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Who Pays the Price for Bad Advice?: The Role of Financial Vulnerability, Learning and Confirmation Bias

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ABSTRACT

What kinds of people will pay bad financial advisers? We show that experimental participants (n=2003) with a proclivity toward confirmation bias are more susceptible to bad advisers. We give participants a sequence of signals of adviser quality that can be clear or ambiguous, depending on each participant's ability to discern bad advice. Rational participants set aside ambiguous signals and do not use them to update beliefs about advisers. Biased participants treat ambiguous signals as favoring their priors, and update accordingly. Younger, more trusting, more impulsive, less financially literate and less numerate participants are most vulnerable to paying a poor-quality adviser.

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The Bernie Madoff case is a high-profile example of financial adviser fraud. Madoff, the now notorious but once highly regarded, financial adviser single-handedly lost investors billions of dollars in a highly publicized Ponzi scheme. In total, Madoff caused $17 billion in losses to over 1,000 individuals and firms.[1] Unfortunately, this is not an isolated case, and adviser fraud is not limited to wealthy clients. In fact, research has uncovered a subset of advisers who are repeat offenders. Even more worrying is evidence that these advisers may intentionally target unsophisticated retail clients, particularly those with lower incomes, the elderly and the less-educated (Egan, Matvos, and Seru (2019)). Evidence of persistent misconduct by advisers, when combined with findings that cast doubt on whether advisers actually improve their clients' portfolio outcomes, underscores the importance of choosing a high-quality financial adviser (Hackethal, Haliassos, and Jappelli (2012), Mullainathan, Noeth, and Schoar (2012), Egan (2019), Egan, Matvos, and Seru (2019), Bucher-Koenen et al. (2021)). Unfortunately, this leaves many unsophisticated clients with a dilemma. They need high-quality advice to compensate for a lack of financial capability or for personality traits that may make them more susceptible to irrational behavior, but these deficiencies also mean that they may not be able to discern between good and bad advisers, making them easier targets for misconduct.

This paper investigates the extent to which certain segments of consumers are more likely than others to "pay the price" for bad advisers. We contribute to the literature by exploring mechanisms that drive consumers' choices of financial advisers and their willingness-to-pay for financial advice. We show how consumers with certain characteristics can incur higher economic costs, and we find that predatory advisers can exacerbate these costs.

This paper studies the adviser choices of 2,003 Australian participants in a large-scale, online, incentivized video experiment where actors, as financial advisers, provide advice on four different topics. We build a model that allows us to investigate the combined impact of consumers'

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[1] For further information on the scandal, see Frank et al. (2008) and Maglich (2013). A complete list of individuals and corporations that lost money can be found at this link https://s.wsj.net/public/resources/documents/st_madoff_victims_20081215.html .

prior beliefs about advisers, their learning processes, and their ability to discern good from bad advice on their willingness-to-pay for financial advice.

In this paper, consumers learn about adviser quality based on their experiences with the adviser. More specifically, they learn from the advice they receive over time. Consumers' memories determine how these experiences feed into their beliefs about the adviser. Since full memory is not necessarily empirically plausible (Nagel and Xu (2019)), we consider both a standard rational Bayesian process and a biased limited memory process based on Fryer, Harms and Jackson (2019) as latent learning processes about adviser quality. While the former process assumes that people ignore ambiguous signals (i.e., advice on unclear topics), the latter process accounts for confirmation bias, a bias where people interpret ambiguous signals in line with their prior beliefs and then update their beliefs based on their interpretation of the signals rather than the signals per se. These latter consumers thus exhibit limited memory of the past as they only recall their interpretation and are more likely to be impacted by first impressions. Extending the work of Agnew et al. (2018), we field an online survey featuring an experimental design with 144 conditions that captures participants' willingness-to-pay for the advisers they observe and allows us to identify the two latent learning processes. This enables us, for the first time, to understand the economic consequences of different learning processes, how these consequences are moderated by consumers' prior beliefs and consumers' ability to discern good from bad advice, and the role that consumer characteristics play in this context. Our analysis yields several results that have important implications for public policy.

First, our results provide insight into how consumers process new information. We find that irrational updating is common. We show that nearly two-thirds of experiment participants express beliefs about the advisers that conform to limited memory updating processes and are, therefore, consistent with a tendency toward confirmation bias. We further show that irrational updating affects consumers' financial decisions. Nearly 80 percent of participants in our study have difficulty discerning good from bad advice for at least one of the four topics presented to them and thus rely on their belief about adviser quality to choose between financial strategies for those topics. We show that consumers with higher impulsiveness are more likely to follow a limited memory updating process, and we confirm previous research by showing that product knowledge, age, gender, financial literacy and numeracy determine consumers' ability to distinguish between good and bad advice (Agnew et al. (2018)).

Second, we assess how prior beliefs about an adviser's quality are formed and how they – combined with a consumers' learning process and ability to discern good from bad advice – can impact a participant's willingness-to-pay for an adviser. We show that if a consumer generally trusts advisers and if an adviser displays credentials, the consumer will hold prior beliefs of higher adviser quality than in the reverse cases. Prior beliefs of higher adviser quality translate into higher initial willingness-to-pay for an adviser. We also show how the sequence in which advice is delivered to consumers matters when confirmation bias is at play. When an adviser makes a good impression by providing understandable, correct advice and then follows up with advice that is difficult to interpret, limited memory learners are willing to pay more than their rational counterparts for ongoing services from the adviser.

Third, we demonstrate how this divergence in willingness-to-pay manifests for contrasting segments of "vulnerable" and "resilient" consumers. We show that the divergence between the willingness-to-pay of vulnerable and resilient consumers widens as advisers offer increasing quantities of bad advice even when the adviser is not strategically manipulating his or her clients. Thus, we show that vulnerable consumers face economic costs from bad advice even when advisers are not attempting to profit from their vulnerability. Moreover, we demonstrate how an adviser can purposefully extract even higher payments from vulnerable clients by intentionally exploiting their biased updating method. Importantly, we can identify the clients most likely to be biased updaters using only observable personal characteristics and responses to simple survey questions. This information is often also (implicitly) available to financial advisers, thus increasing the risk of vulnerable clients becoming targets for bad advice.

Altogether, our findings contribute to several streams of literature, including research examining the market for financial advisers, behavioral decision-making, consumer learning strategies and consumer vulnerability in financial services. In addition, the results have practical implications. The demonstrated economic costs borne by vulnerable clients who follow biased limited memory learning models add to the debate over the need for tighter financial adviser regulations, including mandatory certification and revised fiduciary standards.

This paper is structured as follows. In Section I, we provide a motivation for our paper based on the literature on financial advice and how individuals choose advisers. In Section II, we introduce a choice model that accounts for two possible latent learning processes. Section II also outlines our experimental design. The results from our experiment are described in Section III. Section IV discusses the implications of the findings and concludes the paper.

I. Motivation

Academic studies document substantial variation in the quality of advice given by financial advisers.[2] One proposition is that some advisers have misguided beliefs that not only drive them personally to chase returns, prefer expensive actively managed funds, and underdiversify but also to recommend similar portfolios to their clients (Linnainmaa, Melzer, and Previtero (2020)). Other research suggests that financial firms may have incentives to strategically increase the complexity of products to impede consumer learning and maintain rents (Carlin (2009), Carlin and Manso (2010)), making it even more difficult for consumers to make decisions.

Intentional adviser misconduct is also an issue. There is growing empirical evidence that advisers exploit the biases and lack of sophistication of clients (Hackethal, Haliassos, and Jappelli (2012), Mullainathan, Noeth, and Schoar (2012), Egan (2019), Egan, Matvos, and Seru (2019), Bucher-Koenen et al. (2021)).[3] To provide a sense of the size of the problem, Egan, Matvos, and Seru (2019) find that seven percent of advisers in the U.S. have misconduct records. This figure rises to fifteen percent within some larger firms.

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[2] For studies investigating the quality of advice, refer to Bergstresser, Chalmers, and Tufano (2009), Inderst and Ottaviani (2012a, 2012b), Mullainathan, Noeth, and Schoar (2012), Hackethal and Inderst (2013), Chalmers and Reuter (2015), Anagol, Cole, and Sarkar (2017), Hoechle et al. (2017) and Cici, Kempf, and Sorhage (2017).

[3] It is well known that levels of financial literacy are low globally (Lusardi and Mitchell (2011)).

One factor driving misconduct may be the advisers' compensation packages. Inderst and Ottaviani (2009) use a theoretical model to demonstrate that an adviser's willingness to debias and educate clients can be diluted by incentive structures. Evidence from recent empirical work supports this theory. For example, Egan (2019) uses a unique data set of reverse convertible bonds to show how conflicts of interest between advisers and clients can distort behavior, leading advisers to recommend inferior products. Egan finds that clients are increasingly likely to buy reverse convertibles as brokerage fees increase, even though bonds associated with higher fees tend to have worse payoffs. In another study, Egan, Ge, and Tang (2020) find that variable annuity sales are approximately five times more sensitive to brokers' financial interests than to their clients' interests.

Evidence is also emerging that specific types of consumers should be wary of advisers. Returning to Egan, Matvos, and Seru's (2019) paper, the authors' findings suggest that some firms may be specifically targeting an unsophisticated clientele for exploitation, a result confirmed by Bucher-Koenen et al. (2021) for less financially literate women. Theory can explain such behavior: Egan (2019) develops a theoretical model that explains why advisers can benefit from selling high-fee, dominated products to unsophisticated clients while simultaneously marketing low-fee, superior products to more sophisticated clients. These studies suggest that unsophisticated clients are vulnerable to unscrupulous advisers and should be particularly careful when selecting a financial representative.

Unfortunately, choosing a high-quality adviser may be easier said than done, especially for those lacking financial sophistication (Stolper (2018)). Emerging research suggests that clients do not always base their choice of adviser or their decision to continue with an adviser on objective criteria or the quality of the actual advice given. For instance, Stolper and Walter ((2019)) find that homophily between an adviser and client captured by demographic similarities is positively related to whether a client follows an adviser's financial advice. Trust also plays a role. Georgarakos and Inderst ((2014)) show that clients with limited financial capability are more likely to follow advice if they trust their adviser, and Germann, Loos, and Weber ((2018)) find that clients invest in riskier assets and will pay more when they trust their adviser. Trust depends on many factors, including the client's capability, the accuracy and quality of information provided, and a belief that the adviser and client's incentives are aligned (Yaniv and Kleinberger (2000), Sniezek and Van Swol (2001)).

