investors (Calvet and Sodini, 2014), thus setting implicit expectations that financial advisors should use investor characteristics to judge the risk tolerance of their clients. However this is not what occurs in situations where investors engage financial advisors. A considerable amount of the variation in individual risk tolerance levels (Yook and Everett, 2003) and advisor portfolio recommendations (Foerster et al., 2017) remain unexplained by the personal characteristics and circumstances of investors, findings which we replicate and which are therefore prevalent across the industry and not only found in the mass-affluent segment. Our findings that advisors draw on introspective attributes (Pronin, 2007) when making their recommendations provide ripe territory for future research into the conscious and unconscious influences on the judgements that financial advisors make about their clients to add complication to extant understanding about the rational agency of financial advice (Cooper et al., 2014).

5 Summary and Conclusion

We examine how the personal characteristics of millionaire investors and their financial advisors contribute to portfolio recommendations and the evaluative judgements that advisors make about the investment knowledge and control of prospective millionaire clients. We conduct our analysis using vignette methodology in which we portray ten fictitious millionaire clients considered by a panel of 129 financial advisors. Millionaires form an important demographic that controls nearly half of global personal wealth. With over two thirds of millionaires in the UK who engage advisors, financial advice to this demographic is a powerful industry. Yet financial advice to millionaires is rarely analysed in the literature, not least due to access and confidentiality issues. We circumvent such constraints by using a vignette-based methodology that has the additional advantage of perfectly controlling the information provided about each investor whilst allowing for investor gender to be varied unknown to advisors. By widening the behavioural scope of previous research, we analyse how financial advisors make sense of client characteristics when evaluating their clients and make portfolio recommendations, and how advisors draw on their own characteristics, both measured and unmeasured. Our research thus investigates the social cognitive judgements that advisors make about prospective millionaire investment clients to provide more insight into the social interactions between advisors and investors.

First, our results show that the characteristics of the investors given in the vignettes contribute to both the portfolio recommendations and the judgements that advisors make in ways that is relatively consistent with economic theory and regulatory assumptions. However, we identify a gender bias: advisors judge women to be somewhat less knowledgeable and to have less control over their investments relative to exactly equivalent male millionaires. Advisors also have a tendency to recommend slightly lower risk portfolios to female investors. These findings compare to extant social psychology research that indicate how gender stereotypes can bias judgements about women's abilities and needs relative to men. However, these differences are not economically large and therefore suggest that gender bias attenuates with rising wealth levels.

Second, we show that there is substantial variation in the portfolios that the advisors recommend for the same investor and that these variations are driven by advisor characteristics. For example, experienced advisors and those who have wealthier existing client base make more aggressive recommendations. Potentially advisors therefore inform their client judgements and portfolio recommendations on their own needs. Furthermore, we show that unmeasured advisor characteristics appear much more important and contribute equally to portfolio recommendations as do investor characteristics.

Our results thus demonstrate that advisors of millionaires do not exclusively rely on a predefined set of investor characteristics as recognised by economic theory and financial market regulators when evaluating clients and making portfolio recommendations. Their judgements are obscured by a wide range of influences about the investors they observe and themselves, including gender. Therefore, the asset allocation in the portfolios held by millionaires and indeed the performance of their portfolios are likely to be influenced just as much by who their advisor is as their own investment preferences. The matching of advisor and client is therefore of great importance and worthy of further analysis. Contributing to the literature about financial advice our study provides interesting avenues for future research into the financial advice interaction both to wealthy individuals but also to inform the future development of the financial advice model as it extends to excluded customer groups.

Our findings are pertinent to financial markets regulators and the wealth management industry. We add complexity and insight into potential conflicts of interest within the investment advisory process, placing a spotlight on the need for wealth management institutions to increase their understanding of the interactions between the advisors they employ and the prospective investors they seek to attract as clients. Such investigations need to include the conscious and unconscious motivations of financial advisors with a specific focus on gender bias. The latter is of particular importance to an industry that seeks to address the persistent under-representation of female financial advisors at the same time as they wish to attract the growing proportion of prospective female clients.

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Table I
Portfolios

Asset	Portfolio 1	Conservative Portfolio 2	Portfolio 3	Income Portfolio 4	Balanced Portfolio 5	Growth Portfolio 6	Portfolio 7
UK Equities	11%	19%	27%	35%	38%	40%	42%
International Equities	8%	11%	14%	18%	30%	38%	44%
Bonds	51%	45%	39%	33%	18%	8%	3%
Cash	6%	5%	5%	5%	5%	3%	0%
Commercial Property	6%	5%	5%	5%	5%	5%	3%
Hedge funds/Alternatives	18%	15%	10%	5%	5%	8%	9%
Weighted Average Volality (%)	6.31	7.13	7.91	8.69	9.42	9.98	10.60

Notes: This table gives details of the seven sample portfolios respondents were allowed to select when making recommendations for each vignette. The data in the final row of the table was not given to respondents.

Table II
Vignette Variables

	1	2	3	4	5	6	7	8	9	10
Name (gender)	Lucy/ Adam	Stella/ Andy	Sarah/ Edward	Susan/ Michael	Alison/ Patrick	Paula/ Paul	Martha/ Kevin	Anna/ Nick	Caroline/ Peter	Catherine/ John
(1) Age	45	42	74	36	25	51	47	59	60	38
(2) Retirement	20	23	0	29	40	14	18	6	5	27
(3) Net worth	8M	3.5M	15M	2.6M	35M	0.8M	4M	4M	40M	5M
(4) Income	125K	0	0	180K	0	300K	90K	580K	0	800K
(5) Investment	3M	1.5M	5M	0.5M	3M	0.8M	2M	1M	5M	1.7M
(6) Outgoings	230K	100K	50K	180K	300K	200K	90K	290K	100K	700K
(7) Marital status	Single	Single	Single	Married	Married	Single	Single	Married	Married	Married
(8) Dependents	No	No	No	Yes	No	Yes	Yes	Yes	Yes	Yes
(9) Experience	Yes	No	No	No	No	Yes	No	No	No	Yes
(10) Profession	Entr.	None	Ret.	Empl.	Entr.	Empl.	Entr.	Empl.	None	Empl.

