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First Impressions Matter: An Experimental Investigation of Online Financial Advice

Julie R. Agnew
Raymond A. Mason School of Business, College of William and Mary, Williamsburg, Virginia 23185, julie.agnew@mason.wm.edu

Hazel Bateman
UNSW Business School, UNSW Australia, Sydney NSW 2052, Australia, h.bateman@unsw.edu.au

Christine Eckert
Business School, University of Technology Sydney, Ultimo NSW 2007, Australia, christine.eckert@uts.edu.au

Fedor Iskhakov
Research School of Economics, The Australian National University, ACT 2601, Australia; and ARC Centre of Excellence in Population Ageing Research, UNSW Australia, Sydney NSW 2052, Australia, fedor.iskhakov@anu.edu.au

Jordan Louviere
School of Marketing, University of South Australia, Adelaide SA 5001, Australia, jordan.louviere@unisa.edu.au

Susan Thorp
University of Sydney Business School, University of Sydney, NSW 2006, Australia, susan.thorp@sydney.edu.au

We explore how individuals assess the quality of financial advice they receive and how they form judgments about advisers. Using an incentivized discrete choice experiment, we show that first impressions matter: consumers more often follow advisers who dispense good advice before bad. We demonstrate how clients' opinions of adviser quality can be manipulated by using an easily replicated confirmation strategy that depends on the quality of the advice and the difficulty and order of the advice topics. Our results also reveal how clients benefit from their own past experience and how they use professional credentials to guide their choices.

Data, as supplemental material, are available at https://doi.org/10.1287/mnsc.2016.2590.

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1. Introduction

Unsophisticated individuals are carrying more responsibility for complicated financial decisions, even though financial literacy is generally low (Lusardi and Mitchell 2011). Consequently, academics and regulators are searching for ways to support and improve the financial choices of ordinary people (see Agnew 2010 for examples related to pensions). Engaging a financial adviser could help, but the theoretical and empirical literature suggests that agency problems and poor advice abound (Anagol et al. 2013; Bergstresser et al. 2009; Chalmers and Reuter 2015; Hackethal and Inderst 2013; Inderst and Ottaviani 2009, 2012a, b; Mullainathan et al. 2012). It is also unclear whether consumers can discern which adviser or advice to trust (ASIC 2012). Consumers of advice need to be able to engage with advisers who will deliver unbiased, high quality counsel.

Here we study interactions between ordinary consumers and advisers to determine the extent to which people can distinguish good advice from bad. We also test whether their evaluations of the advice, and of the advisers themselves, can be manipulated over time or influenced by external factors. In a new approach for studies of financial advice, we do this by analyzing the results of an incentivized discrete choice experiment. We show how clients' decisions on which adviser to follow, and whether to continue to trust an adviser, can be manipulated by a simple and easily replicated catering strategy. Advisers who make good first impressions by confirming clients' views are more often followed in subsequent decisions. Results also highlight how an adviser's credentials can positively influence clients' evaluations.

2. Background

Recent research shows that relationships between consumers of advice and financial advisers are complicated and not well understood.[1] Hackethal et al. (2012) suggest that, at least in theory, financial advisers should ameliorate the drawbacks of weak consumer financial literacy. But Hackethal and Inderst (2013) find that advice can be used to exploit a client's lack of financial literacy and inexperience, and Inderst and Ottaviani (2009, 2012a) warn that agency problems are likely.

Other research provides similarly mixed evidence. In favor of financial advice, Bhattacharya et al. (2012) find that clients who follow unbiased computer-generated advice enjoy an improvement in portfolio efficiency. Finke (2013) shows that prior consultation with a financial planner is positively related to higher net worth and retirement wealth and makes the use of tax-preferred savings vehicles more likely. On the negative side, broker-sold funds and broker-constructed portfolios in the United States underperform benchmarks (Bergstresser et al. 2009, Chalmers and Reuter 2015), and advisers do not always undo the behavioral biases and misconceptions of their clients (Bergstresser et al. 2009, Mullainathan et al. 2012). In addition, some advisers encourage clients to trade excessively and purchase unsuitable products, so that even experienced people who do not monitor their advisers are susceptible to manipulation (Hackethal et al. 2012). Advisers sometimes recommend unsuitable products and cater to uninformed clients (Anagol et al. 2013). These studies raise the question of why people seek financial advice, and more puzzlingly, why they continue to follow advice of dubious value.

Both empirical and theoretical studies show that consumers need to carefully select and monitor their advisers, but there is limited research into how they do this. Trust is an important driver of analyst selection and advice use. Industry surveys conducted by the Certified Financial Planner Board of Standards (2004) and State Street Global Advisors (2007) rank trustworthiness as the most important factor in choosing an adviser, a finding supported by academic research (Lachance and Tang 2012). Furthermore, Georgarakos and Inderst (2011) and Hackethal et al. (2010) show that clients with limited financial capability are more likely to follow advice if they trust their advisers. Hence, if we want to understand the adviser/client relationship, we must understand trust formation.

Earned trust depends on many factors, including the consumer's capability in the advice area, the accuracy and quality of information provided, and the belief that adviser and client incentives are aligned (Sniezek and Van Swol 2001, Yaniv and Kleinberger 2000). However, there also is evidence that the trust of many clients is easily won, albeit not always deserved. For example, administrative data and survey data obtained by Hackethal et al. (2010) and field studies conducted by Mullainathan et al. (2012) and the Australian Securities and Investments Commission (ASIC 2012) show that clients often continue to trust advisers who give poor-quality and/or self-interested advice. Indeed, Mullainathan et al. (2012) report that a large majority of the auditors surveyed in their study said they would use the advisers they met during the research for investment advice, even though the auditors had often received biased advice. Similarly, over 80% of the people recruited to report on meetings with financial advisers for the ASIC field experiment said they trusted the adviser they met, despite the fact that according to objective ratings, only 5% of these clients received good advice. The ASIC (2012) report attributes part of the blame for this low discernment on the complexity of the financial decisions.

It is not surprising that advisers might deliberately use strategies to build client trust. For example, to establish credibility with a new client, an adviser might "cater" by initially supporting the client's existing strategy, and only diverge from that strategy after trust has been established (Anagol et al. 2013, Mullainathan et al. 2012). Similarly, Gennaioli et al. (2015) present a model that predicts money managers will pander to investors' beliefs to build trust, even when those beliefs are biased, because the most trusted managers can charge their clients the highest fees.

3. Research Approach

Our approach studies how well individuals can assess the relative quality of financial advice and whether a catering strategy based on confirming a client's opinions and creating good first impressions can influence subsequent judgments and build trust, even in an artificial, video advice setting. We also study whether a signal of expertise (i.e., a credential) influences decisions.

3.1. Motivation for Conducting Study in Australia and Regulatory Background

Research in financial advice has an international scope and reach; however, there are several factors making Australia the ideal country in which to conduct this study: first, the Australian population is experiencing rapid increases in retirement wealth and consequent consumer demand for advisers; second, there is an ongoing and lively public discussion on improving financial adviser service in Australia; and

[1] See Mitchell and Smetters (2013) for a collection of recent research into financial advice on retirement topics. Holden (2013) and Collins (2010, 2012) explore who uses financial advice.

third, we have access to a nationally representative online sample of Australian citizens.

A major cause of the increased demand for advisers, and of the growing retirement wealth of Australians, is the country's mandatory retirement savings program, called "Superannuation." Since the early 1990s, most Australian workers have accumulated retirement savings in personal accounts, and many are now reaching retirement with sizeable defined contribution balances and are needing assistance with wealth management. This expanding group of well-off retirees has attracted attention from advisers, who in turn are facing increasing scrutiny from regulators. These conditions made our research objectives particularly relevant to Australian public policy discussions, while the implications from our results are also pertinent for regulators and the financial industry around the world.

At the time of our survey, regulators were focusing on market conduct and consumer protection, and these priorities remain today. Australia's consumer protection regulation covers provider licensing (Australian Financial Services (AFS) License), financial adviser competency standards, and specific disclosures to clients, including information about fees and charges, related parties, and conflicts of interest. At the time we fielded the survey for this paper in early 2013, new rules aimed at strengthening consumer protection were enacted on a voluntary basis and later became mandatory in July 2013 (Bateman and Kingston 2012).[2] Media coverage of advice regulation was high, and most survey participants would have been at least aware of the regulatory debates, if not fully informed. Since we fielded the survey, several examples of poor practice in financial advice have emerged, and the regulator and industry have begun canvassing improvements to the training and registration of financial advisers, also proposing an indemnity plan to compensate clients who receive bad advice. Thus, the regulation of financial advice remains a hot topic for debate in Australia.

3.2. Survey Overview

To answer our research questions, we designed and implemented an incentivized online choice experiment, which was embedded in a larger survey.[3] We began the survey by screening potential participants to match the age and gender proportions of the Australian population and then progressed through four parts.

The first part measured knowledge on inflation, interest rates, and diversification using questions from Lusardi and Mitchell (2011), tested numeracy skills (Lipkus et al. 2001) and gauged understanding of the four advice topics covered in the choice experiment. This part concluded with questions about a range of financial products and assessed attitudes toward financial advisers in general.

The second survey component was the incentivized choice experiment described in detail in Section 3.3. After the choice experiment, we asked participants to rate the advisers assigned to them on seven personal and professional traits: trustworthiness, competence, attractiveness, understanding, professionalism, genuineness, and persuasiveness. The third component collected demographics (e.g., marital status, household size and number of dependents, education, labor market status, income, gross assets and debts/liabilities) and personal characteristics, including personality traits and risk attitudes. We included two sets of instructional manipulation checks (IMCs), designed to measure whether participants paid attention to the survey (Oppenheimer et al. 2009).

The final component of the survey consisted of a debriefing, where we reminded participants that the experimental task involved only very simplified versions of actual financial situations and we encouraged participants to consult a professional financial adviser when making personal financial decisions. The debriefing explained the correct recommendations for the four advice topics, concluding with four incentivized questions to test whether participants understood the debriefing and with an invitation to provide open-ended feedback on the whole survey.[4] The feedback was strongly positive.

3.3. Basic Design of the Discrete Choice Experiment

The experimental task in the second survey component began with a short introductory video followed by videos of financial advice recommendations from two advisers on four different topics.[5] A production studio created the videos, and professional actors portrayed the advisers and narrator. We pretested narrators from among several actors and chose the one perceived to be the most unbiased and trustworthy to present the introduction. We also pretested other key aspects of the experimental design, including the four actors playing the financial advisers, the adviser

[2] These rules were known as the Future of Financial Advice (FoFA) reforms. For more details, see http://asic.gov.au/regulatory-resources/financial-services/future-of-financial-advice-reforms/fofa-background-and-implementation/ (accessed November 11, 2016).

[3] A full set of screenshots from the survey, including the wording of all questions and instructions, is available in Supplemental Material A (available at https://doi.org/10.1287/mnsc.2016.2590).

