Gender, risk tolerance, and false consensus in asset allocation recommendations

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Abstract

We study the impact of gender on asset allocation recommendations. Graduate business students and professional wealth managers are randomly assigned a male or female client. Participants recommend an allocation and choose an allocation for themselves. Male students choose a riskier allocation than female students, consistent with existing evidence of a gender difference in risk tolerance, and recommend a riskier allocation. In contrast, male and female wealth managers choose and recommend the same allocation, indicating that male and female finance professionals feature similar risk preferences. In both samples, a subject's allocation choice is the strongest predictor of the recommendation provided.

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1. Introduction

Over the past few decades the structure of retirement plans has evolved: the number of U.S. workers with access to a defined contribution plan is now double the number with access to a defined benefit plan.[1] As this phenomenon continues, ever more individual investors will bear responsibility for deciding how much to save and for constructing their retirement portfolio, difficult tasks for which many are ill-equipped. Benartzi and Thaler (2007) show that investors appear to use heuristics when planning for retirement, often delaying participation, rebalancing infrequently, and allocating across available assets naively. Many investors are uncomfortable making financial decisions. In a 2013 survey, 78% of respondents agreed with a statement that they could benefit from some advice and answers to everyday financial questions from a professional.[2] Consequently, the Bureau of Labor Statistics predicts 32% growth rate in financial advisory employment over the next decade.[3] A natural question to ask is the extent to which adviser recommendations help investors construct an appropriate retirement portfolio and achieve satisfaction with their investment choices.[4]

We study the impact of gender on the recommendations provided by advisers to their clients planning for retirement. Gender may be important since prior research has documented in a wide variety of contexts, including financial decision making, that on average men are more risk

[1] Bureau of Labor Statistics, National Compensation Survey, March 2013.

[2] 2013 Consumer Financial Literacy Survey, prepared for the National Foundation for Credit Counseling by Harris International Public Relations Research.

[3] Forbes, 8/8/12, "One of the Fastest Growing Careers is in Desperate Need of Young Talent."

[4] See Merkle et al. (2015) for a study of the determinants of investor happiness among brokerage clients of a large UK bank.

tolerant than women.[5] Our empirical analysis is based on results from an experiment in which subjects take on the role of a financial adviser and recommend an allocation across a risk-free and a risky asset to a hypothetical client, for whom gender is randomly assigned. We also ask subjects to choose an allocation for themselves. We examine the allocation between safe and risky assets, as opposed to the choice among the myriad mutual funds, ETFs, and individual securities available in typical retirement plans, to clearly focus attention on risk preferences. There are other reasons for doing so. John Bogle, noted champion of index investing, states in Bogle on Mutual Funds that "the most fundamental decision of investing is the allocation of your assets." This view is consistent with the lack of evidence supporting persistence in abnormal returns in actively managed mutual funds.[6] Furthermore, in classical mean-variance analysis, the investor's portfolio problem collapses into an allocation choice across the market portfolio and a risk-free asset, known as two-fund separation.[7] The choice is driven by expectations of risk and return as well as investor risk preferences; the optimal allocation to the risky asset is inversely proportional to an investor's level of risk aversion.

We use two groups of subjects: a sample of graduate business students and a sample of professional wealth managers at a regional financial services firm.[8] The two distinct samples allow us to determine whether finance professionals tend to feature risk preferences that differ from the typical person. Sapienza et al. (2009), for example, find that in a sample of MBA students the probability of entering the finance industry is inversely related to risk aversion. We might therefore expect our sample of finance professionals to have higher risk tolerance than our sample of

[5] See Byrnes et al. (1999) for a meta-analysis of 150 studies grouped into 16 types of behavior.

[6] See Carhart (1997).

[7] See Markowitz (1952) and Tobin (1958).

[8] Hereafter we use "adviser" to refer to both subject groups and either "students" or "managers" to refer to one of the groups.

business students. Alternatively, the professional wealth managers, through specialized training and experience, are likely more knowledgeable about financial assets than the average person and this may lead to a greater willingness to accept risk. As shown by Van Rooij et al. (2011), for example, financial literacy increases the rate of stock market participation. Any difference between our two samples may have implications for how advisers and clients should be matched in order to facilitate effective decision making.

In our experiment, the salient characteristics of the investments are provided to the subjects, hence according to standard finance theory only the perceived level of investor risk aversion should affect the allocation recommended to the client. Given average gender differences in risk tolerance, one might expect that recommended allocations may be affected by the randomly assigned gender of the hypothetical client. However, existing research shows that advisers allow their own preferences to affect their recommendations. A recent study of Canadian financial advisers by Foerster et al. (2015) finds that the strongest determinant of an allocation recommendation to a client is the adviser's own allocation choice. Similarly, Roth and Voskort (2014) show in an experiment that advisers, when asked to assess the risk tolerance of a hypothetical client, provide estimates that are highly correlated with their own risk preferences. These results can be interpreted as evidence of a false consensus effect, in which the adviser over-estimates the similarity between their own preferences and those of their client.

Given the robust finding that men are more risk tolerant than women (Hugelschafer and Achtziger, 2014), and the recent evidence that advisers project their own preferences on their clients, we pose four main research questions designed to provide insights useful for matching advisers and clients, as well as incorporating financial advice in the retirement planning process.

First, do asset allocation recommendations provided by advisers differ by client gender? The empirical evidence that men and women on average have different risk preferences is clear, yet it would likely be controversial and perceived as discriminatory if client gender were explicitly incorporated in a recommended asset allocation plan.

Second, do female advisers vary their recommendations by client gender more than male advisers? As discussed later in the paper, existing research argues that women are more empathetic than men. If so, then female advisers may provide less risky recommendations to their female clients than their male clients given the well-established gender difference in risk tolerance.

Third, do average asset allocation recommendations differ by adviser gender? To the extent that recommendations provided by advisers are correlated with their preferences, and given a gender difference in risk tolerance, female advisers may provide less risky recommendations in general than male advisers. Consequently, risk tolerant investors seeking a riskier allocation recommendation might be more likely to obtain one from a male adviser than a female adviser and vice versa. Put another way, forming same-gender dyads would result in a tighter alignment between the risk preferences of the investor and the adviser than if the assignment were random.

Fourth, do the professional wealth managers in our sample recommend riskier allocations than the graduate students? Sapienza et al. (2009) find, in a sample of MBA students, a positive correlation between risk tolerance and the likelihood of entry into the finance industry. A false consensus effect would therefore result in riskier recommendations from a sample of finance professionals than from a general population.

We find that male students choose a higher allocation to the risky asset than female students, consistent with a gender difference in risk tolerance. The male students also recommend a higher risky share than the female students, consistent with a false consensus effect. Neither the male nor the female students provide recommendations that differ by client gender, despite the well-accepted gender difference in risk tolerance. These results suggest that same-gender dyads would likely result in a closer match between client and adviser risk preferences than if the match were random.

In contrast, there is no difference between the allocations selected by male and female wealth managers. Male managers provide on average a slightly higher recommendation to the risky asset than do female managers, but the difference is statistically insignificant. Furthermore, the managers both select and recommend riskier portfolios than the students. If professional advisers tend to feature greater risk tolerance than clients, then there is a risk that many investors may be advised to accept an allocation that weights risky assets more heavily than is optimal given their level of risk aversion.

For both sets of subjects, neither the gender of the adviser nor the gender of the client has a systematic impact on recommendations when we control for the adviser's own allocation, indicating that male and female advisers project their own preferences to the same degree.