Trust also has economic significance in adviser/client relationships. Trusted advisers are likely to be able to charge higher fees and thus take a larger share of the benefits of the advice relationship (Gennaioli, Shleifer, and Vishny (2015)). Loss of trust can also have significant economic ramifications. Returning to the Madoff example, Gurun, Stoffman, and Yonker ((2018)) assert that trust in Madoff played a critical role in his clients' decisions to invest with him. The authors estimate that the resulting lack of trust generated from the scandal caused $363 billion in withdrawals from financial advisers amounting to 20 times more than the dollar figure the courts ordered for restitution.

Research shows that clients rapidly form opinions of their financial adviser (Yaniv and Kleinberger (2000)), and first impressions are important (Agnew et al. (2018)). Agnew et al. (2018) find that advisers who confirm clients' views on straightforward issues early in an advice relationship are subsequently rated as more trustworthy and competent than advisers who contradict clients' views. Furthermore, clients are more likely to accept their later advice on complicated topics. These findings align with empirical evidence observed in the field suggesting that advisers "cater" to clients (Mullainathan, Noeth, and Schoar (2012), Anagol, Cole, and Sarkar (2017)). This can lead to poor decision making and could help explain the findings of a 2012 study by the Australian Securities and Investment Commission (ASIC) that clients credulously continue to trust advisers who deliver poor-quality advice (Australian Securities and Investment Commission (ASIC) (2012)). Powerful first impressions might also explain how Bernie Madoff scammed so many investors. His sterling reputation provided a strong first impression that drew investors to his funds (for example, see Pulliam (2008)).

The Madoff story also suggests that confirmation bias may have played a role in Madoff's ability to maintain his long-running scam, as many examiners and investors exhibited behavior consistent with this bias. Confirmation bias is often founded on a first impression (Beattie and Baron (1988)). Those exhibiting confirmation bias interpret evidence "in ways that are partial to existing beliefs, expectations, or a hypothesis in hand" (Nickerson (1998)) and search harder for information that confirms their beliefs (Snyder and Swann (1978), Muthukrishnan (1995)). Evidence shows that Securities and Exchange Commission (SEC) examiners did not look closely at Madoff's business despite several tips about possible wrongdoing. One examiner told investigators "that it was fair to say that because of Bernard Madoff's reputation at that time as a large broker-dealer, there may not have been any thought to look into Madoff's operation any further." (U.S. Securities and Exchange Commission (SEC) Office of Investigations (2009), page 50.) In this case, it appears that the SEC examiners ignored credible new information about potential fraud because it contradicted their initial beliefs, which is consistent with confirmation bias.

Another notable feature of confirmation bias is that it can explain how two people can reach opposite opinions after they review common evidence (Darley and Gross (1983)). The defining feature of this bias is that additional ambiguous information leads to the polarization, rather than the moderation, of prior opinions. Confirmation bias has proven to be a robust phenomenon in areas as diverse as beliefs about the deterrent effect of the death penalty, nuclear power generation, climate change, brand loyalty and sexual morality.[4] In terms of the selection of financial advisers, Agnew et al. (2018) are able to generate polarized beliefs about advisers' trustworthiness and other characteristics by manipulating the client's first impression of the quality of the adviser and the quality and complexity of the advice that follows. Their findings and others explain how some advisers can successfully use strategies to build and maintain client trust while also providing unhelpful advice (Mullainathan, Noeth, and Schoar (2012), Anagol, Cole, and Sarkar (2017), Agnew et al. (2018)).

[4] See Fryer, Harms, and Jackson (2019), Online Appendix C, Table I, for a summary.

II. A Model of Consumer Learning and Confirmation Bias with an Experimental Test

This research both motivates our exploration of how first impressions and confirmation bias influence clients' selection and payment of financial advisers, and informs the design and direction of our empirical analysis, to which we now turn.

A. Overview of Bayesian and Limited Memory Learning Models

Learning is best understood as a hypothesis-testing process where new information is encoded and integrated with existing beliefs (Hoch and Deighton (1989), Nagel and Xu (2019)). A prime example is when clients decide whether to follow financial advice in an area where they have little experience, such as how to invest retirement savings. Clients who have incomplete information usually rely on signals to reach a decision about the quality of an adviser. For example, clients might rely on an adviser's professional certification, consider past advice given by the adviser on a different topic, or listen to opinions of other people about the quality of different advisers. All these signals help clients form an initial belief. New signals and added experience then help them update these beliefs until they can make better-informed decisions. The problem arises when the new signals are ambiguous for the client, such as when the adviser provides advice that the client cannot classify as good or bad.

In these situations, people may not update their beliefs in a rational way, resulting in behavior consistent with confirmation bias. Confirmation bias cannot be incorporated into traditional models because it violates a basic assumption of conventional Bayesian learning models (Eckstein, Horsky, and Raban (1988), Roberts and Urban (1988), Erdem and Keane (1996)). Whereas a rational Bayesian learner ignores ambiguous new information, confirmation bias causes the learner to 'double update' (Fryer, Harms, and Jackson (2019)). These learners make use of Bayes' rule in an iterative way, first to interpret ambiguous new information in light of prior beliefs and then to update beliefs using this interpretation rather than raw, noninformative evidence. As such, confirmation bias is in line with limited memory updating in that these learners ignore the raw evidence but only recall their interpretation of the evidence. Thus, in contrast to learning models that allow people to give higher weight to new signals from specific sources (Camacho, Donkers, and Stremersch (2011)), learning under confirmation bias not only leads to different *weighting* of signals but actually can reverse the *interpretation* of the signal. Irrespective of the actual signal valence, a person with confirmation bias will treat an ambiguous signal as positive if his or her prior belief is positive and will treat it as negative if his or her prior belief is negative. Such biased updating in turn leads to overconfidence where people may come to believe with near certainty in a false hypothesis despite receiving an infinite amount of information (Rabin and Schrag (1999)). In this paper, we account for confirmation bias and the polarization of opinion that follows by using a biased updating model with the form of limited memory introduced in Fryer, Harms, and Jackson (2019).

Importantly, whether a client uses rational Bayesian versus limited memory updating cannot be directly observed. Instead, these are latent traits that can only be inferred by observing the client's choices in a suitable setting. Therefore, to study this, we use an experiment and an associated model specifically designed for this purpose that allows such inference. We begin by describing the experiment and then provide a formal description of the model. In the final section, we address our method for parameter identification.

B. Experiment

In December 2014, we conducted a four-part online survey that included an incentivized choice experiment. Part one tested the financial knowledge of participants; in part two, participants chose between alternative financial advice messages; in part three, the participants stated their willingness-to-pay for further advice; and in part four, we collected demographic and personal information. We invited members of PureProfile, an Australian nationally representative online panel, to participate. Respondents had to pass two screening questions to meet our age and gender quotas. This resulted in 2,003 participants who completed the survey. To ensure incentive compatibility, we compensated participants who completed the survey for their time (approximately $A4) and rewarded them by giving one entry in a drawing for a $A50 prize for each correct choice of financial advice in each of four choice sets and for each correct answer in a post-experiment quiz. The majority of participants completed the survey in under 30 minutes, and the entire data collection process took less than three weeks.

Participants first answered a set of questions that measured their general financial literacy and numeracy (Lipkus, Samsa, and Rimer (2001), Lusardi and Mitchell (2011)). We used their responses to evaluate their understanding and experience with the four advice topics covered in the choice task that followed. The choice task consisted of a sequence of videos of two advisers who gave financial advice on four common consumer finance topics: credit card debt repayment, retirement savings account consolidation, diversification in equity investments, and index fund fees. Participants chose which advice they would follow on each of four topics. [5] The scripts for each topic are found in Table I.

<INSERT TABLE I ABOUT HERE>

To identify the effect of confirmation bias in the choice task, we ensured that the advice topics, advisers, environment, and mode of advice delivery were uniform. We pretested the actors who played the advisers and their names to ensure that participants would view each of them as equally credible. We also instructed the production company to ensure that the actors were dressed, made-up, and filmed in the same way. Our design allows us to control the content of the videos, the order of advice topics, the quality of advice given, and the adviser attributes.

We used a between-subjects experimental design that varied by adviser characteristics (age, gender, certification). To minimize the between-subjects treatment groups, we used a fold-over design in which we created the complete factorial of possible advisers and paired each of them with their "mirror image" (that is, one with the exact opposite attributes, so that a younger female adviser was matched with an older male adviser). Participants viewed the same pair of

[5] The topics are used by Agnew et al. ((2018)) based on their relevance for people around the world, that they have unequivocally right and wrong answers, and are based on the decisions often made in these areas. To view an example of the video advice from a treatment in Agnew (2018), please follow this link: https://drive.google.com/file/d/0B-1NMLVfExG1ZzFhZWlrRWlsR2s/preview

advisers for all four choice sets. This design produced four between-subject treatment groups and is shown in Panel A of Table II.

<INSERT TABLE II ABOUT HERE>

Further variation in the experimental design relates to between-subject manipulation of the topic sequence and the order in which good and bad advice is given by each adviser. These variations are essential to test between the limited memory and Bayesian learning models. Thus, we combined the above four between-subjects treatment groups with a design to vary the orders of the four topics and the advice quality (good vs. bad). A full factorial design was infeasible because it required 16 possible sequences of good (G) and bad (B) advice and 24 possible sequences of topics. From this complete design, we chose a subset of the most informative sequences that allowed us to test for confirmation bias. This includes six sequences of good and bad advice orders—those where each adviser gives two good and two bad recommendations (see Panel C of Table II)—and topic sequences with an equal number of hard and easy financial topics (see Panel B of Table II).[6]

When we combined the four possible pairs of advisers with the six possible sequences of topics and the six possible sequences of advice quality, we obtained a design with 6*6*4 =144 conditions. We randomly assigned at least 10, and up to 14, participants to each condition.