[4] We maximized incentive compatibility and encouraged attention during the debriefing by offering monetary prizes if participants could correctly answer the test questions. The incentive was one entry for each correct answer in a A$50 draw. The panel provider paid participants who completed the survey approximately A$4.

[5] Supplemental Material B describes the experimental design in detail.

names, the advice topics, and the adviser credentials. Actors playing advisers were selected to be as similar to each other as possible on a range of personal traits (see Supplemental Material C, Section C1).

In the introductory video, the narrator welcomed participants to the study, explained the task, the setting, and the associated questions, and made several important statements stipulated by the Institutional Review Board (IRB) at the university. When the introductory video ended, a separate webpage appeared that explained how participants could increase the payment they received for completing the survey by answering the experimental questions correctly. We offered participants an incentive to choose the adviser giving the correct recommendation for each advice topic of one entry for each correct answer in a A$50 draw. We awarded this same level of incentive for correct answers to the debriefing questions at the end of the survey.

Following the incentive disclosure, participants viewed a series of four pairs of investment advice recommendations related to four different financial topics. Each financial topic began with a short introduction by the narrator describing the scenario, then continued with advice from two advisers pictured next to each other. Participants first viewed the video of the adviser on the left (Adviser 1) and then looked at the video of the adviser on the right (Adviser 2). Each participant viewed the same two advisers in the same position on the screen for every topic (see Supplemental Material A). After watching both videos, participants could review the two advisers' recommendations as many times as they wished before choosing which recommendation they would be most likely to follow. They did this for each of the four topics.

Within each topic both correct (good) and incorrect (bad) advice were given. We manipulated the order in which the four topics appeared, and whether good advice was given by the left- or right-hand side adviser. We paired the advisers to allow for variation in adviser characteristics, namely age and gender. In addition, professional credentials were displayed by one of the advisers in the pairing. A text display showing names and credentials appeared for several seconds while a specific adviser's video was playing.

Combining these orders and pairings resulted in 256 experimental conditions as presented in Table 1. Each of 1,271 participants was randomly assigned to one of these conditions. The theory underlying the design of the conditions is detailed in Supplemental Material B. An online example of one condition of the choice experiment is available in the supplemental material. The design allowed us to test for the effects of the adviser's credential, as well as the influence of advice quality and topic order.

3.4. Selection of Adviser Attributes and Names

We base the selection of the three adviser attributes (gender, age, and credential) on a survey of marketing materials created by Australian firms that provide financial adviser services and through our review of related research on advice use. The promotional material often depicted advisers as women in Australia, which motivated our interest in controlling for gender effects. In addition, we controlled for age because organizational behavior studies examining advice discounting suggested that individuals might be more responsive to advice from older people who have more life experiences or who are perceived to be experts (Feng and MacGeorge 2006, Harvey and Fischer 1997, Nadler et al. 2003).

We focus our analysis on the influence of credentials, as a signal of expertise. Because of the associated policy implications and current debates over their use in several countries, credentials are particularly appealing as an attribute and one of the focuses of our study. Showing that consumers use credentials as signals of adviser quality could be the first step to determining whether they can be a tool to help consumers choose advisers. We designated advisers as "certified financial planners" in our experiment, which is the foremost credential in Australia.[6]

Before using this credential in the experiment, we needed to confirm that participants recognized the name and considered it a positive signal, so we pretested a list of adviser credentials. We showed pretest participants 11 credentials, both real and fake. We asked them to select the credential that would indicate an adviser who would be the "most likely to provide good advice" and the credential for an adviser who would be the "most likely to provide bad advice" and made an aggregate ranking of all the credentials. Pretest results showed that participants viewed the real qualification "certified financial planner" as the highest quality credential but also uncovered a potential downside. The next two most popular credentials ("master financial planner"; and "qualified financial planner with high designation") were fake, yet preferred over other real credentials. Therefore, consumers have difficulty discriminating one credential from another, especially when there are many similar-sounding labels to evaluate.

[6] If a person or institution wants to run a financial services business in Australia, they need to obtain an Australian Financial Services (AFS) License from the Australian Securities and Investments Commission (ASIC). Australian regulation describes a "financial adviser" as someone who is licensed to provide financial advice (either personally or because he or she works for an institution that holds an AFS License). However, a licensed adviser may also call himself a "financial planner"; the labels tend to be used interchangeably and the roles, duties and responsibilities are the same.

Table 1 Experimental Design

Panel A. Design of advisers pairs

	Adviser 1 (shown on the left)			Adviser 2 (shown on right, mirror image)		
Pair	Gender	Age	Accreditation	Gender	Age	Accreditation
1	Male	Young	No	Female	Old	Yes
2	Male	Young	Yes	Female	Old	No
3	Male	Old	Yes	Female	Young	No
4	Male	Old	No	Female	Young	Yes
5	Female	Old	No	Male	Young	Yes
6	Female	Old	Yes	Male	Young	No
7	Female	Young	No	Male	Old	Yes
8	Female	Young	Yes	Male	Old	No

Panel B. Sequence of advice topics

	Sequence 1	Sequence 2	Sequence 3	Sequence 4
1st topic	Debt	Diversification	Consolidation	Fees
2nd topic	Diversification	Debt	Fees	Consolidation
3rd topic	Fees	Consolidation	Diversification	Debt
4th topic	Consolidation	Fees	Debt	Diversification
Clarity	EHHE	HEEH	EHHE	HEEH

Panel C. Design of the sequence of advice quality

	Advice from Adviser 1 (shown on the left)				Advice from Adviser 2 (shown on the right, mirror image)			
Quality sequence	1st topic	2nd topic	3rd topic	4th topic	1st topic	2nd topic	3rd topic	4th topic
1	B	B	B	B	G	G	G	G
2	B	B	G	G	G	G	B	B
3	B	G	B	G	G	B	G	B
4	B	G	G	B	G	B	B	G
5	G	B	B	G	B	G	G	B
6	G	B	G	B	B	G	B	G
7	G	G	B	B	B	B	G	G
8	G	G	G	G	B	B	B	B

Notes. Panel A shows the combination of adviser attributes using a foldover design for each possible adviser. Each participant to the survey viewed only one of the eight rows. Thus, they saw the same two advisers for the entire experiment, and each adviser stayed on the same side of the screen throughout the experiment. Panel B shows the sequence of advice topics for each condition in the experiment. Each participant viewed one of the four columns, interacted with the rows in panel C, where "E" stands for one of the easy topics (debt and account consolidation) and "H" stands for one of the hard topics (fees and diversification). Panel C shows the eight sequences of advice quality for each condition in the experiment. Each participant viewed one of the eight rows. G stands for good advice, whereas B stands for bad advice.

As suggested by recent behavioral finance literature, we also pretested adviser names used in the experiment to ensure that they were approximately equally "liked" and trusted (Kumar et al. 2015). Using these test results, we settled on four adviser names: Michael Adams (younger male), Claire Harris (younger female), David Forbes (older male), and Elizabeth Turner (older female). (Supplemental Material C, Sections C2 and C3, report pretests.) The four adviser images can be found in Supplemental Material C, Section C3.

3.5. Selection of Financial Topics and Advice Content

To select financial topics, we identified straightforward financial issues that are often confronted by individuals around the world and that are also associated with common mistakes. We also wanted to ensure that each topic has only one correct answer. This was a challenge, because good advice usually depends on an individual's specific situation and preferences.

The first topic, choosing a low-fee index fund, is an enduring puzzle in consumer finance, where index funds that are essentially commodities often have a wide range of fees (Elton et al. 2004, Hortacsu and Syverson 2004). Even relatively well-educated investors often fail to account for fees when comparing funds (Choi et al. 2010).

Other research shows that the second topic, diversification, is widely misunderstood (Agnew et al. 2013, Lusardi and Mitchell 2011). For example, only around one-third of surveyed adults knew that a well-diversified fund was less risky than a single stock in the United States, Germany, the Netherlands, and Australia (Agnew et al. 2013, Lusardi and Mitchell 2014). Mistakes related to these two topics are common in practice. In fact, the U.S. Department of Labor, in its final rule related to investment advice for participants in individual account plans, list payment of inefficiently high investment fees and inadequate diversification as two of five distinct errors U.S. residents make in retirement (Department of Labor 2011). The third topic, paying down credit card debt, is a concern to regulators in several economies, such as the United States and Australia, where cardholders commonly incur unnecessary fees and interest charges (Agarwal et al. 2015, Bagnall et al. 2011, Social Research Centre and ANZ 2011, FINRA 2013).

The fourth topic, consolidation of retirement accounts, is an important issue in economies with automatic enrollment in retirement plans. In Australia, contributions to retirement accounts are mandatory for most workers, and many accumulate several accounts along with redundant administrative fees and insurance premiums. There are about 3.4 million lost accounts amounting to approximately A$17 billion in unclaimed savings in Australia (Australian Treasury 2013); in the United States missing 401(k)s, called "zombie accounts," are also a multibillion dollar amount (Pechter 2013). Scripting ensured that each actor delivered both an introduction to the topics and good or bad advice in exactly the same way. Table 2 shows the scripts for the advice.

We pretested these topics to confirm that a majority of people could indeed discern good from bad advice on them. Pretesting also showed that recognizing good advice was easier than discounting bad advice (see Supplemental Material C, Section C4). The pretest results indicate that many people are not completely secure in their opinions and could be open to misleading, persuasive arguments, particularly on the more difficult topics of fees and diversification. In our analysis, we use this difference between the harder topics (diversification and fees) and easier topics (debt reduction and account consolidation) to test catering strategies.

3.6. Sample and Summary Statistics

We recruited a sample from the Pureprofile (https://www.pureprofile.com/us/) online panel that consists of over 600,000 Australians. We screened participants, whom we recruited by an initial email invitation from Pureprofile, to match the population age distribution and ensure equal proportions of men and women. We excluded people who had participated in the pretesting. As noted, a total of 1,271 participants over 18 years of age completed the video survey. Our sample matches the Australian population well, except that we include a larger proportion of university (college) graduates, a larger proportion of married people, and a smaller proportion of people over age 75 (see comparison with the 2011 Australian Census in Supplemental Material D).

To understand the impact of different aspects of financial literacy, knowledge, and numeracy, we construct indices to summarize their key features. We also construct indices for risk tolerance, conscientiousness, and impulsiveness. In addition, experienced people might (or might not) be less susceptible to mental accounting or endowment effects (Haigh and List 2005; List 2003, 2004), so we also count the proportion of correct decisions on each advice topic that participants reported having made previously (labeled "Past correct decisions | topic") and we proxy market experience by four indicators taking the value of one (zero otherwise) when the participant reports using (or having used in the past) the financial security relevant to each of the advice topics. Table 3 defines each variable. Table 4 reports summary statistics on each from the sample.