Our results contribute to the recent literature on financial advisers (Foerster et al. (2015) and Roth and Voskort (2014)) in two ways. First, we examine determinants of risk tolerance and allocation recommendations of two distinct samples, graduate students and professional wealth managers. The wealth managers feature higher risk tolerance than the students overall. Moreover, among the students, a finance concentration is associated with higher financial literacy, confidence, and risk tolerance. These results are consistent with existing evidence in Sapienza et al. (2009) that those selecting a finance career tend to be more risk tolerant than others. Second, we study differences between male and female advisers. Male students are more risk tolerant than female students, consistent with existing evidence of a gender difference in the population at large.

The gender difference narrows when examining finance concentrators. In the sample of wealth managers, the gender difference disappears entirely. For both students and wealth managers, the subject's own risk preference subsumes all other effects.

Taken together, our results indicate that focusing on gender per se will not improve the efficacy of the client-adviser interaction. There is no gender difference in risk tolerance for our sample of professional wealth managers. Furthermore, there is significant variation in risk tolerance within both genders of our student sample, suggesting that gender-based generalizations of clients will not be useful. The responsibility for choosing a risk level that corresponds to the client's risk tolerance may therefore ultimately lie with the individual, highlighting the importance of investor education. These results shed new light on the role of gender in the client-adviser relationship, and contribute more broadly to the literature on gender effects in economic psychology (Masclet et al., 2015; Sharma, 2015).

The rest of the paper is organized as follows. Section 2 reviews prior literature on the impact of gender on risk aversion, and how gender differences in risk aversion can lead to different optimal asset allocations as suggested by finance theory. Section 3 develops hypotheses regarding the impact of client and adviser gender on allocation recommendations. Our experimental design is described in Section 4. Results and discussion follow in Section 5. Section 6 offers a brief conclusion.

2. Gender, risk aversion, and asset allocation

As mentioned above, empirical evidence indicates that men on average invest in riskier portfolios than women. This section addresses the normative question of whether gender should affect asset allocation.

An optimal allocation can be derived by specifying a utility function of wealth or consumption and solving for the portfolio weight *w* that maximizes lifetime utility. A natural default response consistent with a societal goal of gender equality is that male and female investors who are matched on age and income should invest in similarly structured portfolios, under the assumption that their utility functions are identical. Hence in all cases we set the null hypothesis to be equality between the average recommendations of all partitions formed by the gender of the client and/or the adviser. To motivate alternatives, we review below two arguments, rooted in portfolio choice theory, for how optimal allocations for male and female investors could differ.

A. Complete markets

Early theoretical analyses of portfolio optimization assume that investors are exposed only to risk generated by uncertainty in the returns of their financial assets. Merton (1969, 1971) provides explicit solutions for the optimal portfolio when investors have hyperbolic absolute risk aversion utility functions. Merton also shows that under the assumption that asset returns are distributed jointly normal the investor's problem simplifies to an allocation across two assets, one risky and one risk-free. In this sense the market is complete, as the level of risk can be controlled by trading the risky asset. For the case of constant relative risk aversion, the optimal allocation *w* to the risky asset is:

$$w^{*} = \frac{E\left(\tilde{r}\right) - r_f}{2A\sigma^2} \tag{1}$$

where r_f is the risk-free rate of return, $E\left(\tilde{r}\right)$ and σ^2 are the mean and variance of the return of the risky asset, and A is a measure of the investor's risk aversion. For illustration, consider a one-period investment problem involving allocation over a risk-free asset and a risky asset. Further, suppose that investors have quadratic utility functions involving the first two moments of returns of their overall investment portfolio. The investor's problem can be defined as:

$$\max_{w} \quad r_f + w\left[E(\tilde{r}) - r_f\right] - Aw^2\sigma^2 \tag{2}$$

The first order condition results in the optimal weight on the risky asset in (1).

If women on average have higher risk aversion, then according to (1) the optimal weight on the risky asset should be lower on average for women than for men. Charness and Gneezy (2012) assemble results from 15 existing experimental studies that use a common investment choice to study risk aversion. A decision maker is given $*X* and asked to choose an amount $*x* to invest in a risky asset and how much to keep. Despite differences in the participating groups, and other differences in test design, men consistently choose a larger $*x* than women. Agnew et al. (2003) provide corroborating evidence from a field study of 401(k) plan members: men on average have higher allocation to equities than women.

Rubin and Paul (1979) and Eckel and Grossman (2002) suggest gender differences in risk aversion can be explained in a Darwinian fashion by considering gender roles in reproduction. An evolutionary basis for gender differences in risk aversion is less relevant today, yet differences in risk preferences across men and women persist. Some believe they are perpetuated by the impact of societal expectations. Booth and Nolen (2012) determine whether social environment matters in a study of teenage students in the U.K. who attend one of eight schools: four are coeducational, two are all-girls, and two are all-boys. The students are brought together and formed into groups of four, some of which are all-girls, some are all-boys, and some are mixed. The students individually choose between a sure payoff of £5 and a 50-50 gamble with payoffs £2 or £11. A probit analysis measures the impact of determinants on selecting the gamble. Girls from coeducational schools are 36 percentage points less likely to accept the gamble than boys from coeducational schools. Girls randomly placed in an all-girls group accept the gamble 12 percentage points more often than girls placed in a mixed-gender group. And girls from all-girls schools accept the gamble at approximately the same frequency as boys in the study. These results suggest that risk preferences of some women are affected by their interactions with others.

B. Incomplete markets

In the complete markets case, for a given assumption about parameters of the risky and risk-free asset, differences in the optimal risky share occur only when investors have different risk preferences. The finance literature on portfolio choice also considers more detailed models of the investor's problem that incorporate risks that are important for investors but that cannot be hedged by trading assets, i.e., the incomplete markets case. In these models, the term "background risk" refers to uninsurable sources of uncertainty affecting investor wealth and consumption beyond the variation in risky asset returns.[9] The most widely studied background risk is labor income. Heaton and Lucas (1997) show for a broad range of utility functions that the presence of substantial income risk raises the optimal allocation to risky assets as a hedge. More generally, differences across investors in attributes such as life expectancy, parental responsibility, and marital status can result in differences in their optimal risky share even if they have identical risk aversion.

One might conjecture that gender differences in background risk could lead to gender differences in optimal allocations. In other words, in contemporary society, gender differences in risk aversion can be explained without relying on tastes of an ancient evolutionary origin by modeling gender differences in an economic context, in the spirit of Becker (1975). For example,

[9] See Heaton and Lucas (2000) for a review of background risks in portfolio choice.

Bajtelsmit and Bernasek (1996) provide a number of relevant empirical facts regarding gender differences in labor markets and the typical division of labor within the family. A “glass ceiling” constraining upward mobility and expected lifetime earnings for women still exists. According to the U.S. Bureau of Labor Statistics (2013), women comprise about half the working U.S. population, yet women hold just 4.6% of the CEO positions in Fortune 1000 companies.[10] The median wage of women workers in the U.S. was just 62% of the median wage of male workers. Though this gap narrowed to 82% by 2011, women earn only 71% of men in management occupations.[11] Debate continues regarding the source of these gender differences, e.g. are they due to discrimination or can they be explained by differences in education and experience levels. Regardless of their cause, if on average men and women face different lifetime earnings potential and degrees of upward mobility then their optimal allocations to risky assets may differ as well.

Love (2010) constructs a life-cycle model of consumption and investment that includes labor income, life insurance, and a bequest motive, and calibrates parameters for men and women in many household types, including single, married, divorced, widowed, with children of various numbers, and childless. He then solves for decision rules that maximize expected lifetime utility and simulates paths incorporating random stock market returns, changes in marital status, childbirth, and death.[12] In all cases risk aversion is held constant, and yet in Love’s model substantial differences across the optimal risky share of men and women occur, especially following divorce or the death of a spouse. These differences are driven both by calibrated model

[10] Data on CEOs from www.catalyst.org/knowledge/women-ceos-fortune-1000.

[11] See Mandel and Semyonov (2014) for a recent empirical analysis.