After the choice task, participants rated the trustworthiness, competence, attractiveness, understanding, professionalism, financial expertise, genuineness, and persuasiveness of the advisers. They also stated their willingness-to-pay $X for a one-hour session with both, one, or none of the advisers. We assigned fixed fee values $X \in \{\$50, \$100, \$150, \$250, \$500, \$750\}$ to participants to minimize their predictability from the other manipulated characteristics of the experiment. The participants then answered questions about marital status, household size, number

[6] We rely on the results by Agnew et al. (2018) who find that two topics (debt repayment and retirement account consolidation) are relatively easy (E) and that the other two topics (diversification and index fund fees) are relatively hard (H).

of dependents, education, labor market status, income, gross assets, and debts/liabilities, and personal characteristics, including personality traits and risk attitudes. The last part of the survey debriefed participants on the correct advice and then presented an incentivized quiz on the debriefing material.[7]

C. Model

We now turn to the empirical model that allows us to identify the latent learning process our participants employ. Given that the model can be applied in other situations where participants form beliefs and choose based on their beliefs, we first describe the experiment discussed above using general notation.

In the experiment, we provide participant *k, =*1,..., *K*, with a sequence of t_k=1, ..., T_k signals $\sigma_{tk} = (\sigma_{Rtk}, \sigma_{Ltk})$ from two different advisers, *R* and *L*. We assume that both the signals σ_{Rtk} and σ_{Ltk} received at time t_k are either clear or ambiguous to the participant, *k.* The sequence of signals is delivered via choice sets in which the participant views advice on a financial topic and needs to decide which advice to follow. We assume that $(\sigma_{Rtk}, \sigma_{Ltk}) \in \{(a, b), (b, a), (ab, ab)\}$, where from the participant's perspective, *a* is a clear signal of good quality, *b* is a clear signal of bad quality, and *ab* is an ambiguous signal. In each choice set, i) one adviser gives good advice, and the other provides bad advice; ii) conditional on the topic, the participant interprets the advice as either ambiguous or clear; and iii) the participant chooses between the two advisers based on the participant's evolving interpretation of the quality of advice by each adviser. Thus, in our experiment, participant *k* chooses whether to follow the advice of adviser *R* or *L* provided in choice set *t*. We code the choice data as:

[7] In online Appendix A, we compare the characteristics of the sample with Australian Census data from 2011. Our sample results show slightly higher educational attainment and a higher probability of being married than the census data but are otherwise representative of the population.

$$y_{kt} = \begin{cases} 1, & \text{if } R \text{ was chosen at choice } t_k \text{ by participant } k, \\ 0, & \text{if } L \text{ was chosen at choice } t_k \text{ by participant } k. \end{cases} \quad (1)$$

After having received T signals (advice) from each of the advisers, we offer participants the option to purchase an additional unit of advice from each adviser at a certain price p_k. In the experiment, we ask participants whether they would be willing to pay a fixed amount for a one-hour session with the adviser. Let y_k^L (y_k^R) be indicator variables taking value 1 if participant k is willing to pay price p_k for more advice from adviser L (R).[8] We use data on the advice selected by the participant in the choice sequence and the participant's stated willingness to purchase additional advice to estimate i) the initial beliefs of the participants about adviser quality; ii) whether the participants follow a standard Bayesian or limited memory updating scheme; and iii) whether the participants treat an advice signal as clear or ambiguous.

In both the Bayesian learning model and the limited memory learning model, the posterior belief (or updated belief) of participant k depends on his or her initial belief λ_{k0}^r about the quality of adviser $r \in \{R, L\}$. The initial belief depends on characteristics, X_0, of the advisers $r \in \{R, L\}$ and of the participant, with relative importance of characteristics measured by an unknown vector of parameters, β_0. We define the initial belief about adviser quality to be a logit function of X_0, where X_0 is a vector that includes information on whether the adviser displays a credential and the participant's general trust in advisers (see also Table III):

$$\lambda_{k0}^r = \frac{\exp(\beta_0 X_0)}{1 + \exp(\beta_0 X_0)}. \quad (2)$$

<INSERT TABLE III ABOUT HERE>

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[8] Note that the model can be extended to include more entities or more attributes to influence the different choices.

When combined with a calibrated value for signal strength[9], s, we can calculate λ_{kt}^{r}, the updated belief about the quality of the adviser $r \in \{R, L\}$ by participant k after choice set t, conditional on the participant's updating scheme and signal clarity: A Bayesian updater will form beliefs according to the Bayesian rule and ignore the ambiguous information:

$$\lambda_{t+1}^{r} = P(A \mid \lambda_{kt+1}^{r}, \sigma_{t+1}^{r}) = \begin{cases} \dfrac{s\lambda_{kt}^{r}}{s\lambda_{kt}^{r} + (1-s)(1-\lambda_{kt}^{r})}, & \text{if } \sigma_{kt+1}^{r} = a, \\ \dfrac{(1-s)\lambda_{t}^{r}}{(1-s)\lambda_{kt}^{r} + s(1-\lambda_{kt}^{r})}, & \text{if } \sigma_{kt+1}^{r} = b, \\ \lambda_{kt}^{r}, & \text{if } \sigma_{kt+1}^{r} = ab, \end{cases} \tag{3}$$

That is, a Bayesian updater will update beliefs only when given clear signals. In contrast, limited memory updaters will interpret an ambiguous signal as a good signal if they hold a prior belief that an adviser is good quality adviser and as a bad signal if they hold a prior belief that an adviser is poor quality. Based on Fryer, Harms, and Jackson (2019), we assume that a limited-memory client updates beliefs according to:

$$\lambda_{kt+1}^{r} = P(A \mid \lambda_{kt+1}^{r}, \sigma_{t+1}^{r}) = \begin{cases} \dfrac{s\lambda_{kt}^{r}}{s\lambda_{kt}^{r} + (1-s)(1-\lambda_{kt}^{r})}, & \text{if } \sigma_{kt+1}^{r} = a, \text{or } \sigma_{t+1}^{r} = ab \text{ and } \lambda_{kt}^{r} > \dfrac{1}{2}, \\ \dfrac{(1-s)\lambda_{t}}{(1-s)\lambda_{kt}^{r} + s(1-\lambda_{kt}^{r})}, & \text{if } \sigma_{kt+1}^{r} = b, \text{or } \sigma_{t+1}^{r} = ab \text{ and } \lambda_{kt}^{r} < \dfrac{1}{2}, \\ \lambda_{kt}^{r}, & \text{if } \lambda_{kt}^{r} = \dfrac{1}{2}. \end{cases} \tag{4}$$

[9] The signal strength s (s>1/2) denotes the probability that the client receives a clear, good signal, conditional on the adviser being good, $P(a \mid A)=s$. We assume that the probability of receiving a clear, good signal from a bad adviser is $(a \mid B)=1-s$. The parameter s thus determines the extent to which the client's beliefs are influenced by the signal. To enable us to identify parameters, we set s to an arbitrary value greater than 0.5 and check the sensitivity of our estimation to alternative choices. The results we report below use s=0.75.

Equations (3) and (4) show how ambiguous signals create an opportunity for confirmation bias to operate. Rational updaters ignore ambiguous signals and form a posterior belief only over the sequence of clear signals. They thus gradually uncover the true quality of the adviser. However, when clients exhibit confirmation bias and use limited memory updating, they will not overlook an ambiguous signal. Instead, they will interpret it in line with their current belief and thus reinforce their view of the adviser's quality. Limited memory updating thus forces an interpretation of ambiguous signals, which in turn results in confirmation bias and polarization of opinions.

Once the signal is received and the participant has updated his or her beliefs, he or she will make a choice. If the participant perceives the signal to be clear (i.e., the topic is easy for the participant to understand), we assume that he or she selects the adviser who gives the correct advice up to some random error. That is, if the topic is clear and understandable, the participant selects advice based on its quality alone. However, if the participant perceives the adviser's signal to be ambiguous, we assume that he or she makes a selection according to posterior beliefs about the adviser's qualities.

We model the probability of choosing advice in each choice set as a simple binomial logit. Let q_k^t equal to 1 if adviser R gives correct advice (and adviser L gives incorrect advice by our experiment design), and let q_k^t equal -1 otherwise. Then the choice probabilities respectively for the clear signals topic, and the ambiguous signals topic are given by:

$$P(y_{kt}=1\,|\,\sigma_{tk}\text{=clear})=\frac{\exp(\beta_1 q_k^t)}{1+\exp(\beta_1 q_k^t)} \tag{5}$$

and

$$P(y_{kt}=1\,|\,\sigma_{tk}\text{=ambiguous})=\frac{\exp(\beta_2\cdot(\lambda_{kt}^R-\lambda_{kt}^L))}{1+\exp(\beta_2\cdot(\lambda_{kt}^R-\lambda_{kt}^L))}. \tag{6}$$

Note that in the second case, we assume that the choice is made purely on the basis of relative perceived adviser quality. In both cases, we effectively estimate the scale parameters $\frac{1}{\beta_1}$ and $\frac{1}{\beta_2}$ of the extreme value distribution of the random components. As β_1 (β_2) approaches infinity, the expression on the right-hand side of Equation (5) (Equation (6)) approaches 1 for q_k^j =1 ($\lambda_{kt}^R > \lambda_{kt}^L$) and 0 otherwise.

We next examine participants' resulting willingness-to-pay for the advice provided by each adviser in the pair. We model the probability of being willing to pay for adviser r as follows:

$$P(\text{willing to pay for } r) = \frac{\exp(\beta_3^0 + \beta_3^1 \lambda_{kT}^r + X_3 \beta_3^2)}{1 + \exp(\beta_3^0 + \beta_3^1 \lambda_{kT}^r + X_3 \beta_3^2)}, \tag{7}$$

Besides the constant (β_3^0), we estimate the impact of the posterior belief about the adviser quality (β_3^1) and a vector of parameters β_3^2 with the attributes of the participant and the adviser, including the price of an additional unit of advice, X_3 (see Table III).