Notes: This table shows the variables contained within each of the 10 vignettes. Each vignette has a male and a female version, illustrated by 'name'. M = million, K = thousand, Entr. = entrepreneur, Empl. = employed, Retirement = years to retirement, Investment. = total funds available for investment, Experience = investment experience. All monetary figures are given in GBP.

Table III
Advisor Characteristics

	Mean	Std Dev.	Median	Min.	Max.
Panel A: All advisors (N=129)					
Age	41.74	8.83	41	25	67
Experience	12.78	8.01	12	0	40
No. Clients	70.98	94.8	50	0	650
Millionaires (%)	77.45	33.68	70	0	100
Panel B: Male advisors (N=102)					
Age	41.14	8.75	41	25	67
Experience	12.42	8.07	11	0	40
No. Clients	77.52	103.94	50	0	650
Millionaires (%)	79.31	33.01	70	0	100
Panel C: Female advisors (N=27)					
Age	44.00	8.76	43	30	62
Experience	14.15	7.67	15	0	31
No. Clients	46.48	37.96	33	0	150
Millionaires (%)	70.19	36.01	80	0	100

Notes: This table reports summary statistics of the respondents to the survey. Age and experience are given in years. Millionaires gives the proportion of clients who are millionaires. Panel A reports results for the who sample while panels B and C separate male and female respondents, respectively.

Table IV
Correlation Matrix: Dependent Variable and Vignette Variables

	RecPort	Knowledge	Control	Age	Gender	Depend.	Inv. Exp.	Entre.	NW	Inv.Amt.
Knowledge	0.057									
Control	0.053	0.654*								
Age	−0.402*	0.103	0.088*							
Gender	-0.020	-0.030	−0.091*	-0.001						
Depend.	0.014	−0.210*	−0.225*	0.070*	0.011					
Inv. Exp.	0.20*	0.539*	0.404*	−0.104*	0.010	−0.095*				
Entre.	0.179*	-0.056	-0.007	−0.327*	-0.015	−0.103*	0.093			
NW	−0.140*	0.074	0.120*	0.196*	-0.016	−0.703*	−0.175*	0.317*		
Inv.Amt.	−0.165*	0.063	0.114*	0.377*	-0.018	−0.714*	−0.129*	0.343*	0.919*	
Income	-0.008	0.347*	0.228*	0.136*	0.012	0.283*	0.422*	−0.396*	-0.108	−0.291*

Notes: The table illustrates the Spearman's rank correlation (rho) for the aggregated average ratings for the Dependent Variables and the Vignette Variables which describe the investors. * denotes 1% significance. In constructing the *Gender* variable Male = 0, Female = 1. *Depend*, *Inv.Exp.* and *Entre.* are dummy variables taking the value 1 if the vignettes millionaire has dependents, investment experience, or works as an entrepreneur, respectively.

Table V
Correlation Matrix: Dependent Variable and Advisor Variables

	RecPort	Knowledge	Control	Age	Gender	Exp.	No. Clients
Knowledge	0.057						
Control	0.053	0.654*					
Resp. Age	-0.103	-0.065	-0.054				
Resp. Gender	-0.057	-0.064	-0.025	0.123*			
Experience.	0.038	-0.024	-0.017	0.719*	0.089*		
No. Clients	0.002	0.031	-0.010	−0.068*	−0.078*	−0.117*	
Millionaires	0.036	0.019	0.039	−0.170*	−0.078*	0.002	−0.095*

Notes: This table illustrates the Spearman's rank correlation (rho) for the aggregated average ratings for the Dependent Variables and Advisor Variables as collected in the survey. No Clients = no of clients that advisors look after, Millionaires = the proportion of their clients who are millionaires. * denotes 1% significance.

Table VI
Summary Statistics of Recommended Portfolio, Knowledge and Control Ratings

		Rec. Port.				**Knowledge**				**Control**			
	Obs.	Mean	Std. Dev.	Min.	Max.	Mean	Std. Dev.	Min.	Max.	Mean	Std. Dev.	Min.	Max.
Vignette 1	129	4.07	1.40	1	7	8.33	1.52	2	10	4.28	0.97	1	5
Vignette 2	124	3.96	1.31	1	7	5.02	1.57	1	9	2.95	0.65	1	4
Vignette 3	120	2.83	1.35	1	7	5.25	1.82	1	10	3.08	0.96	1	5
Vignette 4	115	4.50	1.49	1	7	4.35	1.61	1	8	2.65	0.78	1	5
Vignette 5	113	4.73	1.54	1	7	4.11	1.79	1	8	2.66	0.88	1	5
Vignette 6	110	4.33	1.36	1	7	6.35	1.46	3	9	3.26	0.73	1	5
Vignette 7	109	4.30	1.35	1	7	3.61	1.70	1	9	2.39	0.81	1	5
Vignette 8	109	2.71	1.46	1	7	6.06	1.94	2	10	3.24	1.11	1	5
Vignette 9	109	3.05	1.43	1	7	5.89	1.52	2	9	3.30	0.70	2	5
Vignette 10	109	4.90	1.26	2	7	7.64	1.62	3	10	3.79	1.05	1	5
Pooled	1147	3.93	1.57	1	7	5.68	2.20	1	10	3.17	1.03	1	5

Notes: The table shows the number of ratings per vignette for Recommended Portfolio, Knowledge and Control Ratings. Min (Max) = highest (lowest) rating per vignette. The final row pools all vignette responses.

Table VII
Recommended Portfolio: Vignette Variables

	(1) Rec. Port	(2) Knowledge	(3) Control	(4) RecPort
Age	-0.081***	0.054*	0.041*	-0.086***
	(-6.113)	(1.909)	(1.745)	(-5.190)
Gender	-0.066**	-0.117**	-0.266***	-0.040
	(-2.556)	(-2.259)	(-4.902)	(-1.440)
Depend	0.847***	-1.448**	-1.161**	0.979***
	(3.254)	(-2.492)	(-2.442)	(3.033)
Inv. Exp.	0.481***	1.374***	0.956***	0.377**
	(3.169)	(4.166)	(3.300)	(2.190)
Entrepreneur	-0.521**	0.681	0.609	-0.588**
	(-2.304)	(1.248)	(1.307)	(-2.142)
Net Worth	-0.033***	0.014	0.010	-0.034***
	(-3.302)	(0.611)	(0.533)	(-2.803)
Inv. Amount	0.580***	-0.511	-0.360	0.625***
	(3.772)	(-1.545)	(-1.327)	(3.280)
Income	-0.000	0.001**	0.001	-0.000
	(-0.496)	(2.078)	(1.576)	(-0.664)
Knowledge				0.009
				(0.408)
Control				0.124**
				(2.189)
Observations	1,147	1,147	1,147	1,147
Advisor FEs	Yes	Yes	Yes	Yes
Pseudo R-squared	0.160	0.173	0.172	0.163
Pseudo R-sq excl FEs	0.064	0.115	0.100	0.065