[12] In practice, asset allocation decisions and recommendations from advisers are often based on simple heuristics involving age, anticipated retirement date, and current income. For example, the risky share is often set to 100 minus a client’s age.

parameters, such as those related to income processes, as well as assumptions about custody, child support, and life insurance. For example, given the lower lifetime earnings potential for women in the average married household, Love assumes that married couples purchase life insurance only on the man. As a consequence, following the death of a spouse, women have less income risk relative to total wealth than men, and hence require less investment in risky assets to hedge. More generally, according to Love, the optimal risky share of men and women can differ even if their tolerance for risk is the same.[13]

C. Empirical evidence

Existing research offers three types of empirical evidence that women feature greater risk aversion than men in financial decision making.

First, survey evidence simply asks investors questions related to their financial decision making. Lewellen et al. (1977) study the clients of a large national retail brokerage firm. In a sample of 972 respondents 80% are male. Of the women, 35% report reliance on a broker as the primary approach to security selection compared to 15% for men. Men report spending significantly more time and money gathering investment information and have a significantly higher expectation for the return of the equity portfolios, all consistent with men being on average more comfortable accepting risk. Dwyer et al. (2002) study data from a national survey of mutual fund investors conducted by the Securities and Exchange Commission. Men are significantly more likely to hold an equity fund and more likely to have an equity fund as the largest position. Interestingly, when investment knowledge is included as a control variable, the impact of gender

[13] In the presence of background risk, one can incorrectly attribute differences in portfolio choice to differences in risk aversion, as defined by the curvature of an investor's utility function for wealth or consumption. That said, one can use the simple complete markets paradigm to generate the optimal allocation for the case of incomplete markets if the risk aversion parameter is altered to incorporate the impact of background risks.

is reduced by roughly 50%, suggesting that a substantial component of the observed differences between men and women is due to differences in financial literacy as opposed to innate differences in risk preferences.

Second, field evidence is obtained by studying actual trading records of investors to infer risk attitudes. Barber and Odean (2001) examine account data for over 35,000 households from a large discount brokerage firm. The risk of the accounts is measured four different ways, including the volatility of monthly returns, the idiosyncratic volatility of monthly returns, exposure to the market, and exposure to small stocks. In all cases, women manage less risky accounts. Agnew et al. (2003), mentioned previously, study choices of mutual fund investors in a 401(k) plan. Men invest more in equity funds than women, consistent with a greater risk tolerance.

Third, experimental evidence asks subjects to make financial choices in a controlled laboratory setting. Agnew et al. (2008), for example, ask subjects questions to gauge their risk aversion and financial literacy before asking them to make decisions. Women feature greater risk aversion and weaker financial literacy. Next, in a retirement simulation, subjects are asked to choose a fixed annuity or a self-directed account consisting of a risk free asset and a market portfolio, with weights chosen by the subject. Women are more likely to choose the annuity, even after controlling for risk aversion and financial literacy. These results indicate that in addition to gender differences in risk aversion there are gender differences in a willingness to exert control over the execution of a retirement plan.

3. Hypothesis development

As discussed in Section 2, previous research in psychology and behavioral economics shows that men are on average more risk tolerant than women. We present in this section three hypotheses regarding allocation recommendations that are based on a gender difference in risk preference. A fourth hypothesis is motivated by evidence in Sapienza et al. (2009) that individuals choosing a finance career are more risk tolerant than others.

In our study male and female participants take on the role of advisers and recommend to either a male or a female client the percentage weight w of the client's retirement portfolio to invest in a risky asset, with the remainder invested in a risk-free asset. The assignment of client gender is random, so that we will have responses from four gender dyads. We will primarily be analyzing average weights of different subsets of the sample partitioned by gender indicated by M (male) or F (female). When we partition by the gender of clients we use subscripts, when we partition by the gender of advisers we use superscripts, and when we partition by both the gender of clients and advisers we use both subscripts and superscripts. For example, w_F is the average recommendation across all advisers to female clients whereas w_M^F is the average recommendation across female advisers to male clients. We also compare average recommended weights for all clients provided by students (S) to the average provided by professional wealth managers (P), which we denote w^S and w^P, respectively.

A. Client gender

If men are more risk tolerant than women, then equation (1) implies that the utility-maximizing allocation to risky assets should be higher on average for men than for women. This leads directly to our first hypothesis.

Hypothesis 1. Advisers seeking to maximize a client's utility recommend a lower allocation weight to risky assets when advising female clients, since women on average are more risk averse than men:

$$
\begin{aligned}
H_0 &: \quad w_F = w_M \\
H_1 &: \quad w_F < w_M
\end{aligned}
\tag{3}
$$

B. Adviser gender

Behavioral studies indicate that women tend to score higher on standard tests of empathy than men.[14] These results may reflect societal and familial expectations for the role of women in relationships as formalized in West and Zimmerman (1987). In addition, recent neuroimaging studies find differences in neural activity of men and women participating in experiments designed to illicit empathetic behavior, including work by Schulte-Rüther et al. (2008). Rueckert and Naybar (2008) confirm gender-related differences in neural activity using an experiment involving "chimeric" facial depictions of people with either smiles or neutral expressions. As described by Davis (1996), empathy encompasses both cognitive and emotional components which facilitate an observer's understanding of another person's state of mind. The cognitive component of empathy involves the ability to recognize the beliefs, intentions, and desires of others. Hence, if female advisers feature more effective empathetic abilities, then they may have a better understanding of gender-related differences in risk aversion.

In our survey, subjects are presented with one of two hypothetical clients who are identical in all respects except for gender. Given the well-established difference in risk tolerance between men and women, our first hypothesis is that advisers recommend a riskier allocation to men than to women. Furthermore, the evidence suggesting that women are more empathetic than men implies that female advisers are more likely to recognize the difference in risk preferences between their male and female clients, and this leads to our second hypothesis.

[14] See Hall et al. (2000) and McClure (2000) for reviews of related literature.

Hypothesis 2. Female advisers recommend that male clients invest in a riskier allocation than female clients more so than do male advisers:

$$\begin{aligned} H_0: &\quad w_M^F - w_F^F = w_M^M - w_F^M \\ H_1: &\quad w_M^F - w_F^F > w_M^M - w_F^M \end{aligned} \tag{4}$$

C. False consensus

The hypothesized difference in allocations recommended to female and male clients in (4) is generated by the advisers' assessments of client risk preferences. Another mechanism by which the gender of the adviser could affect recommendations is through the behavioral bias known as the false consensus effect or assumed similarity. The false consensus effect is typically defined as an egocentric bias to overestimate the degree to which others are like us. Marks and Miller (1987) provide a review of theoretical and empirical research on false consensus, and describe a host of behavioral processes and social contexts which might cause biased perceptions of similarity between others and self. However, in the absence of information about others, Hoch (1987) and Dawes (1989) argue that overweighting one's own attitudes can in fact improve forecast accuracy in a Bayesian sense.

Prior evidence indicates a strong correlation between the allocation choice of advisers and their recommended allocations to clients. If male advisers are on average more risk tolerant than female advisers, consistent with the voluminous evidence about the risk preferences of men and women in general, then the false consensus effect predicts a difference in average recommendations partitioned by adviser gender.

Hypothesis 3. In light of the false-consensus effect, and prior evidence that men on average are more risk tolerant than women, male advisers tend to recommend higher allocations to the risky asset than female advisers:

$$\begin{aligned} H_0 &: \quad w^F = w^M \\ H_1 &: \quad w^F < w^M \end{aligned} \tag{5}$$

In (5), no distinction is made between the recommendations offered to male and female clients since the false consensus effect is based on the idea that the preferences of clients are ignored or underweighted.