The above discussion illustrates how participants form beliefs about advisers that depend on the participants' updating scheme and the clarity of topic signals. Participants' beliefs then determine their choice of advice and willingness-to-pay for advice. Since neither the updating scheme nor the degree of ambiguity of a topic can be observed, in our model, we assign participants to latent classes based on the perceived clarity or ambiguity of the topics in choice set t_k and to latent classes distinguished by the participant's updating scheme. In the interest of parsimony, we assume the latent class probability factor as:

$$P_k(\tau) = P_k(\tau_{\text{clarity}}, \tau_{\text{rationality}}) = P_k(\tau_{\text{clarity}}) P_k(\tau_{\text{rationality}}), \tag{8}$$

and

$$P_k(\tau_{\text{clarity}}) = \prod_{t_k=1}^{T_k} P_k(\sigma_{tk} = \text{clear}). \tag{9}$$

Dependence between the latent classes for any participant k is captured by allowing class membership probabilities to be influenced by participant-specific covariates X_4 and X_5 and associated parameter vectors β_4 , β_5 and topic-specific constants β_5^{tk} .

$$P_k(\tau_{rational}) = \frac{\exp(\beta_4 X_4)}{1 + \exp(\beta_4 X_4)}, \tag{10}$$

and

$$P_k(\sigma_{kt} = \text{clear}) = \frac{\exp(\beta_5^{tk} + \beta_5 X_5)}{1 + \exp(\beta_5^{tk} + \beta_5 X_5)}. \tag{11}$$

We use past literature to inform the choice of covariates X_4 and X_5 (see the previous section's discussion and Table III): Specifically, we allow a participant's level of conscientiousness, as well as his or her relative impulsiveness, to influence his or her likelihood of being a limited memory updater. Conscientiousness is a Big Five personality trait that particularly exhibits the facets of orderliness (i.e., the tendency to be "prepared" and to plan) and industriousness (i.e., the tendency to work hard in the face of challenges and aspire to excellence) (Roberts et al. (2014)). It also correlates with academic success independent of intelligence (Noftle and Robins, 2007). Accordingly, research suggests that conscientious students devote greater effort to their work (Bidjerano and Dai (2007), Chamorro-Premuzic and Furnham (2003), Richardson and Abraham (2009)) and have a greater likelihood of employing an "achieving" learning style, where learners study to obtain rewards associated with high academic results (Stumm and Furnham (2012)). Therefore, we hypothesize that conscientious individuals will devote greater effort to making a choice – particularly in our incentivized scenario – and thus will be more likely to expend more cognitive effort evaluating the advice. As such, they will be less likely to use memory shortcuts, such as limited memory learning, and more likely to rationally evaluate new information according to Bayesian updating.

Impulsiveness, in contrast, is a facet of the Big Five personality factors, but its factors remain a subject of debate. Some feel it is a facet of conscientiousness, while others view it as a facet of neuroticism. Still others see it as a blend of several factors (Borghans, Duckworth, Heckman and terWeel (2008)). Given this debate, we believe that impulsiveness may have explanatory power over and above conscientiousness. Impulsivity is the tendency to act without thinking, make quick cognitive decisions, and a lack of concern for the future. It has been suggested that it is one factor underlying time preferences. In support of this, neuroscience research finds that impulsivity relates to people wanting things as soon as possible (Glimcher, Kable and

Kenway (2007)). It also relates to poor decision making (Franken et al. (2008)) and behavioral biases, such as attentional bias and other cognitive biases (Hou et al. (2011), Yang et al. (2016)). More important, impulsiveness has been shown to be associated with lower cognitive reflection (i.e., the ability to override a – frequently incorrect - premature response and to engage in reflective reasoning, which usually leads to a correct answer), in turn leading to less rational decision making. We therefore hypothesize that impulsive people will be more inclined to use the most easily available information to form beliefs without reflecting on the correctness of this information. As such, since the interpretations of signals rather than the actual signals are more easily retrieved, we hypothesize that impulsive people are more likely to update their beliefs using a limited memory process. Based on Tsukayama, Duckworth and Kim's (2011) findings, we use a finance domain-specific measure of impulsivity, which should provide greater predictive power in our context.

To model participants' probability of perceiving a topic to be clear, we use participants' financial literacy, numeracy, product knowledge and market experience. The different equations of our model show how these participant characteristics together with the characteristics that determine prior beliefs about advisers jointly determine participants' choices and – together with the adviser and participant characteristics that impact willingness-to-pay for advice – the economic costs that participants face.

We use Sequential Adaptive Bayesian Learning (SABL) algorithm developed by Durham and Geweke (2014) to estimate the model. The likelihood function is based on the observed adviser selection data and the replies to the willingness-to-pay questions. Conditional on the participant latent class τ_c:

$$\begin{aligned} l_k(\theta \mid \tau_c) = \prod_{t_k=1}^{T} & P(y_{kt} = 1 \mid \tau_c)^{y_{kt}} \\ & \cdot P(\text{willing to pay for entity } R \mid \tau_c)^{y_k^R} \\ & \cdot P(\text{willing to pay for entity } L \mid \tau_c)^{y_k^L}. \end{aligned} \tag{12}$$

The resulting *unconditional* likelihood of participant k's sequence of is then given by:

$$l_k(\theta) = \sum_{c=1}^{C} P_k(\tau_c) l_k(\theta \mid \tau_c). \tag{13}$$

D. Sketch of Parameter Identification

A formal analysis of identification is not feasible for the complex, nonlinear learning model introduced in Equations (1) to (13) above. Here, we sketch our identification strategy for the key model parameters.

First, consider participant *k*'s initial belief about *r*, that is, λ_{k0}^{r}. This initial belief is the basis for the updated posterior belief λ_{kt}^{r}, which influences both the participant's choice of adviser *r* and his or her willingness-to-pay. The initial belief itself also influences the choices made in choice set 1, as in this set, we assume that (up to uncertainty) if the topic is ambiguous to participants, they will choose the adviser that they initially believe to be of higher quality. Since the experimental design ensures that participants face both easy and hard (ambiguous) signals in choice set 1 (Panel B in Table II), we thus obtain sufficient information to estimate initial beliefs, as well as how those initial beliefs depend on advisers' and participants' characteristics (β_1).

Next, we discuss the signal strength s=Pr ($a \mid A$) = Pr($b \mid$ B), which is the probability that a good (bad) signal comes from a good (bad) adviser. For the purposes of estimation, we set s=0.75 to allow the probability to be greater than 0.5 but less than one that a good adviser delivers good advice to ensure that belief updating can occur. We tested for the sensitivity of the results at s=0.60 and s=0.80, and the results remained largely unchanged.

The parameter β_2 is identified via the initial belief λ_{k0}^{r} and *s*. These two parameters jointly define the updated beliefs, so we treat them as predetermined covariates when participants face an ambiguous topic. Choices made in choice sets with ambiguous signals can thus identify β_2.

Participants' choices of financial advice allow us to identify the latent "clarity classes." Specifically, our assumption on the choice process can be (up to uncertainty in the choice process) summarized as follows. If the participant selects an adviser that gives a bad quality signal, we can conclude that the signal was ambiguous for that participant. We cannot make a similar inference if the participant selects the adviser that gives a good quality signal, as this could imply either that the signal was clear for that participant or that it was ambiguous but he or she chose the adviser because of a higher associated prior belief. The combined information of updated beliefs about advisers and incorrect choices of advice thus allows us to identify the clarity classes.

Since the initial belief about an adviser can be inferred from the data without any assumptions about how participants update their beliefs and since signal strength s is fixed, we can calculate the posterior beliefs for both updating schemes. The posterior belief associated with the higher likelihood then helps to determine the latent rationality classes.

Finally, estimation of our model is complicated by the fact that the likelihood function is discontinuous for those cases where participants update their beliefs according to the limited memory updating scheme. The discontinuity in the likelihood appears along the dimensions of the parameters of beliefs. The SABL Bayesian estimation algorithm that we use does not rely on direct maximization of the likelihood function and therefore allows us to overcome this challenge. SABL is an extension of sequential Monte Carlo methods that additionally exploits the benefits of parallel computing environments. SABL does not require the researcher to specify conjugate priors, and it is also robust to multimodal posteriors that can arise in high-dimensional problems (Jasra, Stephens, and Holmes (2007)), such as ours. In online Appendix B, we provide a discussion of the discontinuity problem and outline the estimation procedure.

III. Results

A. Model Fit and Parameter Estimates

To begin, we assess the fit of our model. We estimate the model in SABL using data from 1,903 of the 2,003 participants and reserved the remaining participants' responses to assess hold-out fit. (Table III provides the variables and associated definitions used in the estimation.) Table IV reports the parameter estimates. For each parameter, we report the mode of its posterior distribution, as well as the 2.5 and 97.5 percentiles of this distribution, that is, the corresponding equi-tailed credible interval (CI). There is a 95% probability that the parameter is not zero if zero does not fall in the CI, denoted with an *. Of the 25 parameters we estimate, 20 satisfy this condition, and we concentrate on these effects in the interpretation below. The interpretation of the CIs is largely analogous to a frequentist 95% confidence interval.

<INSERT TABLE IV ABOUT HERE>

Overall, in-sample fit is satisfactory, and hold-out sample fit did not deviate substantially from the in-sample fit, which shows that our model does not overfit the data. The model also has discriminatory predictive power: for the estimation sample, it predicts an average (over all choice sets) probability of 0.69 that the adviser who is in fact chosen in the data would be chosen and predicts an average probability of 0.69 for the hold-out sample. When the adviser is not chosen in the data, the average model-predicted choice probability that the advisor would be chosen decreased to 0.29 for the estimation sample and 0.28 for the hold-out sample.

The predicted probabilities are less discriminating in the willingness-to-pay choice probabilities. When a participant chose to pay the adviser, the model's average predicted probability that the participant would choose to pay is 0.48 for the estimation sample data and 0.44 for the hold-out data. When a participant chose not to pay the adviser, the average model-predicted probability that the participant would pay is 0.28 for the estimation sample data and 0.34 for the hold-out sample data. Thus, the model slightly underestimates the probability that a participant is willing to pay the proposed fee for the adviser.

We also compared our model to a restricted model that allows for only rational Bayesian updating (where $P_k(\tau_{rational})=1$ for all *k*), in line with conventional learning models. The log marginal density for this restricted (rational) model is -5887.17, compared to a log marginal density of -5827.47 for our model for in-sample fit and -305.62 versus -298.35 for hold-out sample fit. These log marginal densities translate into Bayes factors that suggest that there is strong evidence against the restricted model based on the in-sample fit and substantial evidence against the restricted model based on the hold-out sample fit[10].