Notes: Reports the results of estimating the regression: $Y_{ij} = \alpha + \beta_1 Age_i + \beta_2 Gender_i + \beta_3 Depend_i + \beta_4 Experience_i + \beta_5 Entre_i + \beta_6 NW_i + \beta_7 InvAmount_i + \beta_8 Income_i + \epsilon_{ij}$ for the dependent variables Recommended Portfolio (headed Rec. Port), Knowledge and Control using ordered probit. Each regression contains unreported advisor fixed effects. Robust standard errors clustered by vignette are used to compute the z-statistics reported in parentheses beneath the parameter estimates. *** denotes 1% significance; **5% significance; *10% significance. The final row in the table reports pseudo-R-squared statistics when the advisor fixed effects are excluded from the regressions.

Table VIII
Recommended Portfolio: Advisor Variables

	(1) Rec. Port	(2) Rec. Port	(3) Knowledge	(4) Control
Respondent Age	-0.009***		-0.014***	-0.010*
	(-2.785)		(-4.660)	(-1.696)
Respondent Gender	-0.178*	-0.173	-0.193*	-0.077
	(-1.673)	(1.570)	(-1.893)	(-0.823)
Years Experience	0.015***		0.012**	0.008
	(3.592)		(2.353)	(1.083)
No. Clients	-0.001	-0.001	0.000	0.000
	(-1.516)	(1.287)	(1.423)	(0.026)
Millionaires	0.127**	0.119*	0.201	0.194
	(2.064)	(1.865)	(1.438)	(1.457)
Young		0.216*		
		(1.900)		
Old		-0.016		
		(0.174)		
Low Exp.		0.026		
		(0.478)		
High Exp.		0.309***		
		(4.116)		
Observations	1,137	1,137	1,137	1,137
Vignette FEs	Yes	Yes	Yes	Yes
Pseudo R-squared	0.071	0.074	0.137	0.119
Pseudo-R-squareds:				
Only advisor variables	0.004		0.003	0.002
Only advisor FEs	0.074		0.035	0.053
Both FEs	0.164		0.197	0.192

Notes: Reports the results of estimating the regression: $Y_{ij} = \alpha_i + \beta_1 Age_j + \beta_2 Gender_j + \beta_3 Experience_j + \beta_4 Millionaires_j + \beta_5 NoClients_j + \epsilon_{ij}$ for the dependent variables Recommended Portfolio (headed Rec. Port), Knowledge and Control using ordered probit. Each regression contains unreported vignette fixed effects. Robust standard errors clustered by vignette are used to compute the z-statistics reported in parentheses beneath the parameter estimates. *** denotes 1% significance; **5% significance; *10% significance. The final two rows in the table report pseudo-R-squared statistics when the vignette fixed effects are excluded from the regression and when only vignette and advisor fixed effects are included in the regression.

6 Internet Appendix

6.1 Vignettes

Vignette 1 [Lucy/Adam]

Seven years ago, following a successful banking career Adam, 45, set up a hedge fund together with his business partner Carol. The business has had its ups and downs, but they are now making healthy profits. Adam managed to draw a salary of £125,000 last year, but spends at least £230,000 per year. He dates regularly but isn't interested in settling down or having children. Adam knows exactly what he wants to invest in and argues over the fees you are charging. You believe he is worth about £8 million and may consider investing up to £3 million. He intends to retire at 50 to pursue his interest in vintage cars.

Vignette 2 [Stella/Andy]

Stella, 42, worked for a very successful internet business, which paid bonuses of £3 million over a 5 year period. She is now spending about £100,000 per year enjoying life and wants to continue doing so. She has come to see you as her boyfriend recommends that she invests at least half of her money to make sure she doesn't outlive her savings. She used to dabble in stocks in the past and has a corporate pension portfolio worth about £500,000. She expresses an interest in leveraged investments but also says she doesn't want to take too much risk. Stella and her boyfriend may consider a family but are undecided.

Vignette 3 [Sarah/Edward]

Edward, 74, has portfolios with 3 private banks. You have heard that these are worth about £5 million each. He is complaining of poor returns and thinks his advisors have taken too much risk with his investments. He asks a lot of questions about the differences between discretionary, advisory and execution only investing and says he may consider moving one of his portfolios to you. His money was made through multiple entrepreneurial ventures in a range of industries. He never married and doesn't have any children. His lifestyle appears humble relative to his wealth and he claims he only spent £50,000 last year.

Vignette 4 [Susan/Michael]
Susan, a 36-year old IT consultant, has done well in the London property boom. She has generated liquid wealth of £800,000 in addition to a property portfolio worth £1.8 million net of mortgages. The portfolio generates about £105,000 bringing her total yearly income to £180,000. Together with her long-term partner she is expecting a baby in 3 months. It is her dream to resign from her boring job in 5 years to look after her family. Her partner has got bond and stock investments, but Susan has always focused on property. However she realises that she ought to diversify and is prepared to commit an initial £500,000. Susan loves to travel and may buy a property abroad in the future.

Vignette 5 [Alison/Patrick]
Patrick, 25, comes from a wealthy family. After inheriting £35 million from his father he set up his own charity to support children's education in Africa. He is passionate about the cause and would like to continue building his charity. His wife, who is a trainee accountant, helps with the charity operations alongside her day job. They married recently and despite family pressure they do not yet have any children. They spend at least £300,000 per year, which includes donations to the charity. Patrick has never focused on his own investments, but realises he ought to. He has recently started to educate himself about different asset classes, which he asks you about during the meeting. You suggest he starts by investing £1 million, with the view of increasing to £3 million over the next 2 years.