D. Career choice

Prior research indicates that finance professionals feature relatively high risk tolerance compared to the general population. Sapienza et al. (2009), for example, show that the likelihood of an MBA student in their sample entering the finance industry is positively related to risk tolerance. Further, Sapienza et al. link the risk tolerance of their subjects to two physical markers for prenatal testosterone exposure, suggesting that at least to some extent finance professionals are innately predisposed to be relatively risk tolerant. Given evidence of a false consensus effect in adviser recommendations, professional advisers may therefore recommend relatively risky allocations. This leads to our fourth hypothesis.

Hypothesis 4. In light of the false-consensus effect, and prior evidence that finance professionals feature relatively high risk tolerance, wealth managers in our sample recommend higher allocations to the risky asset than graduate students:

$$\begin{aligned} H_0 &: \quad w^S = w^P \\ H_1 &: \quad w^S < w^P \end{aligned} \tag{6}$$

4. Research design

We solicited participation in the study from two populations: graduate business students and professional wealth managers at a regional financial services firm. Subjects were emailed a link to an electronic survey that was completed online. The two populations completed identical surveys save for an assessment of their expertise, as described below.

A. Survey description

The survey begins with a description of a hypothetical client, either a single man or a single woman, assigned randomly to each subject. See the Appendix for the text of the description. The client seeks an allocation recommendation across the two available investment vehicles in a company-sponsored retirement account: an essentially risk-free money market fund and a risky balanced fund which invests in several asset classes. The money market fund earns 2% for sure, whereas the balanced fund has returned an average of 8% annually with a 15% standard deviation. The survey asks subjects to recommend a percentage allocation to each of the two funds, and for robustness asks subjects to select a recommendation from a set of five choices which vary the allocation to each by 25%. In addition, the survey asks the subjects to assess the willingness of the client to accept risk, the confidence with which the recommendation is provided, and to choose an allocation for themselves.

Additional information is gathered about the subjects, including age and gender. The graduate students are asked whether they are a finance concentrator, and their financial knowledge is assessed through an eight-question quiz. The professional wealth managers are asked how many years they have worked as a wealth manager.

A total of 383 students were invited to participate, 261 men and 122 women. For the professional managers, 288 were invited, 165 men and 123 women. The response rate was significantly higher for women, 58.2% versus 51.0% in the student sample and 71.5% versus 52.1% in the professional manager sample.

B. Incentives

Standard practice in behavioral economics experiments is to include a monetary incentive to elicit effort from participants, and thereby guard against random responses that might not reflect survey takers' true opinions or tendencies. For example, in Gneezy and Potters (1997), participants are endowed with $2 for each of nine rounds of a betting game, with the net proceeds used to wager in three subsequent rounds, and then participants receive a cash payment equal to the final result. Because our study explores financial advice provided to a hypothetical client, and there is no objective better or worse way to respond to our survey items, we do not use explicit incentives in our methodology.

Though we do not include a monetary reward in our research design, participants in both experiments possess an implicit incentive to answer meaningfully. Student participants were recruited to participate by their dean via an email invitation that offered the chance to contribute to the research mission of the school. Similarly, wealth managers were recruited by their division head with an email that asked them to consider participating in order for the firm to gain insight regarding their advisory business. Though participation was anonymous, the high response rates described above indicate that in both samples the participants had a genuine interest in the survey outcomes, and hence were likely to have exerted sufficient effort to provide valid results.

5. Results

Table 1 lists average adviser attributes. Panel A shows results for the graduate students split by gender. The men are one year older, which is statistically significant but not meaningful. The men score higher on the financial literacy assessment, with an average of roughly five questions correct out of eight, compared to four for the women. This result is consistent with a cross-country survey in Bucher-Koenen et al. (2016). The men also indicate a higher confidence level in their recommendation, 5.1 versus 4.5 on a scale of 1 to 7, with 7 being the most confident. Panel B shows results for the professional wealth managers. We use experience of the professionals to proxy for their knowledge. In stark contrast to the results for graduate students, no significant difference exists between the male and female subjects. Both groups are 48 years old on average, both have about 15 years of experience, and both indicate a confidence of 4.0 on a scale of 1 to 5.[15] Given the differences across students and advisers in the measures of knowledge, and the scales of confidence, we standardize age, knowledge, and confidence for the subsequent regression analysis by subtracting the mean and dividing by the standard deviation, where these summary statistics are computed within the two subsamples.

Panel C lists the sample sizes. About two-thirds of the 204 students are male whereas the 174 wealth managers are evenly split by gender.

Panel D reports, for the two sets of subjects, the average choice of allocation to the risky fund, which is our measure of their risk tolerance. The students, who are roughly 20 years younger, choose 71.1% versus 85.4% for the wealth managers.[16] This is inconsistent with the conventional wisdom that optimal allocations to risky assets should decline with age. In the model of Cocco et al. (2005), for example, labor income is a substitute for the risk-free asset, hence as the present value of future labor income declines over the life cycle, so does the optimal weight on risky assets.

[15] The scale is different for the professional advisers given differences in the software packages used for the two samples.

[16] The internal validity of comparing means across the two samples could be questioned if the two experiments were conducted at different times such that subjects in the two groups were affected differently by external stimuli, e.g., a stock market crash. However, the two experiments were run within a year of each other during similar macro-economic conditions and using identical measures.

Several explanations are possible. Individuals selecting a finance career might on average be more risk tolerant, as studied by Sapienza et al. (2009). Alternatively, the professional wealth managers are likely more knowledgeable and experienced in asset allocation than the business students, and this might increase their willingness to accept financial risk. We study determinants of the asset allocation choice below. Perhaps more important, the male students choose a significantly higher allocation to the risky fund than do the female students, 76.1% versus 61.6%. This result is consistent with the widely-held belief that men are on average more risk tolerant than women. In contrast, the male and female wealth managers choose similar portfolios, allocating on average 86.0% and 84.8%, respectively, to the risky fund. The absence of a gender difference in risk tolerance among the wealth managers could be caused by an industry selection effect or the result of experience and professional training.

To gain more insight regarding the impact of training, we return to the students, who are actively engaged in acquiring new skills, and compare finance concentrators to non-concentrators. As shown in Panel A of Table 2, the student sample is evenly split between those that are pursuing a finance concentration (N = 104) and those that are not (N = 100). The finance concentrators are predominantly male (86 vs. 18) whereas the numbers of male and female non-concentrators are about equal (47 vs. 53). In Panel B, finance concentrators choose an allocation of 76.8% to the risky fund compared to 65.1% for non-concentrators. As above, this result can be interpreted as evidence that individuals selecting a finance career are by nature more risk tolerant, or that those with more knowledge and experience in making financial decisions will be more comfortable accepting financial risk. Male finance concentrators choose a riskier portfolio than male non-concentrators, whereas the difference is insignificant for female students. However given the small number of female finance concentrators in our sample, the statistical power of this comparison is limited. Among the women, the average allocation is 66.8% for finance concentrators and 59.9% for non-concentrators. In both the concentrator and non-concentrator subsets men choose a significantly riskier portfolio than women.

Panels C and D show how financial knowledge and confidence varies among the student subsets. In the pooled, male-only, and female-only subsets, finance concentrators have significantly higher knowledge and confidence. Furthermore, the difference between male and female students is smaller among finance concentrators than among non-concentrators. The confidence levels of male and female finance concentrators are in fact indistinguishable. Though we cannot distinguish between the hypotheses that (a) finance concentrators tend to be more financially literate prior to selecting a concentration, or (b) the financial education improves financial literacy, these results suggest that through training and experience the difference between men and women narrows. As shown with the wealth manager sample, the difference across genders disappears entirely in a professional setting.