At the aggregate level, participants chose good over bad advice 83% of the time. Consistent with our pretests (see Supplemental Material C, Section C4), participants found that debt repayment is the easiest topic and chose good advice more than 90% of the time. Choosing the right advice about index fund manager fees was much more difficult, as was deciding on the correct advice about stock diversification strategy. Each adviser gave equal numbers of good and bad recommendations for each topic in total, but the young female adviser's advice was chosen more often, and the older male's advice was chosen less often. Although differences are small, this finding is at odds with stereotypes of financial advisers as middle-aged men, but it fits with patterns we saw in ads for financial planning services, which often feature young women. Participants were slightly more likely to choose the advice delivered when the certified financial planner label accompanied the adviser's name. However, we note that our interpretation of the results related to gender and age should be considered with caution, because our results might be capturing other latent personal differences between the advisers.

4. Empirical Models and Results

The design of our experiment permits us to explore many questions raised and still unanswered by the literature. For example, what characteristics of advice, advisers, and clients influence choices? What are the conditions under which people choose bad advice, and who is more likely to do so? Do credentials influence choice? Do "first impressions" matter such that early advice experiences influence clients' subsequent decisions? How important is "catering," where

Table 2 Financial Advice Script

Narrator introduction	Advice	Narrator introduction	Advice
Paying down debt: In this scenario, you have accumulated some large outstanding credit card debt with a high associated interest rate. Recently, you have inherited some money unexpectedly and would like to know what to do with it. The next two financial advisers will recommend what you should do.	**Good advice**: I understand that you have some large credit card debt but recently inherited money. It is important to think about your overall financial position when making a decision about what to do. *It is easy to simply save this big sum of money in a savings account to achieve a savings goal, but the interest gained is far smaller than the high interest expense of not paying down your credit card debt. Therefore, I recommend you pay off your credit card debt to eliminate the high interest charges.* **Bad advice**: I understand that you have some large credit card debt but recently inherited money. It is important to think about your overall financial position when making a decision about what to do. *It is hard to save big sums of money so it is important to think about your special savings goals when making this decision. Therefore, I recommend you ignore your credit card debt for now and put your inheritance in a separate savings account.*	**Choosing an index fund**: In this scenario, you are thinking about investing in a managed share index fund. The next two financial advisers will recommend what you should do about it.	**Good advice**: I understand you need help regarding your choice of share index fund. Did you know that all share index funds invest with the aim of matching the overall share market return? These various share index funds provide an almost identical product *so why pay a fund manager more than the others for the same thing. Therefore, I recommend that you choose the share index fund with the lowest management fees.* **Bad advice**: I understand you need help regarding your choice of share index fund. Did you know that all share index funds invest with the aim of matching the overall share market return? These various share index funds provide an almost identical product *but some fund managers have better reputations than others and you get what you pay for. Therefore, I recommend that you avoid the share index funds with low management fees.*
Consolidating retirement accounts: In this scenario, suppose you have just changed jobs and started a new superannuation account. Currently, you already have two other superannuation accounts from past jobs. The next two financial advisers will recommend what you should do about it.	**Good advice**: I see that you have three superannuation accounts with different super funds. Did you know that people are typically charged regular fixed administration fees on all of these superannuation accounts? *As a result, I recommend that you roll all of these accounts together so you are not paying extra fees.* **Bad advice**: I see that you have three superannuation accounts with different super funds. Did you know that people are typically charged regular fixed administration fees on all of these superannuation accounts? *Despite that, I recommend that you not roll all of these accounts together so you are diversified across different superannuation funds.*	**Diversifying a stock portfolio**: In this scenario, you are thinking about investing in the share market. The next two financial advisers will recommend what you should do about it.	**Good advice**: I understand you need help regarding how to invest your superannuation money. Did you know money invested in shares can go up and down? *It is good to try to balance out the shares that go up with the shares that go down. Therefore, I recommend that you spread your money across a variety of shares in different types of companies and industries.* **Bad advice**: I understand you need help regarding how to invest your superannuation money. Did you know money invested in shares can go up and down? *That is why it is good to invest in something you know and can easily monitor. Therefore, I recommend that you invest your money in one blue chip company.*

Notes. This table provides the scripts for the four advice topics. Each video begins with the narrator's introduction. The two advisers provide identical advice (the underlined advice) at the beginning of their talk and then depart from one another at the end (the italicized part).

advisers seek favor by confirming (or at least not contradicting) clients' existing views when making recommendations? Can a combination of catering and positive first impressions benefit an adviser in the long run? To address these questions, we analyze the participants' advice choices throughout the experiment and their final evaluations of the advisers' personality traits using three separate econometric models.

4.1. What Factors Influence Choice? Choice at the Initial Meeting

If previous interactions between the advisers and clients influence behavior, then the optimal time to determine what other factors influence choice is immediately after the client's initial meeting. We think of the first of the four choices survey participants make as the outcome of the "initial meeting" between the participant (i.e., the "client") and the two video "advisers." We hypothesize that clients are more vulnerable to bad advice when topics are more difficult and that clients who have less financial capability, such as lower financial literacy or limited experience, are more likely to accept bad advice.

To model initial meetings, we treat the participant as having a conventional, linear indirect random utility function related to the choice of advice, with normally distributed, mean zero, additive errors.

Table 3 Variable Definitions

	Model			
Variable name	1	2	3	Description
Constant	$\mathbf{x}_1$	$\mathbf{x}_3$		
Adviser characteristics				
Female	$\mathbf{x}_1$	$\mathbf{x}_3$	$\mathbf{x}_4$	Indicator variable that equals one if the adviser was female, and zero for male.
Older	$\mathbf{x}_1$	$\mathbf{x}_3$	$\mathbf{x}_4$	Indicator variable that equals one if the adviser was older, and zero for younger.
Displays credential	$\mathbf{x}_1$	$\mathbf{x}_3$	$\mathbf{x}_4$	Indicator variable that equals one if adviser's name and "Certified Financial Planner" was displayed, and zero when only adviser's name was displayed.
Advice				
Bad advice	$\mathbf{x}_1$	$\mathbf{x}_3$		Indicator variable that equals one if the wrong advice was given in the particular choice set, and zero otherwise. Model 1 refers to the first choice set and Model 2 refers to the third choice set.
Topic: Account consolidation	$\mathbf{x}_2$			Indicator variable that equals one if the topic was account consolidation, and zero otherwise.
Topic: Stock diversification	$\mathbf{x}_2$			Indicator variable that equals one if the topic was stock diversification, and zero otherwise.
Topic: Index fund fee	$\mathbf{x}_2$			Indicator variable that equals one if the topic was index fund management fees, and zero otherwise.
Topic: Debt repayment				Reference category for advice topic.
Participant characteristics				
Passed IMC 1	$\mathbf{x}_2$			Indicator variable that equals one if the participant answered the first instructional manipulation check correctly, and zero otherwise.
Passed IMC 2	$\mathbf{x}_2$			Indicator variable that equals one if the participant answered the second instructional manipulation check correctly, and zero otherwise.
Participant female	$\mathbf{x}_2$			An indicator variable that equals one if the participant is a female, and zero otherwise.
Participant age	$\mathbf{x}_2$			A polychotomous variable that equals one if the participant is 18–24 years and rising by one in five-year steps.
Financial literacy	$\mathbf{x}_2$			An indicator variable that equals one if the participant's correct percentage on four financial literacy questions is above the sample median, and zero otherwise. Questions test simple interest, inflation, diversification, and compound interest.
Numeracy	$\mathbf{x}_2$			An indicator variable that equals one if the participant's correct percentage on three numeracy questions is above the sample median, and zero otherwise. Questions test fractions, percentages, and probabilities.
Product knowledge	$\mathbf{x}_2$			An indicator variable that equals one if the participant's correct percentage on four financial product questions is above the sample median, and zero otherwise. Questions test topics used in advice experiment: debt, index funds, account consolidation, diversification.
Conscientiousness	$\mathbf{x}_2$			An indicator variable that equals one if the participant's conscientiousness is above the sample median, and zero otherwise. Participants rated themselves as organized, responsible, hardworking and careless (reverse coded) on a four-point scale. Ratings are averaged.
Impulsiveness	$\mathbf{x}_2$			An indicator variable that equals one if the participant's impulsiveness is above the sample median, and zero otherwise. Participants rated themselves as buying too much, buying impulsively, buying without planning, and/or buying unnecessarily on a five-point scale. Ratings are averaged.
Past correct decisions | topic	$\mathbf{x}_2$			Four variables measuring the percentage of times the participant reported having acted competently in past financial decisions, as measured by two examples relating to each of diversification, debt management, consolidation and investment management fees.
Risk tolerance	$\mathbf{x}_2$			An indicator variable that equals one if the sum of the participant's Likert scale ratings on five of Finametrica's risk survey questions: risk tolerance compared to others; willingness to take risk in financial decisions (job, investments, overall); and confidence in their ability to make good financial decisions is above the sample median, and zero otherwise. (We rescaled ratings with zero indicating very low and one indicating very high tolerance then summed.)
Market experience | topic	$\mathbf{x}_2$			Four indicator variables that equal one if the participant reports owning the financial security related to each advice topic, and zero otherwise. Participants reported whether they owned a credit card (debt), units in an index fund (fees), a superannuation account (consolidation), and stocks (diversification).