B. Latent Updating and Topic-Clarity Classes

A key result from our model is the prevalence of limited memory updaters who are susceptible to confirmation bias. Table V presents estimates of the percentages of participants assigned by the model to latent classes. We estimate that a significant majority – 63 percent – of the participants choose advisers in ways consistent with a limited memory updating process for their posterior beliefs on adviser quality: Bayesian updaters ignore ambiguous signals, while limited memory updaters interpret ambiguous signals in accordance with their priors when forming posterior beliefs. Thus, the implications of limited memory updating for clients' beliefs about adviser quality depend on the mix of clear and ambiguous signals they receive. All participants who find a topic clear will choose good advice (up to some error, Equation (5)). If the participant finds the topic ambiguous, Equation (6) posits that (up to some error) the participant will choose the adviser he or she rates as better, according to his or her posterior beliefs.[11]

<INSERT TABLE V ABOUT HERE>

The model assigns participants to 16 latent classes distinguished by whether members of the class perceive an advice topic as clear or ambiguous. The model assigns the largest percentage of participants (21.9 percent) to the class that treats every topic as clear except for fees, followed

[10] See also Kass and Raftery (1995) for a discussion of model comparison and the use of Bayes factors in the context of Bayesian model comparison.

[11] Estimated parameters associated with the quality of the advice and the belief about the adviser are 4.296 and 2.510, respectively (Table IV, Equations 5 and 6). These estimates mean that the probability that the participant chooses good advice if the topic is clear equals 0.99 from Equation 5 and if the topic is ambiguous, the probability the participant chooses an adviser R, with associated prior belief of 1, instead of adviser L, with associated belief of 0, is 0.92 from Equation 6. This confirms that ambiguous signals are associated with greater uncertainty and variability in participants' choices of advisers.

by 18.2 percent who see *all* the topics as clear. The third largest class (14.0 percent) of participants perceived only debt and consolidation as clear. This latent class assignment implicitly ranks topic clarity – with fees as the most unclear topic and debt and consolidation as the clearest – and is consistent with estimates of topic-specific constants in Table IV (Equation 11) and with rates of correct choices in the raw data.[12]

B.1. Determinates of Latent Class Membership and Prior Beliefs

We now more closely examine how personal characteristics, financial literacy and knowledge change the probability that participants follow one of the two different latent learning processes or perceive topics as clear or ambiguous. Our goal is to determine whether we can identify types of individuals who may be more prone to biased updating and who are more likely to find financial advice ambiguous.

To assess the marginal effect of personal characteristics, financial literacy and knowledge on the probability of following a rational learning process or the probability of perceiving a topic as clear, we set all other variables of the respective equations (10) and (11) at their mean values and calculate the probabilities at the minimum and maximum values for the variable of interest. Figures 1 and 2 display the probabilities and the associated 95 percent CIs, reflecting the marginal influence of each factor. The blue arrows display the difference when the factor confidence intervals do not overlap and the parameters from the CIs in Table IV exclude zero.

<INSERT FIGURE 1 ABOUT HERE>

<INSERT FIGURE 2 ABOUT HERE>

First, Figure 1 graphs how the probability that a participant is a rational Bayesian updater is influenced by personality traits. We focus our discussion exclusively on impulsivity, as it was

[12] We find that 88% of participants accurately choose the correct advice for the credit card debt repayment topic compared to 86% for the retirement account consolidation topic, 79% for the stock diversification topic, and 64% for the index fund fees topic. Overall, participants choose correct advice recommendations 79% of the time.

the only parameter in the estimation with a CI that excludes zero. We find that participants who are not impulsive are 8.31 percentage points more likely to be Bayesian updaters.[13] This is consistent with our earlier hypothesis.

In terms of topic clarity, Figure 2 shows how clarity increases significantly with prior product knowledge (6.54 percentage points), increased age (13.75 percentage points), higher financial literacy (9.10 percentage points) and higher numeracy (8.75 percentage points).

The previous section focused on how participants updated their beliefs about advisers based on their learning process and on their perceived clarity of the topics. However, the actual belief they hold about an adviser – and consequently their willingness-to-pay for this adviser – also depends on the belief they hold about the particular adviser before they receive the first piece of advice (prior belief). Figure 3 displays factors influencing a representative participant's prior belief about the probability that the adviser is good based on Equation (2). Motivated by previous research (discussed earlier), our model allows the prior belief about an adviser's quality to depend on the participant's general trust in financial advisers and whether the adviser displays certification. In Table IV, CIs exclude zero for both the trust and certification parameters. We find that the difference in prior beliefs that an adviser is good between a participant reporting no prior trust in advisers to one reporting trust is large: Participants attribute a 13.45 percent higher likelihood of the adviser being good if they display a general tendency to trust advisers. Similarly, certification matters, which is consistent with previous studies (Guiso, Sapienza, and Zingales (2008), Agnew et al. (2018)). An adviser certification increases the mean participant's prior by 2.22 percentage points.[14]

<INSERT FIGURE 3 ABOUT HERE>

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[13] Note that the CI in table IV for conscientiousness included zero. Therefore, we do not highlight the difference with the blue arrow even though the CI's do not overlap.

[14] We do not model other adviser characteristics because earlier research (Agnew et al. (2018)) indicated that age and gender differences were not relevant and would make identification harder.

Figure 4 illustrates the impact of factors influencing a representative participant's likelihood of paying for advice based on Equation (7). We find that the only participant characteristic that influences willingness-to-pay for advice—apart from price and participants' posterior beliefs about the adviser, which we will discuss in greater detail in the next section—is whether the participant has previously paid for financial advice. Participants who had paid for financial advice before were 5.92 percentage points more likely to pay for advice than those who had not paid for advice before. Since we condition on other covariates such as income, confidence in one's own financial capabilities, risk aversion and whether the participant is the household's financial decision maker, this result provides further evidence that, overall, clients evaluate their interactions with financial advisers as positive.

<INSERT FIGURE 4 ABOUT HERE>

C. Comparison of Adviser Choice and Willingness-to-pay for Advice by Updating Type

The previous section discusses how the certification of, or general trust in, advisers influences prior beliefs about advisers. In this section, we examine how the impact of certification on prior beliefs about advisers indirectly influences participants' choice of and willingness-to-pay for advice.

Our model allows us to do so while simultaneously accounting for participants' learning strategies (Bayesian or limited memory), as well as their ability to discern good from bad advice (i.e., clarity of topics). To illustrate, consider two participants, A and B, who update their beliefs according to the standard Bayesian and limited memory updating processes, respectively. Let the adviser who appeared on the right-hand side of the choice screen – the right adviser (R) – display a certification (+ 0.085 from Table IV, Equation (2)), and the left adviser (L) not display a certification (-0.085 from Table IV, Equation (2)). We arbitrarily assume that the participants distrust financial advisers (the negative of the trust mode of 0.52 from Table IV, Equation (2)), set other characteristics at the medians of the survey sample distributions, and fix estimated parameters at the mode of the posterior distributions. Both A and B will thus have similar prior beliefs about the right (R) and the left (L) adviser of

$\lambda_{A0}^{R} = \lambda_{B0}^{R} = \dfrac{\exp(1.728 + 0.085 - 0.520)}{1 + \exp(1.728 + 0.085 - 0.520)} = 0.785$ and $\lambda_{A0}^{L} = \lambda_{B0}^{L} = \dfrac{\exp(1.728 - 0.085 - 0.520)}{1 + \exp(1.728 - 0.085 - 0.520)} = 0.755$. The only difference is a result of adviser *R* possessing a certification, while adviser *L* does not. Assume that adviser *R* gives good advice on a clear topic in the first choice set and that both advisers give (from the participant's perspective) ambiguous advice in the remaining three choice sets.

Table VI shows the evolution of beliefs and choice probabilities for the advisers in this scenario. Both A and B update their beliefs in the same way in the first choice because they receive clear information about adviser quality. Participant A's beliefs about the advisers, as well as the associated choice probabilities, remain the same throughout the later three choice sets, as this participant simply ignores the ambiguous information and ends the experiment, still favoring adviser *R*. In contrast, participant B interprets all new information in line with current beliefs, so this participant will treat all ambiguous information as evidence that adviser *R* is good and adviser *L* is bad. Thus, participant B's updated beliefs about adviser *R* rise steadily, as does his or her probability of choosing adviser *R*.

<INSERT TABLE VI ABOUT HERE>

The results in Table VI thus show that limited memory updating leads to a choice probability that is very close to one for adviser *R* and close to zero for adviser *L*, while the corresponding probabilities are 0.916 (adviser *R*) and 0.098 (adviser *L*) for the rational updater. It also reveals the difference that a first impression makes and how it is intensified in each period by confirmation bias. An early clear signal has a stronger influence on the limited memory updater, whose opinion approaches certainty over a few choices.

We can also translate these posterior beliefs into willingness-to-pay for more advice. We model participants' willingness-to-pay for an additional hour with the adviser as depending on the actual price charged, several characteristics of the participant, and the participant's posterior belief about this adviser. Based on the parameters in Table IV and Equation (7), we calculate how variations in a participant's posterior beliefs about an adviser change the participant's willingness-to-pay for more advice. As would be expected, the price of advice has a negative impact with a mode of -0.085 and a 95% CI that does not include zero. On the other hand, the impact of posterior beliefs about advisers is positive (18.309), with the associated 95% CI also not including zero. The price difference $\Delta\text{price} = \text{price}_{new} - \text{price}_{old}$ that a participant is willing to pay related to a specific difference in posterior beliefs, $\Delta\text{belief} = \text{belief}_{new} - \text{belief}_{old}$, is:

$$\Delta\text{price} = -\frac{\beta_2^{\text{posterior}}}{\beta_2^{\text{price}}} \cdot \Delta\text{belief} \cdot 100, \tag{14}$$

where multiplication by 100 is necessary because the price was divided by 100 before entering the estimation. Returning to our previous example, this implies that due to the display of certification influencing prior beliefs about advisers, both participants are willing to pay \$646 (=18.309/0.085*(0.785-0.755)) more for certified adviser R than for noncertified adviser L before they even receive any advice from them. This gap widens after receiving good/bad advice on the first topic and ambiguous advice on the remaining topics to \$17,620 for the Bayesian updater and to \$21,383 for the biased limited memory updater.[15]

D. The Price of Vulnerability

The previous section showed how participants' prior beliefs about advisers, learning strategies, and ability to discern good from bad advice (i.e., clarity of advice topics) can impact the choice of adviser and willingness-to-pay for advice. By combining these findings with our model's estimates of how these factors relate, we can illustrate the welfare costs suffered by vulnerable segments of the population.