Table 3 reports results of a regression studying the determinants of subjects' allocation choices. In Panel A, Model 1 shows that the average female student chooses an allocation to the risky fund 14.44% lower than the average male. Model 2 shows that almost half of this difference can be explained by lower confidence and knowledge, as the coefficient on the female indicator is reduced to 7.88%. Model 3 includes interaction terms between the control variables and the female indicator. The coefficient on the female indicator is increased in absolute magnitude to –8.98% but it is still far smaller than the difference in average allocations chosen by male and female students. These results shows that improvements in financial literacy, which would likely also boost confidence, might increase the willingness of women on average to invest in riskier portfolios and thereby increasing their expected retirement wealth. As mentioned previously, Van

Rooij et al. (2011) find that financial literacy increases the rate of stock market participation. Panel B shows that for wealth managers there is no gender-related difference in allocations. Coefficients on knowledge, as proxied for by the experience of the adviser, and confidence are both positive but only one is significant: confidence in Model 2 and knowledge in Model 3 which includes interactions between these variables and the female adviser indicator. In sum, the results in Panel B indicate that among the wealth managers there is quite homogenous preferences, perhaps the result of a selection effect and common training about optimal retirement planning.

Figure 1 shows the entire distribution of allocation choices for the two samples split by gender. In Figure 1A, the male and female student subpopulations feature a similar left-tail, with roughly 5% choosing an allocation to the risky fund of 20% or less. The distributions then diverge, indicating the difference between male and female graduate students is widespread. In Figure 1B, the distributions of male and female wealth managers are quite similar throughout. The contrast between the two figures is consistent with evidence in Sapienza et al. (2009) that biology plays a role in career choice.[17] An interpretation is that finance is perceived as a career requiring substantial risk tolerance, so that the typical finance professional is less risk averse than the average person, regardless of gender.[18] The similarity between male and female professional wealth managers vis-à-vis their revealed risk tolerance is important for this study, since it suggests that one may not be able to rely on the gender of an adviser as a marker for risk preferences.

[17] Sapienza et al. (2009) study graduate business students and report that 36% of female students choose careers in finance compared to 57% of male students. To explain this disparity, they measure pre-natal exposure to testosterone using the "2D:4D" ratio of the length of the second (index) finger to the fourth (ring) finger. They find that, in a probit analysis of career choice, the significance of student gender disappears once the 2D:4D ratio is included as an explanatory variable.

[18] The NSF Survey of Earned Doctorates shows that in 2013 30.4% of finance PhDs in the U.S. were awarded to women versus 43.5% of all other business PhDs, so that even the academic pursuit of finance appears to trigger a gender-related selection effect.

The difference between recommendations provided by male and female students is depicted in Figure 2A. As with the distributions of allocation choice, the distributions of recommendations from male and female students diverge substantially. The distributions of male and female wealth managers are quite close to each other in Figure 2B.

Table 4 shows the average recommendation provided by each subsample of the subjects. Panel A shows recommendations from students split by client gender. Two results are salient. First, the male students recommend a significantly riskier allocation than do the female students. The male students recommend 63.3% in the risky fund to male clients while the female students recommend 54.6%. The male students recommend 64.9% in the risky fund to female clients while the female students recommend 51.1%. Second, neither the male students nor the female students vary their recommendation by client gender. Panel B shows results for the professional wealth managers. The difference between the male and female managers' recommendations is insignificant for male clients, as in Panel A. The female advisers do recommend a significantly lower allocation to the risky fund to female clients than do male advisers, 79.5% versus 86.3%. Note however that as with the students, neither male nor female wealth managers vary their recommendation by client gender.

Panel C shows results for the recommendations pooled across client gender. Students recommend on average a 60.3% allocation compared to 83.1% for the wealth managers. Within the student sample, male subjects recommend an allocation of 64.2% in the risky fund compared to 53.0% for female subjects, with the difference statistically significant at the 1% level. In contrast, there is no difference between the average recommendations provided by male and female wealth managers. The results in Panels A – C mirror the results in Panel D of Table 1 involving the advisers' own allocation choices, suggesting that adviser risk preferences affect their recommendations.

Panel D shows the correlation between allocations and recommendations within each subsample is around 0.60; the risk preference of the adviser appears to predict quite strongly the recommendation provided. Given the difference in risk tolerance for male and female students, an investor could use the adviser gender as a noisy indicator of the adviser's risk preference and the corresponding recommendation that the investor would receive. However since the wealth managers feature no gender-related difference in risk tolerance matching on client and adviser gender would not appear to affect the recommendation. Panel E shows that students recommend an allocation almost 11% lower than they choose for themselves. This could be caused by the subjects' perceptions of the preferences of the hypothetical client, who is roughly 13 years older. There is no difference between the average allocation chosen and recommended by the wealth managers.

For robustness, Table 5 shows the percentage of advisers that choose for themselves, and recommend, one of the five pre-set allocations. In Panel A, 33.8% of the male graduate student subjects choose a 100% allocation to the risky fund, compared to just 12.7% of the female subjects, a highly significant difference. With regards to the recommendations, the largest difference occurs with the 25% allocation to the risky fund, which is selected by 19.6% of the male subjects versus 35.2% of the female subjects. Panel B shows the results for the professional managers. For both allocations selected by the subjects and recommended to their clients, roughly 90% of the managers of both genders choose one of the two highest allocations to the risky fund. These results indicate that the professional wealth managers are much more homogeneous in their risk preferences, and their recommendations, than are the graduate students. As mentioned previously, possible explanations include a selection effect for those choosing a wealth management career, as well as specialized training that generates a similar thought process for determining allocations.

We analyze the determinants of adviser recommendations in a series of cross-sectional regressions in which the dependent variable is the recommended allocation to the risky fund. Results are reported in Table 6. Panel A shows results for graduate students. In Model 1, two indicator variables are included, one for the client and the other for the adviser, which equal one for women and zero for men. The coefficient on client gender is insignificant, whereas the coefficient on adviser gender is –0.1120 and significant at the 1% level, so that on average the female students recommend 11.2% lower allocation to the risky fund than do the male students, consistent with the summary statistics in Table 4. Note, though, that the regression adjusted R^2 is just 3.9%. Adviser gender is an indicator of the recommendation but it is quite noisy. Model 2 adds the subject's own allocation choice as an additional explanatory variable as well as the allocation choice interacted with the indicator variable for a female adviser. The coefficient on adviser gender is now only marginally significant, whereas the coefficient on adviser allocation is a highly significant 0.4936, so that each 1% increase in adviser risk preference (as measured by their own allocation) raises the recommendation by about 0.5%. The interaction between adviser allocation and female adviser is not statistically significant, suggesting that male and female subjects project their own preferences similarly in the sample of graduate students. The regression R^2 jumps to 37.0%. Interestingly, the size of the R^2 is comparable to that reported in Foerster et al. (2015) in their study of actual recommendations of Canadian advisers. Model 3 adds adviser knowledge and confidence. Neither is significant.

Panel B repeats the regressions with the professional wealth managers. In Model 1, the coefficients on client gender and adviser gender are both insignificantly different from zero. In

Model 2, the coefficient on the adviser's own allocation is a highly significant 0.5415 and the coefficient on the interaction between allocation and female adviser is insignificant. The regression R^2 jumps from 0.0% in Model 1 to 34.3% in Model 2. This result suggests that, for the professional wealth managers, both male and female advisers project their preferences, as with the graduate students, and that there is no difference between the actions of male and female advisers.

Table 7 presents results of a regression in which the student and wealth manager samples are pooled. The coefficient on a wealth manager indicator in Model 1 shows that wealth managers recommend an allocation almost 23 percentage points higher than students. Model 2 adds an indicator for female adviser and an interaction between the two indicator variables. The significant intercept therefore measures the average recommendation of male students (64.2%), the significant coefficient on female adviser measures the difference between female and male students (–11.2%), the significant coefficient on wealth manager measures the difference between male managers and male students (21.1%), and the insignificant coefficient on the interaction shows that there is no difference between female and male managers. Models 3 through 5 shows that all of these differences are subsumed by the adviser's own allocation choice, both in the presence of control variables and without.