The experiment structure ensures that the adviser appearing on the left of the computer screen during the first choice set remains on the left for the subsequent choice sets. We call him or her "Adviser 1." The adviser appearing on the right of the screen we call "Adviser 2." The participant's utility of choosing Adviser 1 (denoted $y = 1$) rather than Adviser 2 (denoted $y = 0$) at choice set $i = 1$ is a function of the differences between the attributes of the advisers, the difference in the quality of the advice given, the

Table 3 (Continued)

Variable name	Model 1	Model 2	Model 3	Description
Similarity adviser/Participants				
Adviser female × Participant female		$\mathbf{x}_3$	$\mathbf{x}_4$	Indicator variable that equals one if the adviser and participant are female, and zero otherwise.
Adviser male × Participant female		$\mathbf{x}_3$	$\mathbf{x}_4$	Indicator variable that equals one if the adviser is male and the participant is female, and zero otherwise.
Adviser older × Participant age		$\mathbf{x}_3$	$\mathbf{x}_4$	Variable that equals the participant age (as defined above) if the adviser is older, and zero otherwise.
Adviser younger × Participant age		$\mathbf{x}_3$	$\mathbf{x}_4$	Variable that equals the participant age (as defined above) if the adviser is younger, and zero otherwise.
Advice sequence characteristics				
BB		$\mathbf{x}_3$		Trichotomous variable for bad advice in the first two choice sets (BB = 1, GG = −1, 0 otherwise).
BG		$\mathbf{x}_3$		Trichotomous variable for bad then good advice in the first two choice sets (BG = 1, GB = −1, 0 otherwise).
EH				Indicator variable for easy then hard topics in the first two choice sets (EH = 1, HE = 0).
BB | EH		$\mathbf{x}_3$		Trichotomous variable for interaction of advice quality with advice clarity (BB&EH = 1, GG&EH = −1, 0 otherwise) in the first two choice sets.
BG | EH		$\mathbf{x}_3$		Trichotomous variable for interaction of advice quality with advice clarity (BG&EH = 1, GB&EH = −1, 0 otherwise) in the first two choice sets.
B3 | EH		$\mathbf{x}_3$		Indicator variable that equals one if delivered bad advice on hard topic in third choice set, and zero otherwise.
G3 | EH		$\mathbf{x}_3$		Indicator variable that equals one if delivered good advice on hard topic in third choice set, and zero otherwise.
BBBB			$\mathbf{x}_4$	Trichotomous variable for bad advice for all the four choice sets (BBBB = 1, GGGG = −1, 0 otherwise).
BGGB			$\mathbf{x}_4$	Trichotomous variable for bad advice in the first and fourth choice sets (BGGB = 1, GBBG = −1, 0 otherwise).
BGBG			$\mathbf{x}_4$	Trichotomous variable for bad advice in the first and third choice sets (BGBG = 1, GBGB = −1, 0 otherwise).
BBGG			$\mathbf{x}_4$	Trichotomous variable for bad advice in the first two choice sets (BBGG = 1, GGBB = −1, 0 otherwise).
HEEH				Indicator variable equals one if clarity sequence is HEEH, and zero otherwise.
BBBB × HEEH			$\mathbf{x}_4$	Trichotomous variable for interaction of advice quality with advice clarity (BBBB&HEEH = 1, GGGG&HEEH = −1, 0 otherwise).
BGGB × HEEH			$\mathbf{x}_4$	Trichotomous variable for interaction of advice quality with advice clarity (BGGB&HEEH = 1, GBBG&HEEH = −1, 0 otherwise).
BGBG × HEEH			$\mathbf{x}_4$	Trichotomous variable for interaction of advice quality with advice clarity (BGBG&HEEH = 1, GBGB&HEEH = −1, 0 otherwise).
BBGG × HEEH			$\mathbf{x}_4$	Trichotomous variable for interaction of advice quality with advice clarity (BBGG&HEEH = 1, GGBB&HEEH = −1, 0 otherwise).

Note. This table provides descriptions of the variables used in the analysis.

attributes of the participant, and the topic covered in the first choice set.

More formally, this relationship (Model 1) can be written as

$$P(y = 1 \mid \mathbf{x}_1, \mathbf{x}_2) = \mathbf{\Phi}(\mathbf{x}'_1\boldsymbol{\gamma} + \mathbf{x}_1 \otimes \mathbf{x}'_2\boldsymbol{\beta}), \tag{1}$$

where $\mathbf{\Phi}$ is the cumulative density of the standard normal distribution and is $\mathbf{x}_1$ a (5×1) vector consisting of a constant, three adviser characteristics, and one indicator of advice quality for Adviser 1;[7] $\boldsymbol{\gamma}$ is a (5×1) vector of coefficients on the constant and main effects of adviser attributes; $\mathbf{x}_2$, is a (15×1) vector consisting of three binary indicator variables for advice topics and 12 variables measuring participant attributes; $\mathbf{x}_1 \otimes \mathbf{x}_2$ is a (75×1) vector of the interactions between $\mathbf{x}_1$ and $\mathbf{x}_2$; and $\boldsymbol{\beta}$ is a (75×1) vector of coefficients on interactions between adviser, topic, and participant attributes.[8] Each of the variables in the vectors is carefully described in detail in Table 3. We estimate Model 1 on a total of 1,271 observations of participants' first decisions and report results in Table 5. Here, and in later tests, we report Bonferroni-adjusted

[7] By design, all Adviser 1 attributes are "mirrored" by Adviser 2, so differences in attributes can be represented by indicator variables for gender, age, displaying a credential, and advice quality.

[8] The constant in $\mathbf{x}_1$ and interactions with the constant model capture any order effect associated with Adviser 1 appearing on the left of the screen.

Table 4 **Summary of Survey Responses**

Variable	
	% of total choices
Good advice chosen	
All topics	82.95
Topic: Account consolidation	89.85
Topic: Stock diversification	80.65
Topic: Index fund fee	68.37
Topic: Debt repayment	92.92
Adviser chosen	
Younger male	25.49
Older male	23.62
Younger female	26.26
Older female	24.63
Displays credential	51.28
	(% of participants)
Participant characteristics	
Market experience	
Debt	75.39
Fees	3.76
Consolidation	72.01
Diversification	42.81
Passed IMC 1	89.14
Passed IMC 2	93.08
	Median score
Financial literacy	0.75
Numeracy	0.67
Product knowledge	0.50
Conscientiousness	3.40
Impulsiveness	2.50
Past correct decisions (proportion correct of two questions)	
Debt	0.50
Fees	0.50
Consolidation	0.50
Diversification	0.50
Risk tolerance	2.34

Note. This table provides a summary of participants' survey responses and scores related to financial literacy and personality traits.

p-values to account for multiple hypothesis tests, as well as standard unadjusted p-values.[9]

4.1.1. The Effect of Advice Quality and Complexity on Adviser Choice. Results show that participants consider the quality of advice given when choosing which adviser to follow. Using the estimated coefficients from Model 1, we compute the average predicted probability that Adviser 1 is chosen when he or she gives bad advice, as well as the average predicted probability that Adviser 1 is chosen when he or she gives good advice.[10] The difference between these two average predicted probabilities is the marginal effect of giving bad advice, shown in the fourth row of Table 5, panel A. Adviser 1 is significantly (63 percentage points) less likely to be chosen, on average, when he or she gives bad advice than when he or she gives good advice.

We can conclude that most participants did not choose Adviser 1 if the adviser gave bad advice, but we need to test further to see whether some settings or some characteristics make clients more vulnerable to making a mistake. Changes in the average predicted probability of choosing Adviser 1 when a topic or participant characteristic changes, conditioning on Adviser 1 giving bad advice, and the associated tests of significance, are reported in the first column of Table 5, panel B. Focusing first on advice topics, we see that hard topics make bad choices more likely. Compared with the average effects of other advice topics, the easy debt topic lowers the chance of choosing Adviser 1 when the adviser gives bad advice by 14 percentage points. Conversely, the fee topic raises the probability of choosing Adviser 1 when the adviser gives bad advice by 13 percentage points. The marginal effects of the consolidation and diversification topics also have the expected signs given their relative difficulty (negative and positive respectively), but they are not significantly different from the average effect of the other advice topics.

There is some weak evidence that skilled and experienced participants are less susceptible to bad advice. The average probability that individuals with financial literacy scores above the median choose bad advice is 6 percentage points lower than individuals with scores below the median, and the average probability that participants who report having used a financial security associated with the advice topic, such as having owned shares for the diversification topic, choose bad advice is 8 percentage points lower than for people who have not used a related security. Participants who report that they have made correct decisions in the past related to the advice topic are also 10 percentage points less likely to choose bad advice than people who have not made good past decisions. These effects are economically significant but become statistically insignificant when we adjust p-values for multiple hypothesis testing. However, we also note that the Bonferroni adjustment used here may represent an upper bound on p-values, since it does not fully account for the joint dependence structure of the test statistics and may lack power (List et al. 2016).

[9] In Model 1, we apply the Bonferroni adjustment embedded in Stata to five blocks of (m) hypothesis tests: panel A ($m = 4$); panel B, left-hand column, advice topics ($m = 4$); panel B, right-hand column, advice topics ($m = 4$); panel B, left-hand column, participant characteristics ($m = 12$); panel B, right-hand column, advice topics ($m = 12$).

[10] Stata computes the predicted probability at each observation in the sample, holding "Bad advice" = 1 (or 0) and allowing other variables to take their observed values. We report the average of these predictions.

Table 5 Choice at Initial Meeting: Marginal Effects of Adviser, Topic, and Participant Characteristics

Panel A	
Adviser characteristics	
Female	0.023 (0.020)
Older	−0.056***^^ (0.020)
Displays credential	0.046**^ (0.020)
Delivered bad advice	−0.629***^^^ (0.020)

Panel B	When adviser gives bad advice	When adviser displays credential
Advice topic		
Easy topic: Debt	−0.138***^^^ (0.023)	0.007 (0.024)
Easy topic: Account consolidation	−0.026 (0.030)	0.067** (0.030)
Hard topic: Stock diversification	0.034 (0.032)	−0.042 (0.033)
Hard topic: Index fund fee	0.130***^^^ (0.036)	−0.032 (0.039)
Participant characteristics		
Passed IMC 1	−0.085 (0.060)	0.046 (0.060)
Passed IMC 2	−0.075 (0.069)	−0.061 (0.069)
Participant female	−0.024 (0.027)	0.000 (0.029)
Participant age	−0.006 (0.005)	0.010* (0.006)
High financial literacy	−0.057* (0.029)	−0.038 (0.031)
High product knowledge	−0.007* (0.030)	−0.000 (0.031)
High numeracy	−0.047 (0.028)	0.026 (0.030)
High conscientiousness	−0.010 (0.028)	0.033 (0.030)
High impulsiveness	0.030 (0.028)	0.018 (0.030)
Past correct decisions | topic	−0.103** (0.052)	−0.036 (0.058)
Risk tolerance	−0.015 (0.027)	0.005 (0.029)
Market experience | topic	−0.080** (0.035)	−0.055 (0.038)
Pseudo R^2	0.443	

Notes. This table shows the estimated marginal effects of adviser, advice, and participant characteristics on the probability of advice choice from the probit estimates of Model 1 using 1,271 observations. Dependent variable is binary indicator of choice of Adviser 1 at the first choice set. Variables are defined in Table 3. Standard errors computed by the delta method in parentheses. Unadjusted p-values: $^*p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$; Bonferroni-adjusted p-values: $^\wedge p < 0.1$; $^{\wedge\wedge}p < 0.05$; $^{\wedge\wedge\wedge}p < 0.01$. Bonferroni adjustment applied to five blocks of (m) hypothesis tests: panel A ($m = 4$); panel B, left-hand column, advice topics ($m = 4$); panel B, right-hand column, advice topics ($m = 4$); panel B, left-hand column, participant characteristics ($m = 12$); panel B, right-hand column, advice topics ($m = 12$).

4.1.2. The Effect of Adviser Credentials on Adviser Choice. Given the proliferation of adviser credentials around the world, determining whether a credential can independently influence decision making is an interesting exercise. Unfortunately, in real-world settings, the advice quality, credentials, and experience of advisers are likely to be correlated, and it is difficult to separate their effects. In this experimental setting we can isolate and measure the independent influence of advice quality and professional credentials on the decisions of participants. The balanced experimental design, combined with random assignment of participants and carefully vetted advice topics, ensures that we can assess the marginal effect of the signals. Examining the influence of credentials is important because it is something that regulators can control. Any need for regulation depends on whether and to what extent clients notice qualifications or credentials even when they are not correlated with quality. We can also identify any clients who are likely to be more influenced by credentials than others.