Specifically, we divide the sample into "resilient" and "vulnerable" participants and a benchmark reference group with mean characteristics. First, we define vulnerable (resilient) clients

[15] We note that while this gap seems very large, it has to be viewed in context: a) In both cases, the participants are very certain that one adviser is good and the other is bad. b) The advice is on rather substantial topics with high possible losses in the event of bad decisions.

as those who show above (below) sample median impulsiveness and therefore are more (less) likely to use limited memory processing, who are more predisposed (less predisposed) to trust advisers and thus have higher (lower) prior beliefs of adviser quality, and who score below (above) the sample median for financial literacy and numeracy. Based on our results regarding clarity (Figure 2), we also include younger people in the vulnerable group. We can identify these participants by using their responses to survey questions they answered before they participated in the experiment.

Figure 5, Panel A shows how the resilient, vulnerable and mean reference groups break down into Bayesian versus limited memory updaters. We observe that the percentage of limited memory learners is much higher for the vulnerable group than for the resilient group (67 percent versus 59 percent). In Panel B, the probabilities that resilient and vulnerable groups understand advice topics are also very different. For instance, for the fee topic, which is considered the most difficult topic, the difference between the two groups is 23 percentage points (vulnerable participants have a 51 percent probability of perceiving this topic as clear compared to resilient participants who have a 74 percent probability).

<INSERT FIGURE 6 ABOUT HERE>

Figure 6 plots the probability distribution of each group's willingness-to-pay various adviser fees for different sequences of good versus bad advice. Each panel represents a different sequence of advice quality. Going from Panel A to Panel E, we move from a 'best-case world' where all the advice given is good (GGGG) to a 'worst-case world' where all the advice given is bad (BBBB). The probabilities are averaged over all possible matchings of clear and ambiguous topics at each of the four advice points in the sequence. Thus, while the probabilities in these figures are averaged over topics and therefore are not impacted by strategic manipulation by advisers presenting clear or ambiguous topics and good and bad advice in a specific order (for example, by offering good advice on a clearly understood topic during the first meeting), they still account for the fact that, on average, vulnerable clients will perceive more topics as ambiguous. The figure shows that for all groups of participants, willingness-to-pay for an adviser decreases as more bad advice is given, as shown by the shift of the lines from Panel A to Panel E towards the horizontal axis.

Notice in the best-case world (GGGG) in Panel A, the lines lie on top of each other. This shows that the probability of paying for an adviser at each price is the same for resilient (yellow line) and vulnerable clients (red line). Therefore, in a simplistic world where advisers only give good advice, at average topic clarity, resilient and vulnerable clients are willing to pay the same costs. This changes as bad advice is added. In Panel B, the lines separate from one another when one piece of bad advice is introduced at the end of the sequence (GGGB). The separation widens as additional bad advice is added in Panels C through E.

<INSERT FIGURE 6 ABOUT HERE>

The penultimate Panel D shows the power of a good first impression reinforced by confirmation bias. In this advice sequence (GBBB), only the first advice given is good. This first impression translates into a large difference between what the resilient and vulnerable participants are willing to pay for an adviser. At each price point until just after $A150, the vulnerable client is likely to pay more than the resilient client. Finally, Panel E displays the worst-case world, where the adviser only gives bad advice (BBBB). In this case, clients should be unwilling to pay anything for further advice from the adviser. Unfortunately, vulnerable clients are much more willing to pay for this adviser than resilient clients who find it easier to distinguish good from bad advice and are thus better able to recognize the adviser's lack of value.

Figure 7 allows us to determine whether the differences between the vulnerable and resilient participants are significant. In Panel A of this figure, the differences between the two lines for each quality sequence shown in the panels of Figure 6 are plotted with the 95 percent CIs displayed in the shaded areas. If these shaded areas do not overlap the horizontal axis, the differences between vulnerable and resilient participants are 95 percent or more likely to be different from zero. Not surprisingly, in the best-case world, when all advice is good (GGGG, green line), the difference is close to zero. When the last piece of advice is bad (sequence GGGB, purple line), differences begin to emerge. Once the adviser gives an equal amount of good and bad advice (GGBB, yellow line), the difference becomes more apparent and lies above zero with a high probability.

<INSERT FIGURE 7 ABOUT HERE>

Most striking are the cases in which the adviser sets a good first impression and then delivers bad advice (GBBB, red line) and the worst-case world (BBBB, blue line). For these instances, vulnerable consumers are much more willing to pay advisers for their services than resilient consumers. This finding demonstrates that in a realistic world where advisers do not always deliver good advice, vulnerable clients are willing to pay a higher price for poorer quality advisers, and first impressions and confirmation bias play even greater roles. Again, this is the case when there is no strategic manipulation of topics. This suggests that providing vulnerable consumers with ways to differentiate between the quality of advisers could help decrease this divergence in willingness-to-pay.

We now consider the case in which advisers strategically manipulate advice delivery. Agnew et al. (2018) demonstrate how advisers can manipulate clients by strategically pairing the sequence of advice on clear or ambiguous topics with the (good or bad) quality of their advice. We now investigate the cost of such strategic manipulation for consumers. To best illustrate the possible exploitation of vulnerable clients, we focus in the following only on the quality sequence that exploits the first impression (GBBB). In Figure 7, Panel B, we contrast these probabilities with the probabilities obtained if the topics are presented in the following order (i.e., a strategic scenario): debt, consolidation, diversification and fees. Debt is the clearest topic and thus allows for the strongest positive first impression to be set if good advice is delivered. This is consistent with a strategy found effective in Agnew et al. (2018). We calculate the differences between the probabilities associated with the strategic scenario for vulnerable versus resilient consumers in the GBBB quality sequence. In addition, we show the differences from the nonstrategic case for the GBBB already illustrated in the panel A as a point of comparison. Our figure demonstrates that if an adviser chose to use the participant's observable characteristics to identify vulnerable participants and strategically offer advice to them, the probability of vulnerable clients paying more than resilient clients can be further increased.

IV. Conclusion

Poor financial advice can leave a lasting trail of destruction among unquestioning clients, as the Madoff case and numerous others show. This paper provides an explanation for why some clients are more likely to ignore bad signals about financial advisers and identifies those clients most vulnerable to manipulation by advisers. That is, they are more likely to follow a learning process that is consistent with confirmation bias. Given that learning processes are latent and often unconscious, we employ an online large-scale experiment to separate advice 'clients' into standard Bayesian learners and limited memory learners. In contrast to Bayesian learners, who ignore ambiguous new information, limited memory learners interpret ambiguous information in line with their priors and update their beliefs using these interpretations. This limited memory learning results in behavior heavily influenced by first impressions and is consistent with confirmation bias. In addition, this learning approach can explain polarized opinions despite individuals receiving the same information signals. Our results provide new insight into consumer decision making and have direct public policy implications.

One of our most notable findings is that nearly two-thirds of our experiment's participants make choices that conform to a limited memory updating process. This result is important not only for financial advice but also for other types of decision making where consumers are confronted with information that is open to interpretation (e.g., the formation of political opinions, trust in medical advice). Our experiment is a possible model for tests of limited memory updating in these contexts for the identification of probable markers for limited memory updaters through observable characteristics and personality traits revealed through responses to survey questions.

In the context of financial advice, we demonstrate that prior trust in financial advisers and the presentation of certifications by advisers—combined with a consumer's learning process and ability to discern good from bad advice—impacts a participant's willingness-to-pay for an adviser.

For the first time, we estimate the economic cost in terms of additional advice fees limited memory updaters are willing to pay relative to standard rational Bayesian updaters. We find a significant divergence in willingness-to-pay fees between two segments of participants that we call 'vulnerable' and 'resilient'. Using survey responses, we identify these two groups in our sample as differing by age, financial literacy, numeracy, prior trust of advisers and impulsiveness. Vulnerable participants are more likely to be limited memory updaters and are always willing to pay more for advisers who give bad advice than their resilient counterparts. While resilient participants can pick out the lowest quality advisers (those who give all bad advice) and refuse to employ them, vulnerable participants continue to pay for their advice. This failure by vulnerable clients to discern bad advisers holds even when advisers do not use strategic manipulation or catering, as suggested by earlier studies. Thus, we find that vulnerable participants need help selecting a qualified, high-quality adviser even when advisers are not purposefully targeting them. Further analysis reveals that when advisers strategically target participants, they can collect significantly higher fees. These results raise the following question: How can we help consumers pick high-quality advisers?

Two potential regulatory solutions include i) requiring professional certifications that signal the adviser is knowledgeable and ethical and ii) enforcing a fiduciary standard. Our findings show that displaying a recognizable professional certification has a significant positive impact on initial beliefs of adviser quality or first impressions, which can raise the chance that consumers will accept and be more willing to pay for additional advice. If credentials are signals of superior service, then credentials can provide helpful information to the consumer. However, as it stands, many different credentials of varying quality are available around the world, and consumers of advice need guidance to identify reliable certifications. Regulators could also consider whether they should standardize the qualifications available and must also keep in mind in their response how financial advisers are able to use credentials to increase their fee income.

In addition, to hold advisers accountable, more careful discussion regarding enforcing a fiduciary standard is needed. Egan, Ge, and Tang (2020) demonstrate that even proposing introducing a fiduciary standard can have positive effects. In the variable annuity market, they found that the U.S. Department of Labor's proposed rule to hold advisers to a fiduciary standard reduced the sales of high-expense variable annuities by 52%. At the same time, sales became more sensitive to expenses, and low-expense products from insurance became relatively more available.