One feature of the wealth managers' responses raises an econometric concern: roughly 30% of the allocations and 40% of the recommendations are at the maximum level of 100% exposure to the risky fund. The concentration of observations at the upper boundary is a form of censoring, which typically has the effect of biasing coefficient estimates towards zero. A remedy is to estimate a Tobit censored regression using maximum likelihood. Table 8 shows the results for wealth managers. Panel A compares OLS to the Tobit model for the allocations. Results are qualitatively similar, with the coefficient on confidence larger and more significant using the Tobit model. Panel B shows the results for the recommendations. Again results are very similar, with the coefficient on the adviser's own allocation slightly larger using the Tobit model.

The results in Tables 6 through 8 indicate that the risk preference of the adviser is the primary determinant of the recommendation they provide. For graduate students, this means that markers for adviser risk preference could be used to forecast their recommendations. In this study, gender is used as the marker and this translates to higher recommended allocations to the risky asset from male students than from female students. However, in the sample of professional managers, there is no difference in the risk preferences across gender, and correspondingly no difference in recommendations by gender. An investor, then, when selecting an adviser, must use other means to ascertain the adviser's risk preference. And it appears that the preferences are best revealed through the adviser's own portfolio choice.

An important takeaway from our analysis is that since (a) professional advisers appear to be more risk tolerant than the population at large, as proxied for by graduate students, and (b) advisers tend to project their preferences on their clients, risk averse investors will likely be guided towards an allocation that is sub-optimal from a utility maximization perspective. The difference between client preference and adviser recommendation is likely to be larger for female clients. Naturally, retirement planning involves a tension between discomfort in taking risk today and expected discomfort from a future wealth-shortfall. That said, shoehorning an investor into an allocation that an adviser feels is best smacks of paternalism and runs the risk of a sub-optimal outcome.

It might be the case that investor education regarding the impact of today's allocation on the distribution of future wealth would make some risk averse investors more willing to accept a riskier portfolio, i.e., one that more closely resembles the recommendations we observe in our study of professional wealth managers. As mentioned previously, the shift to defined contribution plans also shifts the ultimate decision-making responsibility to individual investors. It is natural to seek help from an adviser, but the results of this study indicate that investors also need to understand their own risk preferences and the relation between risk and the distribution of future wealth to make appropriate retirement planning decisions.

6. Summary

For a sample of professional wealth managers, average allocation choice and client recommendation do not differ by adviser gender. This result stands in contrast to a sample of graduate business students, suggesting that a selection effect in career choice and/or financial training mitigates a gender difference in risk aversion that might otherwise exist in a general population. As a consequence, one cannot use adviser gender as a proxy for risk preference and a noisy indicator of a likely allocation recommendation. Consistent with Foerster et al. (2015) and Roth and Voskort (2014), adviser recommendations are strongly related to adviser allocations. In neither the graduate student nor professional manager sample does the correlation between adviser recommendations and allocations differ by gender.

While the results involving professional wealth managers are consistent with equality in all dimensions across men and women, it is unclear whether they are consistent with portfolio choice theory. In both the complete markets case, and the case including uninsurable background risks, one can argue that optimal allocations could on average differ across gender. We leave for future research an analysis for whether assumptions regarding gender differences in background risks that can produce gender differences in optimal allocations, as in Love (2010), are supported by current demographic and labor market conditions.

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Appendix.

Subjects read the following description of a hypothetical client prior to making an allocation recommendation, as well as choosing an allocation for themselves.

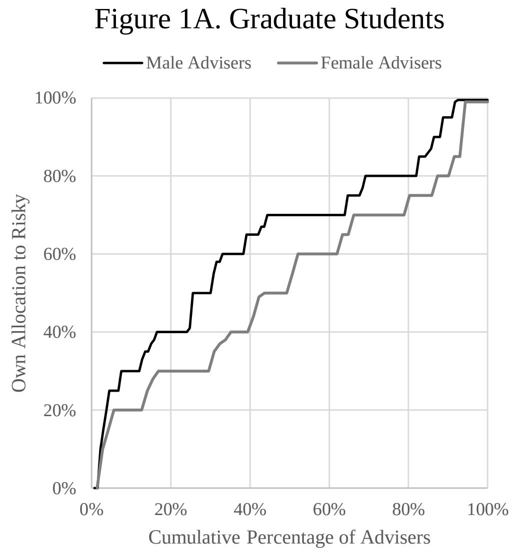
Suppose you were recently contacted by a new client. Please read the following description of their situation, then respond to the questions about the advice you would likely provide:

John (Jane) Smith is forty two years old, divorced, with sole custody of two children ages 7 and 13. He (She) is employed with a successful insurance company, currently earns $115,000 per year, and typically receives an annual raise between 2% and 5%. Mr. (Ms.) Smith has education savings accounts started for the children, and contributes the maximum allowed each year. Mr. (Ms.) Smith also makes the maximum contribution to his (her) company-sponsored 401(k) retirement plan.

Mr. (Ms.) Smith has come to you for advice on the allocation of retirement savings across asset classes. Suppose that Mr. (Ms.) Smith can invest in only two funds in his (her) company's plan: a money market fund and a balanced fund. The money market fund earns approximately 2% per year using short-maturity Treasury securities and certificates of deposit issued by commercial banks of the highest quality. Given the safety of these investments the money market fund is essentially risk-free. The balanced fund invests in stocks, corporate bonds, and real estate investment trusts, with proportions established by a team of fund managers to offer the highest possible reward to risk ratio. Historically, the balanced fund has earned 8% per year with a standard deviation of 15% per year.

Figure 1. Adviser allocations to risky assets.

Depicted are the distributions of allocations to risky assets selected by a sample of graduate students, in Figure 1A, and a sample of professional wealth managers, in Figure 1B. Subjects are asked to choose an allocation across a risk-free account earning 2% annually and a risky account, consisting of a blend of stocks and bonds with annual returns normally distributed with expected return of 8% and standard deviation of 15%. Distributions are constructed for subsamples based on subject gender.



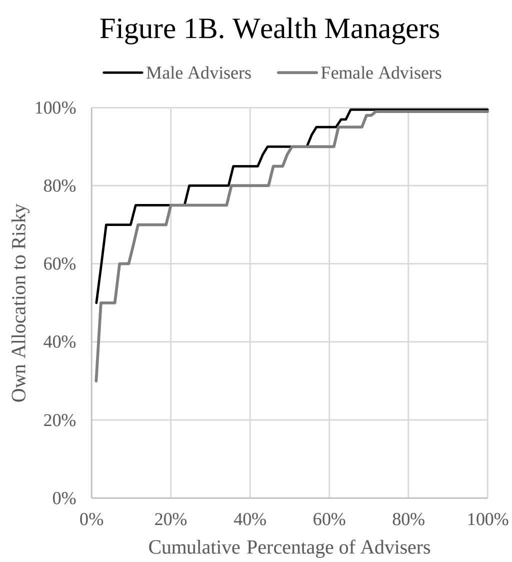
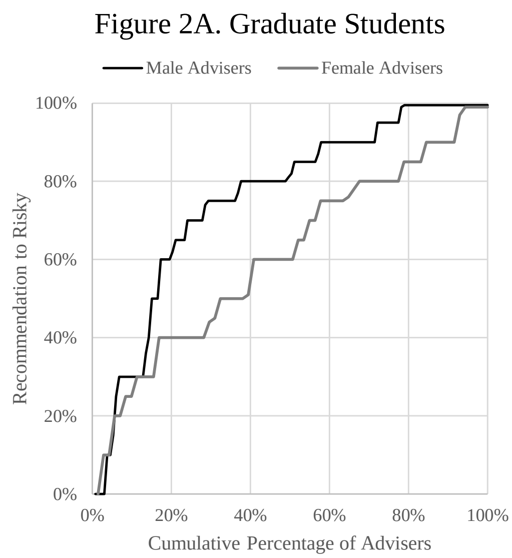


Figure 2. Adviser recommendations to risky assets.