Vignette 6 [Paula/Paul]
Paula, 51, is recently divorced with 2 teenage children who she'd like to see through private school and university. Both Paula and her ex work and earn around £300,000 per year, of which they have been able to save about £100,000 annually. Paula has existing investments with another private bank, business you are keen to win. Her £800,000 portfolio consists of

equities, bonds and hedge funds. In the past she has also invested in structured products. Particularly considering the change in her circumstances, Paula thinks she will have to work until she is at least 65.

Vignette 7 [Martha/Kevin]

Kevin, 47, struck gold when he wrote his first book. Originally from a working class background, his lifestyle concept book enjoyed incredible success. His father was a market trader and his mother a homemaker. Kevin has been married twice and has 3 children. He is now dating a younger woman who is encouraging him to think more carefully about his finances. He tells you that he has £2 million in cash, which he would like to invest. In addition, he has 10 buy to let properties, which provide an income of £90,000, fully covering his yearly expenses. He does not intend to work again and would like to give each of his children one of the apartments by the time he is 55.

Vignette 8 [Anna/Nick]

Anna, 59, is the CEO of a FTSE250 company. You are aware that she has about £1.5 million exposure to the company stock through incentive schemes. She is paid £580,000 including bonuses per year, of which she only spends half. It is very hard to get time in her diary, but she is polite and forthcoming when you meet. She has expressed an interest in bonds and asks you what alternative investments are. She confesses to having panic-sold her portfolio and lost a lot of money during the credit crisis. Anna would like to hedge her single stock exposure and invest an initial £1 million of her £2.5 million savings. She is married, and her twins will be graduating from University this year. Her husband would like her to retire at 62 so that they can move to the Caribbean.

Vignette 9 [Caroline/Peter]

Peter, 60, sold an agriculture products business for £10 million last year bringing his total wealth to £40 million. The business was originally started by Peter's father. Peter is married for the second time and has 2 adult children from his first marriage. He has relationships with 2 other private banks but is not forthcoming about his existing portfolios. You have heard from others that he likes fixed income investments. Peter seems unsure about his future plans but suggests wanting to invest at least £5 million to fund his yearly spending of £100,000.

Vignette 10 [Catherine/John]

Catherine, a 38 year-old commodity broker, lives with her partner. She lived in Hong Kong for a few years as an expatriate and has generated wealth of about £5 million. Catherine currently earns about £800,000 per year but spends £700,000. Due to a busy working life she has not had any time to focus on her investment portfolio, but understands that she needs to invest at least 1/3 of her wealth to secure her future and be able to pay for a potential future family. During your first meeting she interviews you extensively about your bank's investment offering. She says she would like to retire at 45 to start her own entrepreneurial venture, which she is confident she will find investors for.

6.2 Robustness Tests

Table IX
Recommended Portfolio

Here we repeat regression (1) with Recommended Portfolio as dependent variable sequentially excluding one vignette. The first column repeats the baseline results for convenience.

	(1) Base	(2) Exc V1	(3) Exc V2	(4) Exc V3	(5) Exc V4	(6) Exc V5	(7) Exc v6	(8) Exc V7	(9) Exc V8	(10) Exc V9	(11) Exc V10
Age	-0.081***	-0.073***	-0.088***	-0.081***	-0.120***	-0.084***	-0.102***	-0.069***	-0.047***	-0.081***	-0.056***
	(-6.113)	(-22.365)	(-8.300)	(-5.958)	(-23.223)	(-6.207)	(-25.931)	(-13.367)	(-2.993)	(-6.043)	(-4.722)
Gender	-0.066**	-0.065**	-0.056**	-0.062**	-0.072**	-0.062*	-0.076***	-0.055**	-0.055**	-0.089***	-0.070**
	(-2.556)	(-2.145)	(-2.104)	(-2.118)	(-2.528)	(-1.957)	(-2.998)	(-1.963)	(-2.173)	(-5.256)	(-2.497)
Depend	0.847***	0.653***	1.238***	0.842***	1.604***	0.921***	0.449***	0.467***	0.366	0.867***	0.835***
	(3.254)	(8.610)	(4.366)	(3.082)	(21.824)	(3.335)	(13.256)	(4.417)	(1.569)	(3.272)	(4.484)
Inv. Exp.	0.481***	0.700***	0.606***	0.488***	0.416***	0.490***	-0.553***	0.750***	0.230*	0.484***	0.523***
	(3.169)	(14.573)	(4.644)	(3.148)	(27.026)	(3.098)	(-20.318)	(14.741)	(1.853)	(3.127)	(5.346)
Entrepreneur	-0.521**	-0.195***	-0.525***	-0.500**	-1.138***	-0.585**	-0.136***	-0.798***	-0.018	-0.537**	-0.333**
	(-2.304)	(-2.837)	(-2.902)	(-2.213)	(-22.144)	(-2.478)	(-8.378)	(-8.769)	(-0.079)	(-2.277)	(-2.068)
Net Worth	-0.033***	-0.033***	-0.035***	-0.032***	-0.054***	-0.041***	-0.072***	-0.012**	-0.016	-0.032***	-0.007
	(-3.302)	(-11.111)	(-4.141)	(-2.686)	(-23.738)	(-3.990)	(-22.886)	(-2.358)	(-1.538)	(-2.853)	(-0.692)
Inv. Amount	0.580***	0.525***	0.744***	0.561***	0.992***	0.650***	0.868***	0.349***	0.150	0.589***	0.305**
	(3.772)	(10.734)	(5.276)	(3.076)	(22.889)	(4.067)	(23.180)	(5.191)	(0.793)	(3.801)	(2.113)
Income	-0.000	-0.000**	0.000	-0.000	-0.000***	-0.000	0.001***	-0.000***	0.000	-0.000	-0.001***
	(-0.496)	(-2.260)	(0.375)	(-0.305)	(-13.731)	(-0.018)	(17.076)	(-5.003)	(1.278)	(-0.319)	(-3.064)
Observations	1,147	1,018	1,023	1,027	1,032	1,034	1,037	1,038	1,038	1,038	1,038
Pseudo R-squared	0.160	0.171	0.166	0.157	0.171	0.172	0.168	0.165	0.154	0.160	0.163

Robust z-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table X
Recommended Portfolio

Here we repeat regression (1) with Recommended Portfolio as dependent variable sequentially excluding different subsets of the advisors. The first column repeats the baseline results for convenience.