We find that participants preferred advice from advisers who displayed a credential, regardless of the quality of advice they gave and their personal characteristics. Using Model 1 again, we compute the change in the average predicted probability that Adviser 1 is chosen when the adviser displays a credential over when he or she does not (third row of Table 5, panel A), and we test whether this change is significantly different from zero. The chance of the credentialed adviser being chosen was 4.6 percentage points higher. The effect of credentials we estimate here could be larger in complex real-world settings where clients may find good advice harder to discern. Our result suggests that advisers who do not display a credential could be at a competitive disadvantage to advisers who do, and it also provides an explanation for the proliferation of credentials in many countries, including the United States. Then again, the effect could be partly based on participants' trust in the experimenter who assigned the credential to the adviser, and people might be more wary of credentials in actual practice. More research is needed on this finding.[11]

Our results also raise the question of whether some types of clients are more influenced by credentials than others. Using an approach similar to our investigation of the factors that influence the choice of bad advice, we condition on Adviser 1 displaying a credential and compute the change in the average predicted probability that Adviser 1 is chosen when a participant characteristic variable increases by one, or when the advice topic changes. The last column of Table 5, panel B, reports these marginal effects, none of which is significant at the Bonferroni-adjusted p-values. In other words, the influence of credentials is not isolated to a particular group of participants or associated with specific advice topics.

Considering the combined results from Model 1, we conclude that better financial literacy along with experience in the market place could possibly make people more discriminating, especially if they are getting advice on a familiar issue. But since clients are not likely to be consulting advisers about decisions they understand well on their own, it is unclear from these estimates how much literacy and experience can help when people are really out of their depth. As we will discuss, clients appear to judge the quality of a financial adviser by the advice the adviser gives on topics that the clients feel they understand. So a more financially literate client has a better chance of identifying a poor quality adviser than a client with low literacy and little experience. And while the signs on the interactions (not reported here) among accreditation and financial literacy, product knowledge, and experience are all negative, indicating that literacy and experience could lessen the independent influence of accreditation on choices, the effects are small and statistically insignificant. This leads us to conclude that even the more savvy clients are probably not immune to the influence of credentials.

4.2. Effects of First Impressions and Catering on Advice Choice in Subsequent Meetings

Two well-known proverbs capture the main hypotheses tested in our analysis: "First impressions are the most lasting"; and "If you want people to think you are wise, agree with them." The former captures the continuing influence of first impressions, while the latter supports the practice of catering to clients by agreeing with their existing views. We test whether these strategies influence participants' incentivized choices of adviser at later meetings. We contend that advice given in the first meeting will form a lasting impression on participants (first impressions), particularly if it confirms, or does not contradict, participants' firmly held views on easy topics (catering).

We hypothesize that the sequence in which clients receive advice will affect their evaluations of advisers. For example, a client might begin an advice relationship holding a neutral view of the adviser's quality and a favorable opinion of his own portfolio. The adviser can signal that he or she is a good quality adviser by giving recognizably good advice early on. This might be done by confirming the client's current financial choices, and hence inducing the client to update his opinion of the adviser favorably. Once an adviser has made a good impression on the client, he or she can then follow with advice on a topic the client finds difficult, making the next advice hard to evaluate. A client who has formed a good impression of an adviser is likely to evaluate advice on a difficult topic as favorably as earlier advice on topics where the client holds a firm opinion, regardless of the true quality of the advice. Using this approach, the adviser could move clients to a final recommendation that is very different from that confirmed at the starting point, and despite receiving biased advice, a client could remain more convinced than ever that

[11] Adviser age also has a significant marginal effect on choices, but this effect could be specific to the adviser in the video and so not generalizable.

an adviser is trustworthy.[12] This outcome is noted by Mullainathan et al. (2012), who observe that the final strategies recommended to their field study auditors differed greatly from the strategies the advisers confirmed at the start. It also emphasizes the effect of the complexity of many financial problems, which makes the evaluation of advice quality difficult (ASIC 2012).

We can use the sequences of good and bad advice in the experiment to explore the influence of complexity and catering. Using the results from our pretesting of topic difficulty, we label topics as hard (H) (index fund fees and stock diversification topics) or easy (E) (debt repayment and account consolidation topics). The experimental design generates two orderings of hard and easy topics, EHHE and HEEH, which we label "clarity" sequences (Table 1, panel B). The design also involves eight orderings of good and bad advice: GGGG, GGBB, GBGB, and GBBG and their opposites for the matched adviser, that we label "quality" sequences (Table 1, panel C). Each participant views Adviser 1 delivering one clarity sequence combined with one quality sequence, with Adviser 2 following the *reverse* quality sequence but the *same* clarity sequence. In the tests to follow, we consider interactions of advice quality sequences with clarity sequences for choices of Adviser 1.

For these tests, we model the incentivized choices (i.e., which adviser to follow) made by participants at the third of the four choice sets, where the dependent variable for the third choice is defined in the same way as in Model 1. By the time participants make their third choice, they should have formed an impression of Adviser 1 over the two earlier topics, having seen the adviser deliver either two good pieces of advice (GG), or two bad pieces of advice (BB), or one good and one bad piece of advice (GB) or (BG). At the third choice, half the participants then view Adviser 1 giving bad advice and half view Adviser 1 giving good advice. We use the third choice rather than the fourth because it is a more powerful test of first impressions: the cases where Adviser 1 has delivered one good and one bad piece of advice in either order give us a clean test of the effect of order, whereas if we tested at the fourth choice, good and bad advice quantities for the two advisers could be unequal.

We hypothesize that if first impressions matter, participants hearing GB advice from Adviser 1 should be significantly more likely to choose him or her at their third choice than participants who hear BG from Adviser 1, assuming that the quality of the advice given in the third choice set is the same (either good or bad). In other words, conditioning on the characteristics of both adviser and participant, when Adviser 1 delivers the sequence GBG they would be more likely to be chosen than when they deliver the sequence BGG, and choices of GBB would be more likely than choices of BGB.

We also hypothesize that catering matters, so that the third choice will be influenced by the preceding clarity sequence (EH combination). Advisers cater by confirming, or at least not contradicting, the prior views of clients. Therefore, we would expect that that advice on easy topics, where most participants know the correct answer, will be more influential than advice on hard topics, where fewer participants know which advice is correct. Likewise, the sequence GB | EH is one that combines both a catering and first impressions effect because the first piece of advice is good on a well-understood topic.

For Model 2, we again treat the participant as having a linear indirect random utility function for choice of Adviser 1's advice at the third choice set, with jointly normally distributed mean zero additive errors. The probability of observing choice of advice of Adviser 1 at the third set is

$$P(y=1 \mid \mathbf{x}_3) = \mathbf{\Phi}(\mathbf{x}_3, \boldsymbol{\varphi}), \tag{2}$$

where $\mathbf{x}_3$ is a (15×1) vector consisting of a constant, three indicator variables for adviser characteristics, one indicator for Adviser 1's advice quality at the third choice set, four controls for adviser/participant similarity, and six variables that capture different combinations of clarity and quality sequences. For the quality sequence variables, we exploit the symmetry of the design to ensure that the sequence BG has the same impact whether it is delivered by Adviser 1 or Adviser 2: we define trichotomous variables that take, for example, the value 1 for the sequence BG, -1 for the (mirroring) sequence GB, and 0 otherwise. All the variables in this model are defined in Table 3. A (15×1) vector of coefficients is denoted by φ. This model is also estimated over 1,271 choices with results presented in Table 6.[13] Panel A confirms that bad advice is also significant in the third choice set. An adviser dispensing bad advice is 64 percentage points less likely to be chosen than one giving good advice, averaging over all advisers, topics, and participants. Panels B and C report hypothesis test results on first impressions and catering.

[12] Fryer et al. (2013) present a theory of Bayesian updating with limited memory that can explain polarization of opinion when a judge receives a sequence of clear and noisy signals. Our intuition about the updating of clients' opinions draws on their theory for inspiration. We think of hard advice topics as noisy signals and easy topics as clear signals.

[13] Table 6 reports Bonferroni-adjusted p-values where the Bonferroni adjustment is applied to three blocks of (m) hypothesis tests: panel A, rows 1–8 ($m = 4$); panel A, rows 9–12 ($m = 2$); panel C, rows 2–6 ($m = 5$).

Table 6 Choice at Third Choice Set: Tests of Catering and First Impressions

Panel A. Marginal effects on probability of choice of Adviser 1 at third choice set	
Adviser characteristics	
Female	0.024
	(0.020)
Older	−0.046**^
	(0.020)
Displays credential	0.017
	(0.020)
Bad advice at choice set 3	−0.642***^^^
	(0.020)
Advice sequence characteristics	
BB	−0.012
	(0.014)
BG	−0.030**^
	(0.015)
Pseudo R^2	0.393

Panel B. Average predicted probability of choice at third choice of Adviser 1 for advice sequence	
1: Delivered good then bad advice in the first two choice sets (GB)	0.507
2: Delivered bad then good advice in the first two choice sets (BG)	0.447
3: Delivered good (easy) then bad (hard) advice in the first two choice sets (GB | EH)	0.493
4: Delivered bad (easy) then good (hard) advice in the first two choice sets (BG | EH)	0.400
5: Delivered bad (hard) then good (easy) advice in the first two choice sets (BG | HE)	0.496
6: Delivered good (hard) then bad (easy) advice in the first two choice sets (GB | HE)	0.523

Panel C. Hypothesis tests	$\chi^2_{(1)}$
1: H_0: BG = GB (first impressions);	4.19**^^
2: H_0: BG | EH = GB | HE (first impressions);	11.57***^^^
3: H_0: GB | EH = BG | HE (first impressions);	0.01
4: H_0: BG | EH = BG | HE (catering);	7.71***^^
5: H_0: GB | EH = GB | HE (catering);	0.68
6: H_0: BG | EH = GB | EH (catering and first impressions);	3.38*

Notes. Panel A shows the estimated marginal effects of adviser, advice, and participant characteristics on the probability of advice choice at the third choice set from probit estimates of Model 2 over 1,271 observations. Dependent variable is binary indicator of choice of advice given by Adviser 1 at the third choice set. Variables are defined in Table 3. Standard errors computed by the delta method in parentheses. Panel B shows the average predicted probability of choice of Adviser 1 at third choice set at advice sequence specified. Panel C shows $\chi^2_{(1)}$ test statistics. Unadjusted p-values: *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$. Bonferroni-adjusted p-values: ^$p < 0.1$; ^^$p < 0.05$; ^^^$p < 0.01$. Bonferroni adjustment applied to three blocks of (m) hypothesis tests: panel A, rows 1–8 ($m = 4$); panel A, rows 9–12 ($m = 2$); panel C, rows 2–6 ($m = 5$).