Finally, possible interventions that target the individual include improving financial literacy to skill clients to evaluate financial advice and curbing client impulsiveness by stipulating cool-down periods between getting, and acting on, advice.

In closing, we find that consumers who tend toward confirmation bias are particularly vulnerable to harm from advisers who nurture clients' beliefs in their expertise. Confirmation bias, when combined with limited consumer expertise in finance, can make a client too ready to follow an adviser of dubious quality and make them willing to pay more in fees.

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Table I. Financial Advice Script

This table reports the scripts for the four advice topics used in the choice experiment. Participants make four choices, one for each advice topic, with topic orders following the experimental design shown in Table II. Advice is delivered to participants in videos. Each choice set begins with a narrator's introduction; then, two advisers provide identical advice (good or bad advice) at the beginning of their talk and divergent advice at the end (the italicized part).

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 2 financial advisers will recommend what you should do about it.	**Good Advice**: <u>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.</u> *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**: [Insert underlined above] *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 2 financial advisers will recommend what you should do about it.	**Good Advice**: <u>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</u> *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** [Insert underlined above] *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.*

Narrator Introduction	Advice	Narrator Introduction	Advice
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 2 financial advisers will recommend what you should do about it.	**Good Advice**: <u>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?</u> *As a result, I recommend that you roll all of these accounts together so you are not paying extra fees.* **Bad Advice**: [Insert underlined above] *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 2 financial advisers will recommend what you should do about it.	**Good Advice**: <u>I understand you need help regarding how to invest your superannuation money. Did you know money invested in shares can go up and down?</u> *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**: [Insert underlined above] *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.*

Table II. Experimental Design

This table shows the structure of our experiment. Each participant in the experiment makes four choices of financial advice, and the design of the four choice sets consists of the following: one row from Panel A (adviser characteristics); one row from Panel B (sequence of advice topics); and one row from Panel C (sequence of delivery of good or bad advice from Adviser 1 and Adviser 2). Panel A shows the combinations of adviser characteristics: each pair of advisers consisted of an adviser with three characteristics (gender, age, certification) and an adviser with the reverse. Adviser 1 appeared on the left-hand side of the choice set screen, and Adviser 2 appeared on the right-hand side. Each participant 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, where "E" stands for one of the easy topics (credit card debt and account consolidation) and "H" stands for one of the hard topics (mutual fund fees and diversification). Panel C shows the eight sequences of advice quality for each condition where "G" stands for good advice and "B" stands for bad advice.

Panel A. Design of adviser pairs

	Adviser 1			Adviser 2		
Pair	Gender	Age	Certification	Gender	Age	Certification
1	Female	Young	Yes	Male	Old	No
2	Female	Old	No	Male	Young	Yes
3	Male	Young	No	Female	Old	Yes
4	Male	Old	Yes	Female	Young	No

Panel B. Sequence of advice topics

Sequence	Choice 1	Choice 2	Choice 3	Choice 4	Difficulty
1	Diversification	Fees	Consolidation	Debt	HHEE
2	Consolidation	Debt	Diversification	Fees	EEHH
3	Diversification	Consolidation	Fees	Debt	HEHE
4	Consolidation	Diversification	Debt	Fees	EHEH
5	Diversification	Consolidation	Debt	Fees	HEEH
6	Consolidation	Diversification	Fees	Debt	EHHE

Table II. Experimental Design -Continued-

Panel C. Design of the sequence of advice quality

	Advice from Adviser 1				Advice from Adviser 2			
Quality Sequence	1st topic	2nd topic	3rd topic	4th topic	1st topic	2nd topic	3rd topic	4th topic
1	G	G	B	B	B	B	G	G
2	G	B	G	B	B	G	B	G
3	G	B	B	G	B	G	G	B
4	B	G	G	B	G	B	B	G
5	B	G	B	G	G	B	G	B
6	B	B	G	G	G	G	B	B

Table III. Variable Descriptions

This table reports definitions of variables used in the estimation of the choice model (Equation 13), where X_i are vectors of explanatory variables for the components of the model (consisting of elements marked with an "x" in the corresponding column). Variables are computed from responses to an online survey of a representative sample of 2003 Australian adults conducted in December 2014.

Variable Name	X_0	X_3	X_4	X_5	Description
Constant	x	x	x	x	Constant; topic specific for X_5.
Adviser Characteristics					
Displays NO credential	x				Indicator variable that equals 1 if only the adviser's name was displayed and -1 when "Certified Financial Planner" and adviser's name were displayed.
Price		x			Price in $ (divided by 100) for one additional hour with this adviser.
Posterior		x			Posterior belief about adviser after advice on all four topics has been provided – estimated within the model.
Advice					
Good advice					Indicator variable that equals 1 if the wrong advice was given in the particular choice set, -1 otherwise. Enters the model via the choice specification in Equation (5).
Topic: Account consolidation				x	Indicator variable that equals 1 if the topic was account consolidation, 0 otherwise.
Topic: Stock diversification				x	Indicator variable that equals 1 if the topic was stock diversification, 0 otherwise.
Topic: Index fund fee				x	Indicator variable that equals 1 if the topic was index fund management fees, 0 otherwise.
Topic: Debt repayment				x	Indicator variable that equals 1 if the topic was debt repayment, 0 otherwise.
Participant Characteristics					
Participant female				x	An indicator variable that equals 2 if the participant is female, 1 otherwise.
Participant older than 39 years				x	An indicator variable that equals 1 if the participant is older than 39 years, 0 otherwise.
Trust in advisers	x				An indicator variable that equals 1 if the participant reported general trust in financial advisers, -1 if distrust, 0 otherwise.
Paid for advice		x			Indicator variable that equals 1 if the participant has ever paid for financial advice, -1 if he or she has not.
Household income		x			Household income ($'000, mean centered).
Confidence in financial decisions		x			Indicator variable that equals 1 if participant has high confidence in his or her ability to make financial decisions, -1 if low.
Financial risk tolerance		x			Indicator variable that equals 1 if participant's risk tolerance is high and -1 if low.
Decision maker		x			Indicator variable that equals 1 when the participant is most responsible for financial decisions, 0 when jointly responsible, and -1 when someone else is responsible.
Financial literacy				x	An indicator variable that equals 1 if the participant's correct percentage on four financial literacy questions is above the sample median, 0 otherwise. Questions test simple interest, inflation, diversification, and compound interest.

Variable Name	X_0	X_3	X_4	X_5	Description
Numeracy				x	An indicator variable that equals 1 if the participant's correct percentage on three numeracy questions is above the sample median, 0 otherwise. Questions test fractions, percentages, and probabilities.
Product knowledge				x	An indicator variable that equals 1 if the participant's correct percentage on four financial product questions is above the sample median, 0 otherwise. Questions test topics used in the advice experiment: credit card debt, index funds, account consolidation, diversification.
Conscientiousness			x		An indicator variable that equals 1 if the participant's conscientiousness is above the sample median, 0 otherwise. Participants rated themselves as organized, responsible, hardworking, or careless (reverse coded) on a four-point scale. Ratings are averaged.
Impulsiveness			x		An indicator variable that equals 1 if the participant's impulsiveness is above the sample median, 0 otherwise. Participants rated themselves as buying too much, buying impulsively, buying without planning, and/or buying unnecessarily on a fiv point scale. Ratings are averaged.
Market experience				x	An indicator variable that equals 1 if the participant's percentage on owning four financial securities is above the sample median, 0 otherwise. Participants reported whether they owned a credit card (debt), units in an index fund (fees), a superannuation account (consolidation), and stocks (diversification).

Table IV. Estimated Parameters

This table reports statistics from the posterior belief distributions of estimated parameters of the choice model (Equation 13). Data are survey responses of 2003 participants collected in December 2014. Variables are defined in Table III. For each parameter, we report the mode of its posterior distribution, as well as the 2.5 and 97.5 percentiles of this distribution, i.e., the equi-tailed credible interval (CI). There is a 95% probability that the parameter is not zero if zero does not fall in the CI. The mode includes an * in those cases. Estimation was conducted using SABL. See the next page for the full table.

	Mode	2.5 Percentile	97.5 Percentile
Prior Belief about Adviser, Eq. (2)			
Trust in financial advisers	0.520*	0.421	0.610
Displays NO credential	-0.085*	-0.199	-0.009
Constant	1.728*	1.511	1.903
Choice of Advice, Eqs. (5) & (6)			
Quality (β_1)	4.296*	3.599	5.060
Posterior belief (β_2)	2.510*	1.494	3.622
Willingness-to-Pay, Eq. (7)			
Constant	-7.782*	-9.687	-6.228
Price	-0.085*	-0.124	-0.043
Posterior	18.309*	14.808	22.230
Paid for advice	0.466*	0.348	0.570
Household income	0.094	-0.021	0.163
Confidence in financial decisions	-0.088	-0.186	0.051
Financial risk tolerance	0.055	-0.047	0.156
Decision maker	0.034	-0.125	0.186
Rational vs. *BIASED Updating, Eq. (10)*			
Constant	-0.454*	-0.994	-0.185
High Conscientiousness	0.243	-0.046	0.485
High Impulsiveness	-0.344*	-0.724	-0.154
Clarity of Topics, Eq. (11)			
High market experience	0.073	-0.046.	0.151
High product knowledge	0.267*	0.171	0.358
Participant older than 39	0.554*	0.441	0.646
Participant female	0.138*	0.053	0.237
High financial literacy	0.372*	0.244	0.458
High numeracy	0.357*	0.278	0.482
Consolidation	1.405*	1.148	1.632
Diversification	0.615*	0.395	0.814
Fees	-0.545*	-0.794	-0.358
Debt	1.768*	1.511	1.995

Table V. Proportion of Participants in Latent Classes

This table shows the estimated posterior belief percentage of participants assigned to 2 latent classes differentiated by the learning process (Bayesian or limited memory) and 16 latent classes differentiated by the clarity or ambiguity of the four advice topics. A "1" indicates that participants in that class treated the topic as clear, and "0" indicates that they treated the topic as ambiguous. For example, the model assigns 18.2% of participants to latent class 1 (row 1), which treats all topics as clear, and assigns 3.8% of participants to latent class 16 (row 16), which treats all topics as ambiguous. We infer latent classes from estimation of the choice model (Eq. 13) – see Table IV for estimation results.