	(1) Base	(2) Exc Young	(3) Exc Old	(4) Exc Women	(5) Exc Hi Exp	(6) Exc Lo Exp	(7) Exc Few Mills
Age	-0.081***	-0.075***	-0.083***	-0.087***	-0.083***	-0.077***	-0.083***
	(-6.113)	(-5.287)	(-7.018)	(-6.217)	(-6.095)	(-5.874)	(-5.772)
Gender	-0.066**	-0.059	-0.152***	-0.063*	-0.081*	-0.061**	-0.142***
	(-2.556)	(-1.426)	(-3.270)	(-1.735)	(-1.740)	(-2.255)	(-4.212)
Depend	0.847***	0.784***	0.797***	0.905***	0.884***	0.751***	0.864***
	(3.254)	(2.845)	(3.480)	(3.350)	(3.313)	(2.996)	(2.989)
Inv. Exp.	0.481***	0.521***	0.433***	0.530***	0.414***	0.509***	0.397**
	(3.169)	(3.215)	(3.272)	(3.438)	(2.694)	(3.401)	(2.446)
Entrepreneur	-0.521**	-0.461*	-0.455**	-0.578**	-0.510**	-0.504**	-0.442*
	(-2.304)	(-1.928)	(-2.246)	(-2.427)	(-2.192)	(-2.297)	(-1.836)
Net Worth	-0.033***	-0.026**	-0.034***	-0.028***	-0.034***	-0.031***	-0.037***
	(-3.302)	(-2.501)	(-3.877)	(-2.668)	(-3.435)	(-3.137)	(-3.507)
Inv. Amount	0.580***	0.457***	0.583***	0.562***	0.617***	0.515***	0.621***
	(3.772)	(2.808)	(4.342)	(3.523)	(3.944)	(3.457)	(3.696)
Income	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	0.000
	(-0.496)	(-0.498)	(-0.520)	(-0.862)	(-0.029)	(-0.128)	(0.296)
Observations	1,147	857	839	919	859	826	856
Pseudo R-squared	0.160	0.159	0.169	0.182	0.145	0.155	0.162

Robust z-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table XI
Knowledge

Here we repeat regression (1) with Knowledge as dependent variable sequentially excluding one vignette. The first column repeats the baseline results for convenience.

	(1) Base	(2) Exc V1	(3) Exc V2	(4) Exc V3	(5) Exc V4	(6) Exc V5	(7) Exc V6	(8) Exc V7	(9) Exc V8	(10) Exc V9	(11) Exc V10
Age	0.054*	0.034***	0.068***	0.052*	0.152***	0.057**	0.106***	0.029**	-0.014	0.054*	-0.015
	(1.909)	(7.907)	(2.899)	(1.811)	(22.708)	(2.083)	(14.592)	(2.418)	(-0.343)	(1.930)	(-0.625)
Gender	-0.117**	-0.163***	-0.128**	-0.099*	-0.138**	-0.113*	-0.111**	-0.141**	-0.149***	-0.094*	-0.095*
	(-2.259)	(-3.212)	(-2.236)	(-1.781)	(-2.307)	(-1.926)	(-2.005)	(-2.521)	(-2.953)	(-1.863)	(-1.903)
Depend	-1.448**	-0.968***	-2.109***	-1.371**	-3.405***	-1.645***	-0.529***	-0.643**	-0.522	-1.504**	-1.473***
	(-2.492)	(-7.947)	(-3.142)	(-2.222)	(-23.874)	(-2.715)	(-4.224)	(-2.120)	(-0.861)	(-2.551)	(-3.843)
Inv. Exp.	1.374***	0.923***	1.170***	1.378***	1.644***	1.432***	3.975***	0.829***	1.944***	1.342***	1.337***
	(4.166)	(10.901)	(3.876)	(4.087)	(25.924)	(4.234)	(21.081)	(7.495)	(6.397)	(4.047)	(6.405)
Entrepreneur	0.681	-0.158	0.713	0.532	2.272***	0.866	-0.229***	1.355***	-0.297	0.739	0.188
	(1.248)	(-1.339)	(1.482)	(1.011)	(20.751)	(1.582)	(-3.547)	(4.590)	(-0.476)	(1.320)	(0.555)
Net Worth	0.014	0.014***	0.018	0.005	0.066***	0.039*	0.109***	-0.034**	-0.021	0.008	-0.060***
	(0.611)	(2.745)	(0.856)	(0.196)	(15.468)	(1.887)	(11.551)	(-2.049)	(-0.790)	(0.303)	(-2.617)
Inv. Amount	-0.511	-0.365***	-0.783**	-0.371	-1.540***	-0.709**	-1.224***	0.001	0.344	-0.540	0.252
	(-1.545)	(-4.918)	(-2.452)	(-0.929)	(-20.555)	(-2.123)	(-11.924)	(0.007)	(0.697)	(-1.638)	(0.850)
Income	0.001**	0.001***	0.001	0.001	0.001***	0.001	-0.002***	0.002***	0.000	0.001*	0.004***
	(2.078)	(10.469)	(1.269)	(1.584)	(14.275)	(1.293)	(-8.945)	(6.005)	(0.408)	(1.648)	(5.553)
Observations	1,147	1,018	1,023	1,027	1,032	1,034	1,037	1,038	1,038	1,038	1,038
Pseudo R-squared	0.173	0.169	0.184	0.185	0.201	0.178	0.202	0.178	0.194	0.176	0.182

Robust z-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table XII
Knowledge

Here we repeat regression (1) with Knowledge as dependent variable sequentially excluding different subsets of the advisors. The first column repeats the baseline results for convenience.