4.2.1. The Effect of Advice Quality Order on Adviser Choice. Since half the participants receive the EH sequence and half receive the HE sequence, we can test for first impressions by averaging over both clarity sequences, "integrating out" the influence of catering. Using the estimated coefficients from Model 2, we compare the average predicted probability of Adviser 1 being chosen at the third choice set when the adviser has given GB at choice sets 1 and 2 (panel B, row 1, 51%) with predicted probability when he or she has given BG (panel B, row 2, 45%). The difference between these average predicted probabilities is statistically and economically significant at 6 percentage points (panel C, row 1). In other words, the order in which the good and bad advice was received influenced participants' later choices, averaging over the easy and hard topics.

Further testing shows that a bad first impression is stronger than a good first impression. For example, the only difference between the sequences BG | EH and GB | HE is that in the first sequence the bad, easy advice is given first and the hard, good advice given second, while in the second sequence the order is flipped. From panel B, we see the adviser who gives bad advice first (panel B, row 4, 40%) is less likely to be chosen than when that same adviser gives good advice first (panel B, row 6, 52%), which is a significant difference (panel C, row 2). On the other hand, we do not find a significant impact for good easy advice when comparing GB | EH with BG | HE (panel C, row 3).

4.2.2. The Effect of Catering on Adviser Choice. We expect that advice given on easy topics that confirm firmly held views will be more influential on clients' later choices than advice given on hard topics. This catering effect could be strengthened if the confirming (or contradictory) advice comes earlier in the choice sets.

Participants are particularly critical of advisers who give bad advice on easy topics. If Adviser 1 gives bad advice on an easy topic and good advice on a hard topic (BG | EH), the adviser is about 9 percentage points less likely to be chosen at the third choice (panel B, row 4) than if Adviser 1 gave bad advice on a hard topic followed by good advice on an easy topic (BG | HE–panel B, row 5; panel C, row 4). However, good advice on an easy topic followed by bad advice on a hard topic (GB | EH–panel B, row 3) does not make an adviser significantly more likely to be chosen than good advice on a hard topic followed by bad advice on an easy topic (GB | HE–panel B, row 6; panel C, row 5). We conclude that this is evidence of a type of "negative catering," where what matters is not the benefit of confirming client views on an easy topic so much as the damage caused if an adviser contradicts a client's firm belief.[14]

4.3. Evaluating the Traits of the Adviser: Do First Impressions and Catering Matter After the Initial Meeting?

Over time we expect that participants will form lasting opinions about their advisers' individual traits, like trustworthiness and professionalism. These opinions might be influenced by first impressions and by catering. We collected participants' views on adviser traits after they had made their four advice choices and after they viewed the screen showing the total number of times they had chosen the correct advice (entries in the prize draw). Consequently, it is possible that some participants revised their opinions of the advisers after they saw their correct choice score and before we elicited the ratings. For example, a participant could have followed the same adviser through the choice sets only to be disappointed to find that she had consistently chosen bad advice. However, it also follows that the chance that some participants revised their opinions after learning the accuracy of their choices strengthens any evidence we find for the effects of confirmation strategies on adviser ratings.

Participants compared the two advisers on trustworthiness, competence, attractiveness, understanding, professionalism, genuineness, and persuasiveness, and they could rate either adviser as higher than the other on each of these traits, or rate both advisers the same. We predict that advisers who give good advice on easy topics, particularly if delivered early in the sequence, will be rated more favorably than advisers who give bad, early advice on easy topics.

We estimate an ordered probit choice model, assuming that the participant gives each of the two advisers a latent score for a personal trait, such as trustworthiness, that is a function of adviser characteristics, participant characteristics and clarity and quality sequences as described in Table 3, with a jointly normally distributed error. As the difference between these unobserved scores, Y^*, passes some thresholds, k_1 and k_2, the observed response that Adviser 1 shows less, an equal amount or more of the characteristic than Adviser 2, takes the corresponding values

$$\begin{aligned} y &= -1 \quad \text{if } Y^* < k_1, \\ y &= 0 \quad \text{if } k_1 < Y^* < k_2, \\ y &= 1 \quad \text{if } k_2 < Y^*, \end{aligned}$$

and thus the related probability distribution can be modeled as

$$\begin{aligned} P(y=-1 \mid \mathbf{x}_4) &= \boldsymbol{\Phi}(k_1 + \mathbf{x}_4'\boldsymbol{\lambda}), \\ P(y=0 \mid \mathbf{x}_4) &= \boldsymbol{\Phi}(k_2 + \mathbf{x}_4' - \boldsymbol{\Phi}(k_1 + \mathbf{x}_4'\boldsymbol{\lambda}), \\ P(y=1 \mid \mathbf{x}_4) &= 1 - \boldsymbol{\Phi}(k_2 + \mathbf{x}_4'\boldsymbol{\lambda}), \end{aligned}$$

where $\mathbf{x}_4$ (15×1) is the vector of covariates consisting of indicator variables of Adviser 1 characteristics, four variables capturing the similarity between the adviser and participants, four trichotomous variables capturing the quality sequence over the four choice sets, and four interactions between the advice quality and clarity sequence (e.g., GGGG × HEEH). These variables are defined in Table 3. A (15×1) vector of coefficients is denoted by λ, and k_1 and k_2 are thresholds. This results in seven models, one for each adviser trait, each estimated using 1,271 observations. Table 7 reports key results.[15]

[14] There is weak evidence that an adviser delivering confirming advice early in the choice sequence (combining first impressions and catering) is more likely to be chosen (GB | EH–panel B, row 3) than an adviser giving contradicting advice early in the choice sequence (BG | EH–panel B, row 4), though the difference is not significant according to the Bonferroni-adjusted p-value.

[15] Table 7 reports unadjusted and Bonferroni-adjusted p-values. In each model, the Bonferroni adjustment is applied to one block of (m) hypothesis tests: panel B, rows 2–11 $(m = 10)$. Estimated coefficients of the model are presented in Supplemental Material E.

Table 7 Participant Evaluations of Adviser Personal Traits: Model 3

Panel A: Trait	Trustworthiness		Competence		Attractiveness		Understanding		Professionalism		Genuineness		Persuasiveness	
Clarity	EHHE	HEEH	EHHE	HEEH	EHHE	HEEH	EHHE	HEEH	EHHE	HEEH	EHHE	HEEH	EHHE	HEEH
1. GGGG	59%	61%	60%	65%	32%	33%	58%	62%	35%	47%	45%	50%	35%	40%
2. BBBB	4%	3%	2%	2%	12%	12%	2%	1%	5%	3%	4%	3%	9%	7%
3. GGBB	27%	29%	21%	17%	23%	23%	19%	20%	15%	18%	21%	18%	26%	20%
4. BBGG	17%	16%	17%	21%	19%	19%	16%	16%	15%	13%	14%	17%	14%	18%
5. GBGB	23%	23%	21%	20%	19%	20%	18%	18%	18%	17%	18%	15%	20%	19%
6. BGBG	21%	20%	17%	17%	22%	22%	16%	17%	13%	14%	16%	20%	18%	20%
7. GBBG	40%	15%	41%	12%	26%	20%	33%	11%	30%	9%	33%	12%	28%	18%
8. BGGB	9%	29%	6%	28%	16%	22%	8%	26%	7%	23%	7%	23%	12%	20%

Panel B: Trait	Trustworthiness	Competence	Attractiveness	Understanding	Professionalism	Genuineness	Persuasiveness
1. Displays credential	$0.043^{**\wedge\wedge}$	$0.068^{***\wedge\wedge\wedge}$	0.006	0.014	$0.062^{***\wedge\wedge\wedge}$	0.006	$0.052^{***\wedge\wedge\wedge}$
2. GGGG | EHHE = GGGG | HEEH	0.16	0.93	0.04	0.65	5.04^{**}	1.03	1.09
3. BBBB | EHHE = BBBB | HEEH	0.16	0.90	0.04	0.63	4.4^{**}	1.00	1.08
4. GGBB | EHHE = GGBB | HEEH	0.18	1.20	0.01	0.00	0.76	0.92	1.85
5. BBGG | EHHE = BBGG | HEEH	0.18	1.20	0.01	0.00	0.76	0.92	1.84
6. GBGB | EHHE = GBGB | HEEH	0.03	0.01	0.01	0.00	0.28	1.50	0.25
7. BGBG | EHHE = BGBG | HEEH	0.03	0.01	0.01	0.00	0.28	1.49	0.25
8. GBBG | EHHE = GBBG | HEEH	$36.87^{***\wedge\wedge\wedge}$	$54.61^{***\wedge\wedge\wedge}$	3.48^{*}	$33.84^{***\wedge\wedge\wedge}$	$30.33^{***\wedge\wedge\wedge}$	$30.51^{***\wedge\wedge\wedge}$	$7.08^{***\wedge}$
9. BGGB | EHHE = BGGB | HEEH	$33.65^{***\wedge\wedge\wedge}$	$45.62^{***\wedge\wedge\wedge}$	3.49^{*}	$30.41^{***\wedge\wedge\wedge}$	$28.6^{***\wedge\wedge\wedge}$	$27.80^{***\wedge\wedge\wedge}$	$6.97^{***\wedge}$
10. GBBG | HEEH = BGGB | EHHE	5.48^{**}	$7.02^{***\wedge}$	1.60	2.78^{*}	1.78	5.22^{**}	4.16^{**}
11. GBBG | EHHE = BGGB | HEEH	5.72^{**}	$7.66^{***\wedge}$	1.60	2.86^{*}	1.82	5.48^{**}	4.21^{**}

Notes. This table reports results based on estimation of ordered probit models of adviser ratings using 1,271 observations. Dependent variable is a trichotomous indicator taking the value −1 if the participant rates Adviser 1 as showing less of the personal trait, is equal to 0 if advisers 1 and 2 are rated equal in the personal trait, and takes the value 1 if the participants rates Adviser 1 as showing more of the personal trait. Variables are defined in Table 3. Panel A displays the average predicted probabilities of a higher adviser rating for each trait for each of the eight quality (BG) sequences, conditioning on the two clarity (HE) sequences. Panel B's first row reports marginal effects of the adviser displaying a credential. Remaining rows display $\chi^2_{(1)}$ statistics for tests of equality of marginal effects of clarity-quality sequences on adviser ratings. Unadjusted p-values: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$ significance levels marked. Bonferroni-adjusted p-values: $^{\wedge}p < 0.1$; $^{\wedge\wedge}p < 0.05$; $^{\wedge\wedge\wedge}p < 0.01$. In each model the Bonferron adjustment is applied to one block of (m) hypothesis tests: panel B, rows 2–11 ($m = 10$).