Depicted are the distributions of allocations to risky assets recommended by a sample of graduate students, in Figure 2A, and a sample of professional wealth managers, in Figure 2B. Subjects are asked to recommend to a hypothetical client an allocation across a risk-free account earning 2% annually and a risky account, consisting of a blend of stocks and bonds with annual returns normally distributed with expected return of 8% and standard deviation of 15%. Distributions are constructed for subsamples based on subject gender.



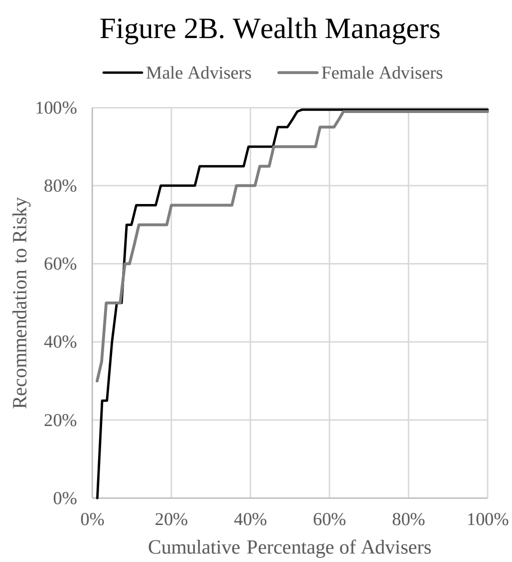


Table 1. Adviser attributes.

Listed in Panels A and B are summary statistics of adviser attributes for a sample of graduate students and professional wealth managers, respectively, split by the advisers' gender. Also listed are two-sided *p*-values measuring the significance of differences in means using a standard *t*-test. For students, attributes include: Age, in years, Knowledge, based on the number of correct responses on a quiz of eight investments questions, and Confidence, on a scale of 1 to 7. For professional wealth managers, attributes include: Age, in years, Knowledge, measured as years spent as a wealth manager, and Confidence, on a scale of 1 to 5. Panel C shows sample sizes. Panel D compares the average allocations to risky assets of gender subsets within and across the graduate student and professional wealth manager samples.

Panel A. Graduate Student Attributes

	Male Advisers				Female Advisers				
	Avg	Std Dev	Min	Max	Avg	Std Dev	Min	Max	*p*-value
Age	29.1	3.7	23	42	28.1	2.2	23	33	0.0176
Knowledge	5.1	1.3	1	7	3.7	1.4	1	7	0.0000
Confidence	5.1	1.3	1	7	4.5	1.3	1	7	0.0005

Panel B. Wealth Manager Attributes

	Male Advisers				Female Advisers				
	Avg	Std Dev	Min	Max	Avg	Std Dev	Min	Max	*p*-value
Age	47.8	10.2	29	74	48.5	9.4	24	65	0.6237
Knowledge	15.3	10.5	0	40	14.9	9.9	0	40	0.7780
Confidence	4.0	0.9	1	5	4.0	0.8	1	5	0.9297

Panel C. Sample Sizes

	Students (N = 204)		Managers (N = 174)	
	Male Advisers	Female Advisers	Male Advisers	Female Advisers
Male Clients	63	38	43	42
Female Clients	70	33	43	46
All Clients	133	71	86	88

Panel D. Comparison of Allocations

	All Advisers	Male Advisers	Female Advisers	*p*-value
Students	71.1%	76.1%	61.6%	0.0002
Managers	85.4%	86.0%	84.8%	0.6786
p-value	0.0000	0.0026	0.0000	

Table 2. Finance education.

Listed are the average allocation to a risky asset, financial knowledge, and confidence among subsets of the student sample split by whether the student is a finance concentrator and gender.

Panel A. Number of Observations

	All Students	Male Students	Female Students
Finance	104	86	18
Non-Finance	100	47	53

Panel B. Allocation to Risky Asset

	All Students	Male Students	Female Students	*p*-value
Finance	76.8%	78.9%	66.8%	0.0820
Non-Finance	65.1%	70.9%	59.9%	0.0295
p-value	0.0015	0.0871	0.3240	

Panel C. Knowledge

	All Students	Male Students	Female Students	*p*-value
Finance	5.40	5.51	4.89	0.0885
Non-Finance	3.77	4.23	3.36	0.0011
p-value	0.0000	0.0000	0.0003	

Panel D. Confidence

	All Students	Male Students	Female Students	*p*-value
Finance	5.22	5.28	4.94	0.2406
Non-Finance	4.55	4.85	4.28	0.0411
p-value	0.0002	0.0777	0.0391	

Table 3. Determinants of adviser allocations.

Listed in Panel A are the results of regressions assessing the determinants of graduate students' allocations to risky assets. Independent variables in include Female Adviser, which takes a value of one if the subject is female and zero otherwise, Age, in years, Knowledge, based on the number of correct responses on a quiz of eight investments questions, and Confidence, on a scale of 1 to 7. Panel B lists results for a sample of professional wealth managers, for which Knowledge is proxied by the number of years spent as a wealth manager. In both panels Age, Knowledge, and Confidence are standardized within each sample to permit comparisons across attributes and across samples. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Panel A. Graduate Students			Panel B. Wealth Managers		
Independent Variable	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
Intercept	0.7608***	0.7379***	0.7299***	0.8600***	0.8593***	0.8591***
p-value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Female Adviser	-0.1444***	-0.0788*	-0.0898**	-0.0122	-0.0108	-0.0109
p-value	0.0002	0.0598	0.0392	0.6776	0.7061	0.7032
Age		-0.0281	-0.0329*			
p-value		0.1138	0.0930			
Knowledge		0.0527***	0.0728***		0.0209	0.0357*
p-value		0.0072	0.0038		0.1560	0.0751
Confidence		0.0516***	0.0640***		0.0322**	0.0139
p-value		0.0044	0.0047		0.0298	0.4632
Age × Female Adviser			0.0420			
p-value			0.3862			
Knowledge × Female Adviser			-0.0542			-0.0367
p-value			0.1747			0.2147
Confidence × Female Adviser			-0.0312			0.0482
p-value			0.4045			0.1096
# Obs	204	204	204	173	173	173
R^2	6.3%	13.7%	14.0%	-0.5%	3.2%	4.0%

Table 4. Adviser recommendations.

Listed below are average recommended allocations to risky assets provided by subjects while advising a hypothetical client. Results are split by adviser gender and client gender and *p*-values are listed for standard *t*-tests of differences in means. Panel A lists results for a sample of graduate students. Panel B lists results for a sample of professional wealth managers. Panel C compares the average recommendation of graduate students to the average recommendation of wealth managers. Panel D shows the correlation between recommendations and allocations subjects choose for themselves.

Panel A. Graduate Student Recommendations

	Male Advisers	Female Advisers	*p*-value
Male Clients	63.3%	54.6%	0.1046
Female Clients	64.9%	51.1%	0.0043
p-value	0.6900	0.5447	

Panel B. Wealth Manager Recommendations

	Male Advisers	Female Advisers	*p*-value
Male Clients	84.1%	82.7%	0.7556
Female Clients	86.3%	79.5%	0.0809
p-value	0.5881	0.4769	

Panel C. Comparison of Pooled Recommendations

	All Advisers	Male Advisers	Female Advisers	*p*-value
Students	60.3%	64.2%	53.0%	0.0020
Managers	83.1%	85.2%	81.0%	0.1615
p-value	0.0000	0.0000	0.0000	

Panel D. Correlations: Allocations and Recommendations

	All Advisers	Male Advisers	Female Advisers
Students	0.61	0.55	0.66
Managers	0.59	0.63	0.56

Panel E. Differences: Allocations and Recommendations

	All Advisers	Male Advisers	Female Advisers
Students	-10.8%	-11.9%	-8.7%
p-value	0.0000	0.0001	0.0402
Managers	-2.3%	-0.8%	-3.8%
p-value	0.2753	0.8037	0.1864

Table 5. Adviser allocations and recommendations by quartiles.