	(1) Base	(2) Exc Young	(3) Exc Old	(4) Exc Women	(5) Exc Hi Exp	(6) Exc Lo Exp	(7) Exc Few Mills
Age	0.054*	0.056**	0.059**	0.059**	0.058**	0.056*	0.058**
	(1.909)	(2.034)	(2.087)	(2.109)	(2.108)	(1.834)	(2.017)
Gender	-0.117**	-0.139**	-0.104**	-0.076	-0.082	-0.177***	-0.101
	(-2.259)	(-2.277)	(-2.458)	(-1.294)	(-1.416)	(-3.161)	(-1.532)
Depend	-1.448**	-1.505***	-1.509***	-1.535***	-1.467***	-1.462**	-1.479**
	(-2.492)	(-2.691)	(-2.622)	(-2.720)	(-2.626)	(-2.347)	(-2.519)
Inv. Exp.	1.374***	1.359***	1.311***	1.416***	1.305***	1.378***	1.427***
	(4.166)	(4.228)	(3.987)	(4.460)	(4.071)	(3.890)	(4.265)
Entrepreneur	0.681	0.662	0.777	0.710	0.761	0.741	0.836
	(1.248)	(1.251)	(1.428)	(1.335)	(1.433)	(1.257)	(1.506)
Net Worth	0.014	0.013	0.012	0.022	0.013	0.010	0.017
	(0.611)	(0.605)	(0.535)	(0.973)	(0.585)	(0.438)	(0.744)
Inv. Amount	-0.511	-0.538*	-0.548*	-0.576*	-0.545*	-0.481	-0.541
	(-1.545)	(-1.686)	(-1.668)	(-1.780)	(-1.698)	(-1.363)	(-1.621)
Income	0.001**	0.001**	0.001**	0.001*	0.001**	0.001**	0.001***
	(2.078)	(2.156)	(2.296)	(1.825)	(2.411)	(2.014)	(2.596)
Observations	1,147	857	839	919	859	826	856
Pseudo R-squared	0.173	0.171	0.174	0.170	0.172	0.176	0.185

Robust z-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table XIII
Control

Here we repeat regression (1) with Control as dependent variable sequentially excluding one vignette. The first column repeats the baseline results for convenience.

	(1) Base	(2) Exc V1	(3) Exc V2	(4) Exc V3	(5) Exc V4	(6) Exc V5	(7) Exc V6	(8) Exc V7	(9) Exc V8	(10) Exc V9	(11) Exc V10
Age	0.041*	0.024***	0.050***	0.039*	0.125***	0.043**	0.084***	0.020*	-0.013	0.041*	-0.021
	(1.745)	(7.979)	(2.632)	(1.647)	(14.501)	(1.963)	(10.447)	(1.741)	(-0.371)	(1.785)	(-1.051)
Gender	-0.266***	-0.304***	-0.291***	-0.241***	-0.298***	-0.271***	-0.278***	-0.288***	-0.283***	-0.252***	-0.232***
	(-4.902)	(-5.818)	(-4.747)	(-4.677)	(-4.820)	(-4.485)	(-4.482)	(-5.185)	(-4.609)	(-4.533)	(-6.203)
Depend	-1.161**	-0.758***	-1.626***	-1.081**	-2.816***	-1.325***	-0.360**	-0.470	-0.427	-1.218***	-1.212***
	(-2.442)	(-9.425)	(-2.981)	(-2.126)	(-14.574)	(-2.813)	(-2.424)	(-1.599)	(-0.785)	(-2.580)	(-4.224)
Inv. Exp.	0.956***	0.532***	0.774***	0.963***	1.164***	0.994***	3.148***	0.479***	1.422***	0.934***	0.934***
	(3.300)	(7.654)	(3.021)	(3.203)	(18.806)	(3.360)	(16.901)	(4.974)	(5.123)	(3.165)	(4.796)
Entrepreneur	0.609	-0.121	0.611	0.448	1.983***	0.780*	-0.152**	1.187***	-0.182	0.668	0.184
	(1.307)	(-1.430)	(1.499)	(0.984)	(17.182)	(1.731)	(-2.194)	(4.582)	(-0.329)	(1.416)	(0.640)
Net Worth	0.010	0.011***	0.012	0.002	0.054***	0.033**	0.090***	-0.030**	-0.018	0.004	-0.057***
	(0.533)	(2.624)	(0.735)	(0.103)	(10.829)	(2.034)	(10.000)	(-2.134)	(-0.753)	(0.183)	(-3.097)
Inv. Amount	-0.360	-0.239***	-0.551**	-0.225	-1.234***	-0.535**	-0.959***	0.079	0.323	-0.390	0.329
	(-1.327)	(-4.612)	(-2.137)	(-0.668)	(-12.836)	(-2.066)	(-8.734)	(0.440)	(0.745)	(-1.462)	(1.316)
Income	0.001	0.001***	0.000	0.001	0.001***	0.000	-0.002***	0.001***	0.000	0.001	0.003***
	(1.576)	(10.344)	(0.919)	(1.055)	(10.664)	(0.813)	(-10.687)	(4.938)	(0.073)	(1.155)	(5.985)
Observations	1,147	1,018	1,023	1,027	1,032	1,034	1,037	1,038	1,038	1,038	1,038
Pseudo R-squared	0.172	0.154	0.180	0.186	0.199	0.179	0.202	0.183	0.199	0.176	0.197

Robust z-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table XIV
Control

Here we repeat regression (1) with Control as dependent variable sequentially excluding different subsets of the advisors. The first column repeats the baseline results for convenience.

	(1) Base	(2) Exc Young	(3) Exc Old	(4) Exc Women	(5) Exc Hi Exp	(6) Exc Lo Exp	(7) Exc Few Mills
Age	0.041*	0.046**	0.044*	0.041*	0.038*	0.045*	0.033
	(1.745)	(2.171)	(1.739)	(1.745)	(1.720)	(1.847)	(1.482)
Gender	-0.266***	-0.352***	-0.149**	-0.216***	-0.155**	-0.318***	-0.233***
	(-4.902)	(-5.023)	(-2.391)	(-3.107)	(-2.395)	(-4.607)	(-2.653)
Depend	-1.161**	-1.227***	-1.247**	-1.155**	-1.114**	-1.229**	-0.905**
	(-2.442)	(-2.911)	(-2.329)	(-2.424)	(-2.444)	(-2.531)	(-1.984)
Inv. Exp.	0.956***	0.937***	1.013***	1.050***	0.911***	1.025***	0.979***
	(3.300)	(3.614)	(3.012)	(3.594)	(3.291)	(3.593)	(3.541)
Entrepreneur	0.609	0.669	0.650	0.609	0.597	0.616	0.573
	(1.307)	(1.593)	(1.276)	(1.300)	(1.326)	(1.275)	(1.278)
Net Worth	0.010	0.011	0.011	0.013	0.008	0.009	0.007
	(0.533)	(0.652)	(0.560)	(0.691)	(0.439)	(0.457)	(0.368)
Inv. Amount	-0.360	-0.410*	-0.410	-0.358	-0.349	-0.381	-0.232
	(-1.327)	(-1.687)	(-1.385)	(-1.318)	(-1.372)	(-1.362)	(-0.893)
Income	0.001	0.001*	0.001	0.000	0.001*	0.001*	0.001
	(1.576)	(1.924)	(1.427)	(1.130)	(1.694)	(1.814)	(1.446)
Observations	1,147	857	839	919	859	826	856
Pseudo R-squared	0.172	0.170	0.178	0.175	0.162	0.187	0.159

Robust z-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table XV
Recommended Portfolio

Here we repeat regression (2) with Recommended Portfolio as dependent variable sequentially excluding one vignette. The first column repeats the baseline results for convenience.