4.3.1. The Effect of Credentials on the Ranking of Adviser Traits. We compute the difference in the average predicted probability of a higher evaluation of Adviser 1 when the indicator for displaying a credential is at zero or one (Table 7, panel B, row 1). Advisers who did display a credential were significantly more likely to be rated as trustworthy (0.04), competent (0.07), professional (0.06), and persuasive (0.05) than a noncertified adviser. But credentials had no effect on ratings of attractiveness, genuineness or understanding, so the positive results are not likely to be a "halo" effect. When combined with findings from Models 1 and 2, these results suggest that people attribute more professionalism and competence to an accredited adviser than to an unqualified adviser giving the same quality of advice.

4.3.2. The Effect of First Impressions on the Ranking of Adviser Traits. Advisers could also make a favorable first impression that influences clients' later evaluations of their personal traits. To maximize the power of the test of first impressions this time, we condition on catering. Consider the sequences BGGB | EHHE and GBBG | HEEH. In both cases, bad advice is given on two easy topics, and good advice is given on two hard topics; but in the first sequence, the bad advice on the easy topic comes first. If first impressions matter, then advisers giving the first sequence will be evaluated as worse than advisers giving the second sequence. The same argument applies to the pair of sequences GBBG | EHHE and BGGB | HEEH, but in this case the adviser giving the first sequence gives a good first impression and might receive better evaluations. Using Model 3, we compute the average predicted probabilities that participants rate Adviser 1 higher than Adviser 2 when Adviser 1 delivered each quality-clarity sequence, averaging over all other variables. We then test to see if the average predicted probabilities are significantly different in the pairs of interest. Table 7, panel B, reports $\chi^2_{(1)}$ test statistics for the differences.

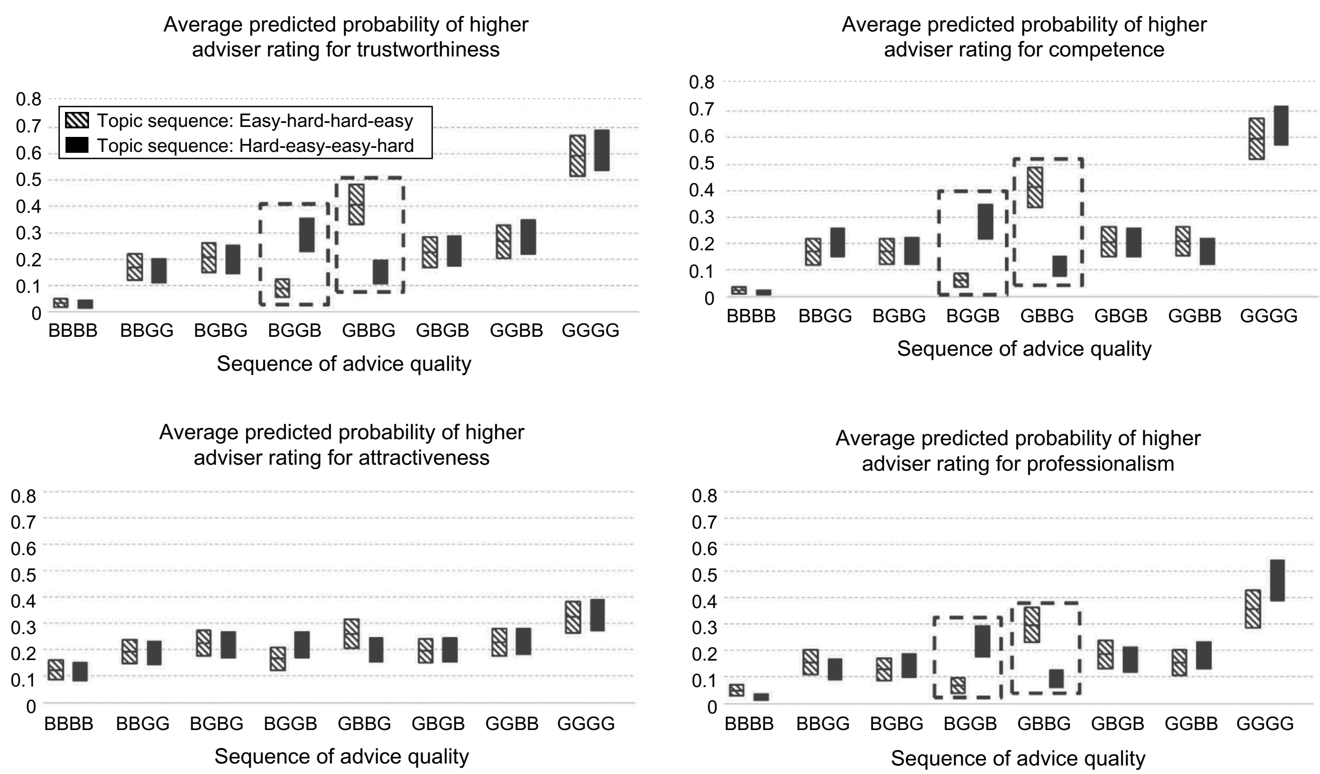
To test this, we compare average predicted probabilities across different rows within a trait in Table 7. Early bad advice makes Adviser 1 six percentage points less likely to be rated as more competent (6% for BGGB | EHHE–row 8, third column, compared with 12% for GBBG | HEEH–row 7, fourth column), and the chi-squared statistic rejects equality (panel B, row 10, second column). Favorable opinions of competence are also made when the good easy advice comes first rather than second.

4.3.3. The Effect of Complexity and Catering on the Ranking of Adviser Traits. As in Model 2, catering can be tested when the total number of good advice elements in the sequence is equal to the number of bad advice elements, but good advice is given exclusively on either hard or easy topics. After four choices, there are two clarity-quality combinations that allow this test: we compare BGGB | EHHE with BGGB | HEEH (panel A, row 8). We predict that the adviser giving good advice on easy topics will be rated higher than the adviser giving good advice on hard topics. Similarly, we predict that advisers who deliver GBBG | EHHE will be evaluated higher than advisers who deliver GBBG | HEEH (panel A, row 7).

Advisers who failed to confirm the views of clients are rated much worse than advisers who did not, suggesting catering matters. Ratings are dramatically affected by the concentration of good and bad advice on hard or easy topics. For example, if we look at the average predicted probabilities of a higher trustworthiness rating (Table 7, panel A, row 7, first and second columns), we see that an adviser who offered bad advice on two easy topics and good advice on two hard topics (GBBG | HEEH–row 7, second column) was 25 percentage points less likely (40% compared with 15%) to be rated equal to or better than an adviser who gave the good advice on the easy topics and bad advice on the hard topics (GBBG | EHHE–row 7, first column). The related $\chi^2_{(1)}$ test statistic in panel B, row 8 confirms that this difference is highly significant. We see a similar outcome for the sequences BGGB | EHHE (row 8, first column) and BGGB | HEEH (row 8, second column), where the significant difference in probabilities was 20 percentage points (panel B, row 9, first column).

These dramatic differences are highlighted in Figure 1. Each panel of Figure 1 plots the average predicted probability of a higher adviser rating for each quality-clarity combination. The differences in these average predicted probabilities reflect the marginal effects of one quality-clarity combination versus the other. The striped boxes graph the 95% confidence interval around the average predicted probabilities when the clarity sequence was EHHE for the quality

Figure 1 **Average Predicted Probabilities of Advice Sequence on Ratings of Adviser Traits**



Notes. Each panel of the figure displays the average predicted probabilities of a higher adviser rating for a specific trait (for example, trustworthiness, competence, attractiveness, and professionalism) for each of the eight possible quality sequences (BG combination) in the experiment, conditioning on the two “clarity” sequences (HE combination). The striped box graphs the 95% confidence interval around the average predicted probabilities of the quality sequence shown on the horizontal axis, when the clarity sequence was EHHE, and the black box graphs the same for the clarity sequence HEEH. Dashed outlines highlight two significantly different average predicted probabilities based on a chi-square test of equality at the 1% level. These outlined average predicted probabilities are also significant at the same level with the Bonferroni adjustments.

Table 8 Summary of Main Findings by Section

4.1 What factors influence choice? Choice at the initial meeting
4.1.1 The effect of advice quality and complexity on adviser choice
Result 1: An adviser giving good advice is more likely to be chosen than one giving bad advice
Result 2: An adviser giving bad advice is more likely to be chosen when advising on hard topics compared to easy topics
Result 3: Participants with higher financial literacy scores and those with financial experience are slightly less likely to choose the adviser giving bad advice
4.1.2 The effect of adviser credentials on adviser choice
Result 1: Participants preferred advice from advisers who displayed a credential, regardless of the quality of advice the adviser gave and the participant's personal characteristics
4.2 Effects of first impressions and catering on advice choice in subsequent meetings
4.2.1 The effect of advice quality order on adviser choice
Result 1: The order in which the good and bad advice was received influenced the participants' later choices of adviser
Result 2: A bad first impression has stronger effects than a good first impression
4.2.2 The effect of catering on adviser choice
Result 1: "Negative catering," where an adviser contradicts a client's firm belief (for example, providing bad advice on an easy topic early on) makes an adviser significantly less likely to be chosen
4.3 Evaluating the traits of the adviser: Do first impressions and catering matter after the initial meeting?
4.3.1 The effect of credentials on the ranking of adviser traits
Result 1: Advisers who display a credential are significantly more likely to be rated trustworthy, competent, professional, and persuasive than a noncredentialed adviser
Result 2: Credentials had no effects on ratings of attractiveness, genuineness, and understanding
4.3.2 The effect of first impressions on the ranking of adviser traits
Result 1: Early bad, easy advice lowers an adviser's competency ratings
Result 2: Early good, easy advice increases an adviser's competency rating
4.3.3 The effect of complexity and catering on the ranking of adviser traits
Result 1: Participants give lower ratings to advisers who contradict their opinions
Result 2: An adviser's relative ranking for trustworthiness, competence, and professionalism can be significantly influenced by the quality of the advice and the difficulty and order of the advice topics
Result 3: Participants penalize bad advice on difficult topics much less than bad advice on easy topics for every trait but attractiveness

sequence shown on the horizontal axis, and the black boxes graph the equivalent probability for the clarity sequence HEEH. Dashed outlines highlight two significantly different average predicted probabilities based on a $\chi^2_{(1)}$ test of equality at the 5% level. Therefore, the results discussed above are shown graphically within the dashed rectangular outlines that highlight their statistical difference. Notice from the chart that the same pattern holds for competence and professionalism but not for attractiveness.[16]

Figure 1 also shows that participants are likely to rate advisers who give advice on an easy topic, followed by bad advice on two difficult topics (GBBG | EHHE), as more trustworthy than those giving the equivalent amount of good and bad advice but who neither started with good advice nor paired the good advice with easy topics. This holds not only for trustworthiness, but also for competence, demonstrating again the importance of complexity and catering. By contrast, if an adviser begins with bad advice on an easy topic (BGGB | EHHE), participants rated them less trustworthy than all advisers (except for those giving only bad advice), despite that adviser having given good advice half the time. Comparing effects within the dashed outlines shows that participants penalized bad advice on difficult topics much less than bad advice on easy topics in every case except for the trait of attractiveness.