Listed below are the percentage of allocations to risky assets in each of five categories selected by subjects for their own account and recommendations for their clients. Results are split by adviser gender and *p*-values are listed for standard *t*-tests of differences in means. Client gender is assigned randomly. Subjects are asked to recommend an allocation across a risk-free account earning 2% annually and a risky account, consisting of a blend of stocks and bonds with annual returns normally distributed with expected return of 8% and standard deviation of 15%. Allocation choices are the five listed. Panel A lists results for a sample of graduate students. Panel B lists results for a sample of professional wealth managers.

Panel A. Graduate Students

	Allocations			Recommendations		
	Male Advisers	Female Advisers	*p*-value	Male Advisers	Female Advisers	*p*-value
0% Risky	6.0%	5.6%	0.9122	1.5%	2.8%	0.5193
25% Risky	9.8%	21.1%	0.0248	19.6%	35.2%	0.0139
50% Risky	6.0%	22.5%	0.0005	16.5%	21.1%	0.4182
75% Risky	44.4%	38.0%	0.3829	48.9%	33.8%	0.0387
100% Risky	33.8%	12.7%	0.0011	13.5%	7.0%	0.1626

Panel B. Wealth Managers

	Allocations			Recommendations		
	Male Advisers	Female Advisers	*p*-value	Male Advisers	Female Advisers	*p*-value
0% Risky	3.5%	2.3%	0.6313	7.0%	0.0%	0.0117
25% Risky	3.5%	3.4%	0.9771	3.5%	3.4%	0.9771
50% Risky	3.5%	5.7%	0.4898	1.2%	4.6%	0.1818
75% Risky	32.6%	43.2%	0.1487	43.0%	53.4%	0.1705
100% Risky	57.0%	45.5%	0.1285	45.4%	38.6%	0.3697

Table 6. Determinants of adviser recommendations.

Listed below are regression results in which the dependent variable is the recommended allocation to risky assets provided by subjects for a hypothetical client. Client gender is assigned randomly. Subjects are asked to recommend an allocation across a risk-free account earning 2% annually and a risky account, consisting of a blend of stocks and bonds with annual returns normally distributed with expected return of 8% and standard deviation of 15%. Panel A lists results for a sample of graduate students. Panel B lists results for a sample of professional wealth managers. Model 1 includes Female Client, an indicator variable that equals one for female clients and zero otherwise, and Female Adviser, an indicator variable that equals one for female advisers and zero otherwise. Model 2 includes Adviser Allocation, the adviser's own allocation to risky assets, and Adviser Allocation interacted with Female Adviser. Model 3 includes a set of control variables. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Panel A. Graduate Students			Panel B. Wealth Managers		
Independent Variable	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
Intercept	0.6424***	0.2684***	0.2772***	0.8551***	0.3815***	0.3788***
p-value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Female Client	-0.0016	-0.0045	-0.0038	-0.0055	0.0102	0.0112
p-value	0.9620	0.8687	0.8890	0.8553	0.6795	0.6567
Female Adviser	-0.1120***	-0.1328*	-0.1255	-0.0422	-0.1853	-0.1856
p-value	0.0017	0.0986	0.1194	0.1647	0.1112	0.1162
Adviser Allocation		0.4936***	0.4728***		0.5415***	0.5441***
p-value		0.0000	0.0000		0.0000	0.0000
Female Adviser × Adviser Allocation		0.1492	0.1636		0.1761	0.1764
p-value		0.1842	0.1479		0.1861	0.1927
Knowledge			0.0214			-0.0026
p-value			0.1665			0.8389
Confidence			-0.0003			-0.0005
p-value			0.9839			0.9673
# Obs	204	204	204	173	173	173
R^2	3.9%	37.0%	37.0%	0.0%	34.3%	33.5%

Table 7. Determinants of adviser recommendations in the pooled sample.

Listed below are regression results in which the dependent variable is the recommended allocation to risky assets provided by subjects for a hypothetical client. Model 1 includes a Wealth Manager indicator. Model 2 includes a Female Adviser indicator, and the interaction between Female Adviser and Wealth Manager. Model 3 includes Adviser Allocation, the adviser's own allocation to risky assets, and Adviser Allocation interacted with Wealth Manager. Models 4 and 5 include control variables. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Independent Variable	Model 1	Model 2	Model 3	Model 4	Model 5
Intercept	0.6026***	0.6416***	0.2281***	0.2973***	0.2973***
p-value	0.0000	0.0000	0.0000	0.0000	0.0000
Wealth Manager	0.2283***	0.2107***	0.1040	0.0347	0.0374
p-value	0.0000	0.0000	0.1706	0.7040	0.6898
Female Adviser		-0.1119***	-0.0334	-0.0181	-0.0186
p-value		0.0006	0.2222	0.5407	0.5373
Female Adviser × Wealth Manager		0.0695	-0.0016	-0.0170	-0.0165
p-value		0.1369	0.9670	0.6730	0.6846
Adviser Allocation			0.5435***	0.5288***	0.5297***
p-value			0.0000	0.0000	0.0000
Adviser Allocation × Wealth Manager			0.0614	0.0777	0.0751
p-value			0.4772	0.3760	0.4004
Knowledge				0.1158	0.1160
p-value				0.1746	0.1751
Knowledge × Wealth Manager				-0.1176	-0.1181
p-value				0.1722	0.1717
Confidence					-0.0011
p-value					0.9266
Confidence × Wealth Manager					0.0039
p-value					0.8690
# Obs	384	384	384	384	384
	20.4%	22.7%	49.1%	49.0%	48.8%

Table 8. Censored Regressions.

Listed below are comparisons between OLS estimates and maximum likelihood estimates for Tobit censored regressions. For the Tobit regressions are the adjusted McFadden's pseudo-R^2. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A. Allocations

	OLS		Tobit	
Independent Variable	Model 1	Model 2	Model 1	Model 2
Intercept	0.8600***	0.8336***	0.6421***	0.6059***
p-value	0.0000	0.0000	0.0000	0.0000
Female Adviser	-0.0122	-0.0111	-0.0275	-0.0254
p-value	0.6776	0.7022	0.3857	0.4216
Age		-0.0381		-0.0375
p-value		0.1950		0.2426
Confidence		0.0553		0.0742**
p-value		0.1193		0.0170
# Obs	173	173	173	173
R^2	-0.5%	0.6%	-0.8%	-0.2%

Panel B. Recommendations

	OLS		Tobit	
Independent Variable	Model 1	Model 2	Model 1	Model 2
Intercept	0.8551***	0.3815***	0.7000***	0.2352*
p-value	0.0000	0.0000	0.0000	0.0682
Female Client	-0.0055	0.0102	-0.0075	0.0099
p-value	0.8553	0.6795	0.8141	0.7095
Female Adviser	-0.0422	-0.1853	-0.0475	-0.2002
p-value	0.1647	0.1112	0.1334	0.1637
Adviser Allocation		0.5415***		0.5529***
p-value		0.0000		0.0002
Female Adviser × Adviser Allocation		0.1761		0.1899
p-value		0.1861		0.2631
# Obs	173	173	173	173
R^2	0.0%	34.3%	-1.5%	59.9%