	(1) Base	(2) Exc V1	(3) Exc V2	(4) Exc V3	(5) Exc V4	(6) Exc V5	(7) Exc V6	(8) Exc V7	(9) Exc V8	(10) Exc V9	(11) Exc V10
Respondent Age	-0.009***	-0.008**	-0.007**	-0.007**	-0.009**	-0.008**	-0.009**	-0.010***	-0.010***	-0.008**	-0.010***
	(-2.785)	(-2.343)	(-2.337)	(-2.277)	(-2.472)	(-2.297)	(-2.502)	(-3.639)	(-3.514)	(-2.445)	(-2.877)
Respondent Gender	-0.178*	-0.196*	-0.184	-0.246***	-0.141	-0.108	-0.154	-0.195*	-0.184	-0.196*	-0.172
	(-1.673)	(-1.648)	(-1.559)	(-2.704)	(-1.260)	(-1.194)	(-1.341)	(-1.678)	(-1.552)	(-1.682)	(-1.465)
Years Experience	0.015***	0.014***	0.013***	0.014***	0.016***	0.015***	0.013***	0.018***	0.016***	0.016***	0.015***
	(3.592)	(3.056)	(3.301)	(3.044)	(3.465)	(3.158)	(3.157)	(5.000)	(3.460)	(3.445)	(3.393)
No. Clients	-0.001	-0.001	-0.001	-0.001*	-0.000	-0.001**	-0.000	-0.001	-0.001	-0.001	-0.000
	(-1.516)	(-1.618)	(-1.400)	(-1.689)	(-1.059)	(-2.310)	(-1.110)	(-1.410)	(-1.284)	(-1.470)	(-1.125)
Millionaires	0.127**	0.132*	0.119*	0.127*	0.148**	0.107	0.160***	0.090	0.142**	0.106	0.140**
	(2.064)	(1.888)	(1.745)	(1.826)	(2.284)	(1.613)	(2.789)	(1.631)	(2.125)	(1.625)	(2.128)
Observations	1,137	1,009	1,014	1,018	1,023	1,025	1,028	1,029	1,029	1,029	1,029
Pseudo R-squared	0.0710	0.0780	0.0755	0.0623	0.0735	0.0713	0.0733	0.0751	0.0602	0.0685	0.0652

Robust z-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

6.3 Respondent data

The following charts plot the distributions of respondent characteristics.

Figure 1 gives the distribution of respondent age (in years)

Figure 2 gives the distribution of the experience of respondents (in years)

Figure 3 gives the distribution of the number of clients of each respondent

Figure 4 gives the proportion of clients who are millionaires for each respondent (1=100%)