In summary, participants gave low ratings to the advisers who contradicted their opinions of what good advice should be but still favored advisers who gave bad advice on difficult topics. The first advice an adviser gave had a persistent effect on final ratings, either positive or negative. Our results line up with the conjectures of Mullainathan et al. (2012) and ASIC (2012) that the interaction between catering and complexity may be a key to understanding the tendency of clients to return to advisers who offer poor advice.

5. Conclusion

Documented low levels of financial literacy around the world and the increasing responsibility consumers have for their own financial well-being raise important questions about how individuals evaluate advice and financial advisers. Using a unique online experiment, we investigated how well individuals discern bad financial advice from good and whether their advice choices and evaluations of advisers can be manipulated over time. Our results (see Table 8 for a summary) show several interesting patterns that should help inform the public policy debate and motivate further research.

First, our results highlight the influence of credentials on advice selection and adviser evaluation. Advisers lacking credentials in our study were rated

[16] Table 7 reveals that those patterns also hold for the traits not shown in the charts due to space limitations.

as less trustworthy, and their advice was less likely to be followed. While more research is needed to confirm this result, these findings are an important first step toward determining whether credentials could be an effective tool for helping consumers choose qualified advisers, as well as indicating that credentials can also place an adviser at a competitive advantage. Our pretest findings also suggest policy makers should proceed with caution before encouraging consumers to use credentials, as we found some individuals have difficulty discerning real credentials from fake ones.

Participants in the experiment were more likely to select the wrong advice when it related to difficult topics, so complexity matters. Then again, there is some weak evidence that past experience with the decision and financial knowledge might help individuals make better choices in this situation. Thus, even if all potential clients plan to rely solely on their financial advisers' recommendations for their financial decisions, the debate over the benefits of building financial literacy in consumers and whether financial education leads to better decisions remains.

Advisers can win favor by confirming the client's prior views in early interactions (for example, providing good advice on an easy topic that the client understands). Having catered to the client to make a good first impression, the adviser can go on to give bad advice on hard topics and still maintain a client's trust. This is a strategy other research shows may already be in use (Mullainathan et al. 2012). Since most people will be vulnerable to catering, independent checks of advice or getting second opinions could offer some protection.

Supplemental Material

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References

Agarwal S, Chomsisengphet S, Mahoney N, Stroebel J (2015) Regulating consumer financial products: Evidence from credit cards. *Quart. J. Econom.* 130(1):111–164.

Agnew J (2010) Pension plan behavior. Baker HK, Nofsinger J, eds. *Behavioral Finance* (John Wiley & Sons, Hoboken, NJ), 577–594.

Agnew J, Bateman H, Thorp S (2013) Financial literacy and retirement planning in Australia. *Numeracy* 6: Article 7.

Anagol S, Cole S, Sarkar S (2013) Understanding the advice of commissions-motivated agents: Evidence from the Indian life insurance market. Working paper, Harvard Business School, Boston.

Australian Securities and Investments Commission (ASIC) (2012) Shadow shopping study of retirement advice. Report 279, ASIC, Sydney. Accessed September 14, 2012, http://asic.gov.au/regulatory-resources/find-a-document/reports/rep-279-shadow-shopping-study-of-retirement-advice/.

Australian Treasury (2013) Lost and unclaimed superannuation money. Discussion paper, June 7, Australian Treasury, Canberra, Australia. http://www.treasury.gov.au/ConsultationsandReviews/Consultations/2013/Lost-and-unclaimed-superannuation-money.

Bagnall J, Chong S, Smith K (2011) Strategic review of innovation in the payments system: Results of the Reserve Bank of Australia 2010 Consumer Payments Use Study. June 2011. Reserve Bank of Australia, Sydney, Australia.

Bateman H, Kingston G (2012) The future of financial advice and MySuper. *JASSA: Finsia J. Appl. Finance*, Issue 3:49–53.

Bergstresser D, Chalmers J, Tufano P (2009) Assessing the costs and benefits of brokers in the mutual fund industry. *Rev. Financial Stud.* 22(10):4129–4156.

Bhattacharya U, Hackethal A, Kaelser S, Loos B, Meyer S (2012) Is unbiased financial advice to retail investors sufficient? Answers from a large field study. *Rev. Financial Stud.* 25(4):975–1032.

Certified Financial Planner Board of Standards (2004) 2004 consumer survey. Report, CFP, Denver. http://www.cfp.net/docs/news-events—research-facts-figures/cfpboard2004conssurvey.pdf?sfvrsn=2.

Chalmers J, Reuter J (2015) Is conflicted investment advice better than no advice? NBER Working Paper 18158, National Bureau of Economic Research, Cambridge, MA.

Choi JJ, Laibson D, Madrian BC (2010) Why does the law of one price fail? An experiment on index mutual funds. *Rev. Financial Stud.* 23(4):1405–1432.

Collins JM (2010) A review of financial advice models and the take-up of financial advice. Working Paper 10-5, Center for Financial Security, Madison, WI.

Collins JM (2012) Financial advice: A substitute for financial literacy? 2012. *Financial Services Rev.* 21(4):307–322.

Department of Labor (2011) Investment advice—Participants and beneficiaries; final rule. *Federal Register* 76(206): 66136–66167.

Elton E, Gruber M, Busse J (2004) Are investors rational: Choices among index funds. *J. Finance* 59(1):261–288.

Feng B, MacGeorge EL (2006) Predicting receptiveness to advice: Characteristics of the problem, the advice giver and the recipient. *Southern J. Comm.* 71(1):67–85.

Finke M (2013) Financial advice: Does it make a difference? Olivia OS, Smetters K, eds. *The Market for Retirement Financial Advice* (Oxford University Press, Oxford, UK), 229–248.

FINRA (2013) Financial capability in the United States: Report of findings from the 2012 National Financial Capability Study. Report, FINRA Investor Education Foundation, Washington, DC.

Fryer RG, Harms P, Jackson MO (2013) Updating beliefs with ambiguous evidence: Implications for polarization. NBER Working Paper 19114, National Bureau of Economic Research, Cambridge, MA.

Gennaioli N, Shleifer A, Vishny R (2015) Money doctors. *J. Finance* 70(1):91–114.

Georgarakos D, Inderst R (2011) Financial advice and stock market participation. Working Paper 1296, European Central Bank, Frankfurt, Germany.

Hackethal A, Inderst R (2013) How to make the market for financial advice work. Olivia SM, Smetters K, eds. *The Market for Retirement Financial Advice* (Oxford University Press, Oxford, UK), 213–228.

Hackethal A, Haliassos M, Jappelli T (2012) Financial advisers: A case of babysitters? *J. Banking Finance* 36(2):509–524.

Hackethal A, Inderst R, Meyer S (2010) Trading on advice. CEPR Discussion Paper 8091, Center for Economic and Policy Research, Washington, DC.

Haigh MS, List JA (2005) Do professional traders exhibit myopic loss aversion? An experimental analysis. *J. Finance* 60(1): 523–534.

Harvey N, Fischer I (1997) Taking advice: Accepting help, improving judgment, and sharing responsibility. *Organ. Behav. Human Decision Processes* 70(2):117–133.

Holden S (2013) When, why, and how do mutual fund investors use financial advisers? Olivia SM, Smetters K, eds. *The Market for Retirement Financial Advice* (Oxford University Press, Oxford, UK), 249–272.

Hortacsu A, Syverson C (2004) Product differentiation, search costs, and competition in the mutual fund industry: A case study of S&P 500 index funds. *Quart. J. Econom.* 119(2):402–456.

Inderst R, Ottaviani M (2009) Misselling through agents. *Amer. Econom. Rev.* 99(3):883–908.

Inderst R, Ottaviani M (2012a) How (not) to pay for advice: A framework for consumer financial protection. *J. Financial Econom.* 105(2):393–411.

Inderst R, Ottaviani M (2012b) Financial advice. *J. Econom. Literature* 50(2):494–512.

Kumar A, Niessen-Ruenzi A, Spalt OG (2015) What is in a name? Mutual fund flows when managers have foreign-sounding names. *Rev. Financial Stud.* 28(8):2281–2321.

Lachance M, Tang N (2012) Financial advice and trust. *Financial Services Rev.* 21(3):209–226.

Lipkus IM, Samsa G, Rimer BK (2001) General performance on a numeracy scale among highly educated samples. *Medical Decision Making* 21(1):37–44.

List JA (2003) Does market experience eliminate market anomalies? *Quart. J. Econom.* 118(1):41–72.

List JA (2004) Neoclassical theory versus prospect theory: Evidence from the marketplace. *Econometrica* 72(2):615–625.

List JA, Shaikh AM, Xu Y (2016) Multiple hypothesis testing in experimental economics. NBER Working Paper 21875, National Bureau of Economic Research, Cambridge, MA.

Lusardi A, Mitchell OS (2011) Financial literacy around the world. *J. Pension Econom. Finance* 10(4):497–508.

Lusardi A, Mitchell OS (2014) The economic importance of financial literacy: Theory and evidence. *J. Econom. Literature* 52(1):5–44.

Mitchell OS, Smetters K (2013) *The Market for Retirement Financial Advice* (Oxford University Press, Oxford, UK).

Mullainathan S, Noeth M, Schoar A (2012) The market for financial advice: An audit study. NBER Working Paper 17929, National Bureau of Economic Research, Cambridge, MA.

Nadler A, Ellis S, Bar I (2003) To seek or not to seek: The relationship between help seeking and job performance evaluations as moderated by task-relevant expertise. *J. Appl. Soc. Psych.* 33(1): 91–109.

Oppenheimer DM, Meyvis T, Davidenko M (2009) Instructional manipulation checks: Detecting satisficing to increase statistical power. *J. Experiment. Soc. Psych.* 45:867–872.

Pechter J (2013) Zombie 401(k) accounts. *Retirement Income J.* 213(July 31).

Social Research Centre and ANZ (2011) Adult financial literacy in Australia—2011 ANZ survey. Report, Australia and New Zealand Banking Group, Melbourne, Australia.

Sniezek JA, Van Swol LM (2001) Trust, confidence and expertise in a judge-advisor system. *Organ. Behav. Human Decision Processes* 84(2):288–307.

State Street Global Advisors (2007) Bridging the trust divide: The financial advisor-client relationship. Knowledge@Wharton special report, University of Pennsylvania, Philadelphia. https://knowledge.wharton.upenn.edu/special-report/bridging-the-trust-divide-the-financial-advisor-client-relationship-2/.

Yaniv I, Kleinberger E (2000) Advice taking in decision making: Egocentric discounting and reputation formation. *Organ. Behav. Human Decision Processes* 33(2):260–281.