Figure 1. Distribution of Respondent Age

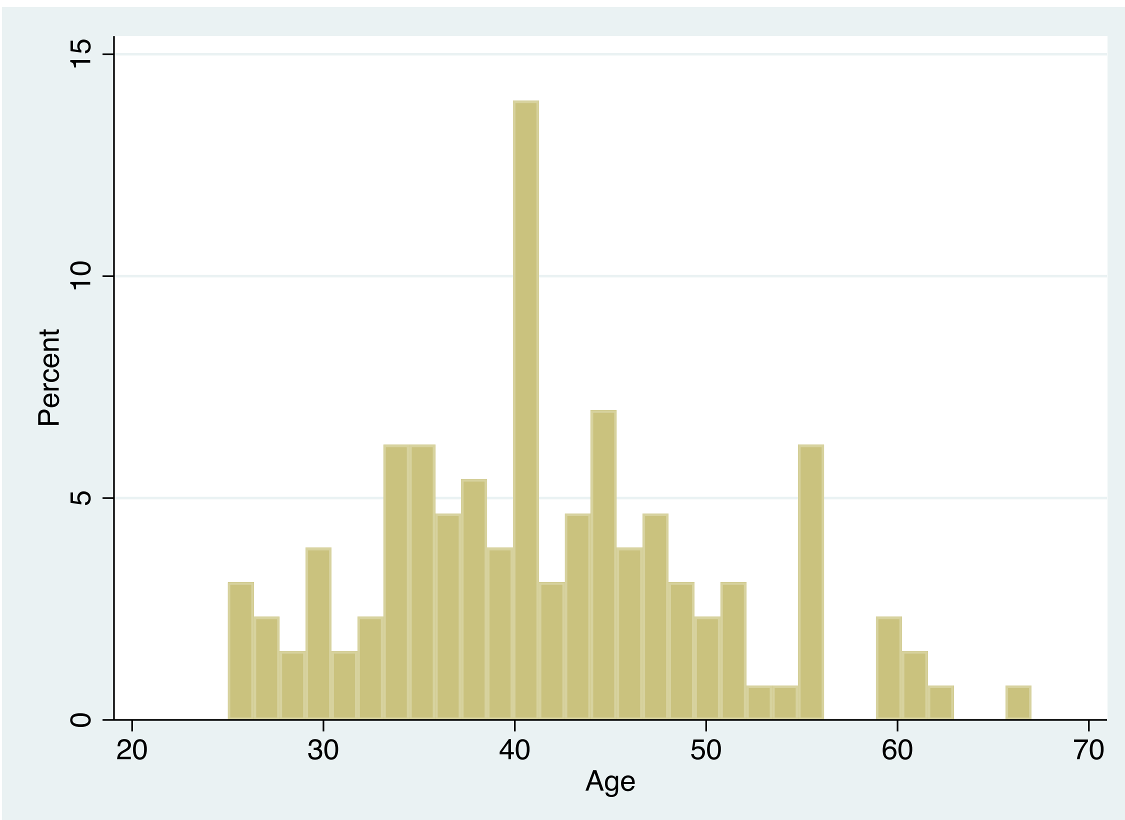

Figure 2. Distribution of Respondent Experience

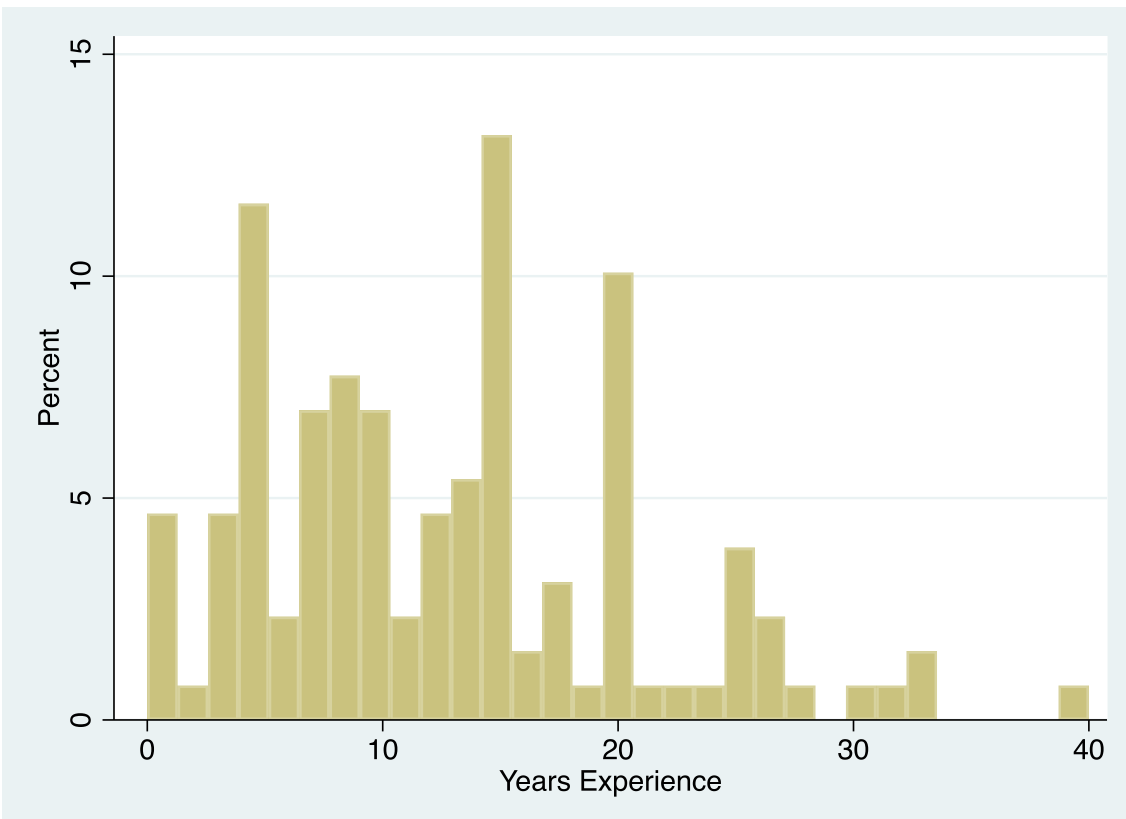

Figure 3. Distribution of No. of Clients

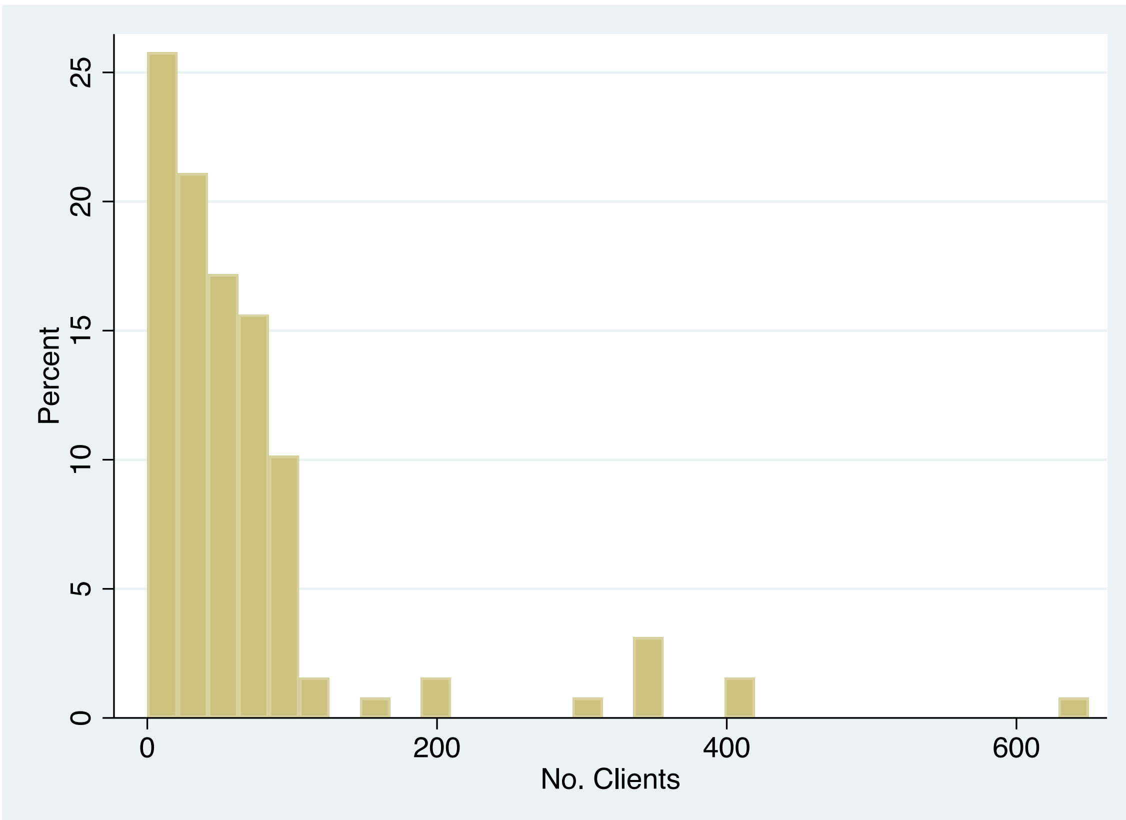

Figure 4. Distribution of Millionaire Proportions