Latent Class					Segment Size (%)
Learning process					
Bayesian updater					37.11
Limited Memory updater					62.89
Clarity of topics					
Clarity class	*Consolidation*	*Diversification*	*Fees*	*Debt*	
1	1	1	1	1	18.2
2	1	1	1	0	2.2
3	1	1	0	1	21.9
4	1	1	0	0	4.5
5	1	0	1	1	6.9
6	1	0	1	0	1.4
7	1	0	0	1	14.0
8	1	0	0	0	4.8
9	0	1	1	1	3.1
10	0	1	1	0	0.6
11	0	1	0	1	6.4
12	0	1	0	0	2.3
13	0	0	1	1	2.0
14	0	0	1	0	0.7
15	0	0	0	1	7.2
16	0	0	0	0	3.8

Table VI. Evolution of Beliefs with One Clear and Three Ambiguous Topics

This table presents the effects of first impressions on subsequent choices when clients use either a standard Bayesian or limited memory process to update beliefs about adviser quality. In the example, we assume Bayesian Updater A uses rational updating and Limited Memory Updater B uses limited memory updating, that both participants are initially distrusting of financial advisers, and that otherwise both participants have characteristics at the medians of the sample distributions. Parameters are set to the modes of the posterior distributions. Adviser *R* shows a professional certification, and Adviser *L* does not. Both participants thus have the same prior beliefs that the right (*R*) and the left (*L*) advisers are of good quality, λ_0. Adviser *R* delivers good advice on a clear topic at choice 1, but topics 2-4 are ambiguous to both clients. Both clients update their beliefs in the same way in the first choice because they obtain clear information about adviser quality λ_1. Bayesian Updater A's beliefs about the advisers $(\lambda_2 - \lambda_4)$ and choice probabilities, $\Pr(y_2 = 1)$ to $\Pr(y_4 = 1)$, remain constant because the rational client does not update using ambiguous signals. Limited Memory Updater B treats ambiguous information as evidence in favor of his or her priors and continues to update in favor of Adviser *R*.

	λ_0	$\Pr(y_1 = 1)$	λ_1	$\Pr(y_2 = 1)$	λ_2	$\Pr(y_3 = 1)$	λ_3	$\Pr(y_4 = 1)$	λ_4
Adviser *R*, Bayesian Updater A	0.785	0.987	0.916	0.886	0.916	0. 886	0.916	0. 886	0.916
Adviser *R*, Limited Memory Updater B	0.785	0.987	0.916	0.886	0.970	0.913	0.990	0.921	0.997
Adviser *L*, Bayesian Updater A	0.755	0.013	0.098	0.114	0.098	0. 114	0.098	0. 114	0.098
Adviser *L*, Limited Memory Updater B	0.755	0.013	0.098	0.114	0.035	0.087	0.012	0.079	0.004

$\lambda_i =$ prior belief about adviser quality at choice set i;

$\Pr(y_i = 1) =$ probability of choosing to follow advice of adviser at choice set i

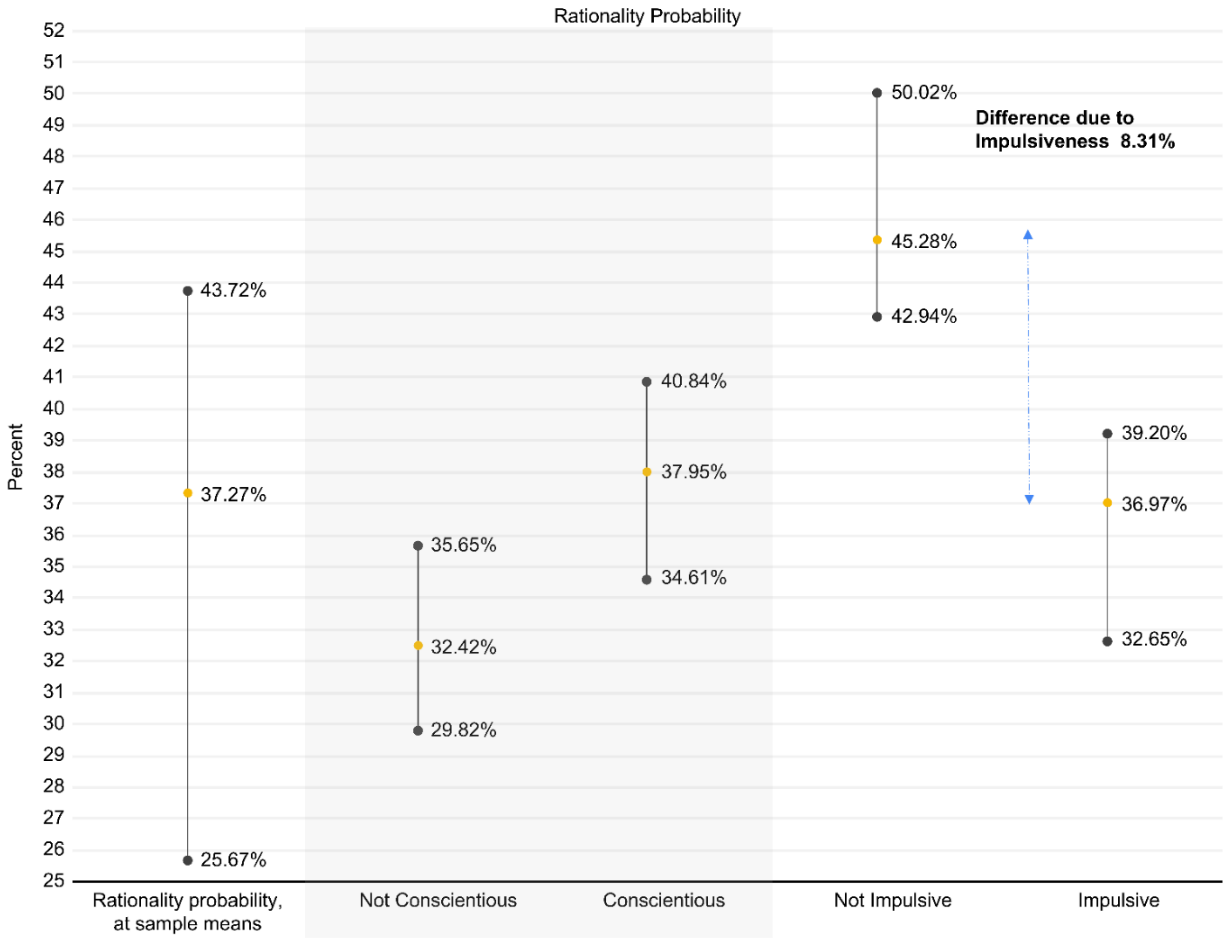

Figure 1. Probability of Being a Rational Bayesian Updater

This figure displays the probabilities and associated 95 percent CIs that a participant is a rational Bayesian updater given certain personality traits. The blue arrows display the difference between the probabilities reflecting the marginal influence of each factor. Rounding may result in the displayed difference being slightly different than the calculated. Blue arrows are displayed when the factor CIs do not overlap and the parameters from the CIs found in Table IV exclude zero.

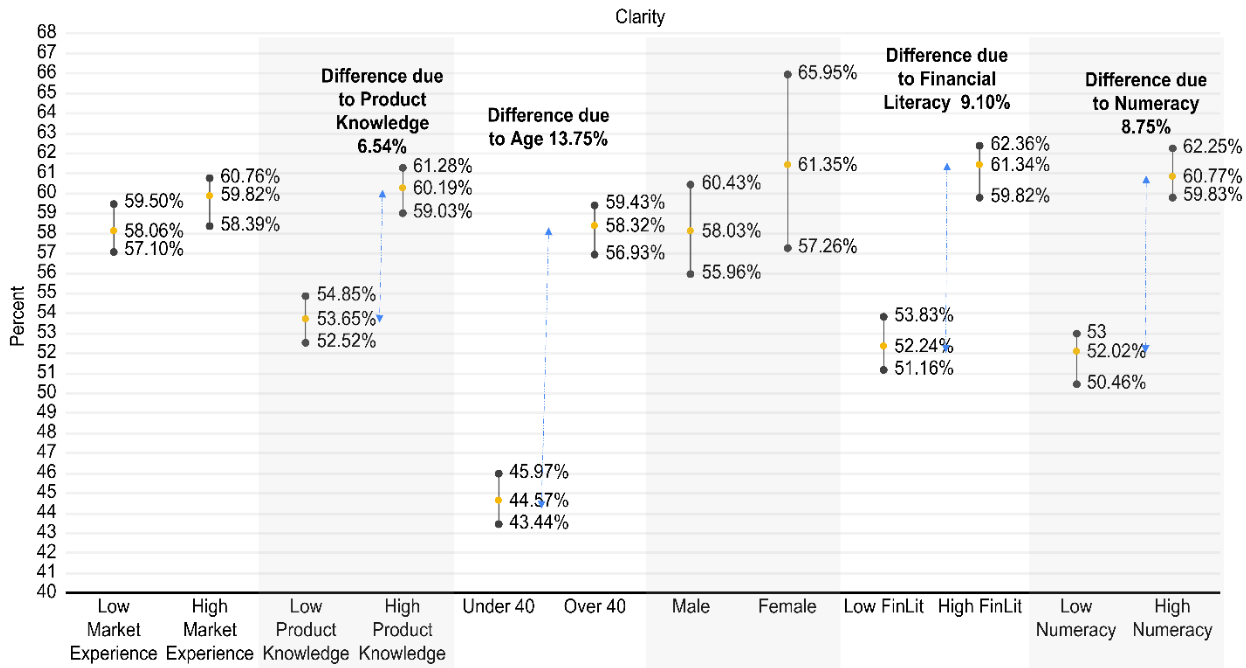

Figure 2. Probability Participant Views Topic as Clear

This figure displays the probabilities and associated 95 percent CIs that reflect whether participants view a topic as clear given different factors. The blue arrows display the difference between the probabilities reflecting the marginal influence of each factor. Rounding may result in the displayed difference being slightly different than the calculated. Blue arrows are displayed when the factor CIs do not overlap and the parameters from the CIs found in Table IV exclude zero.

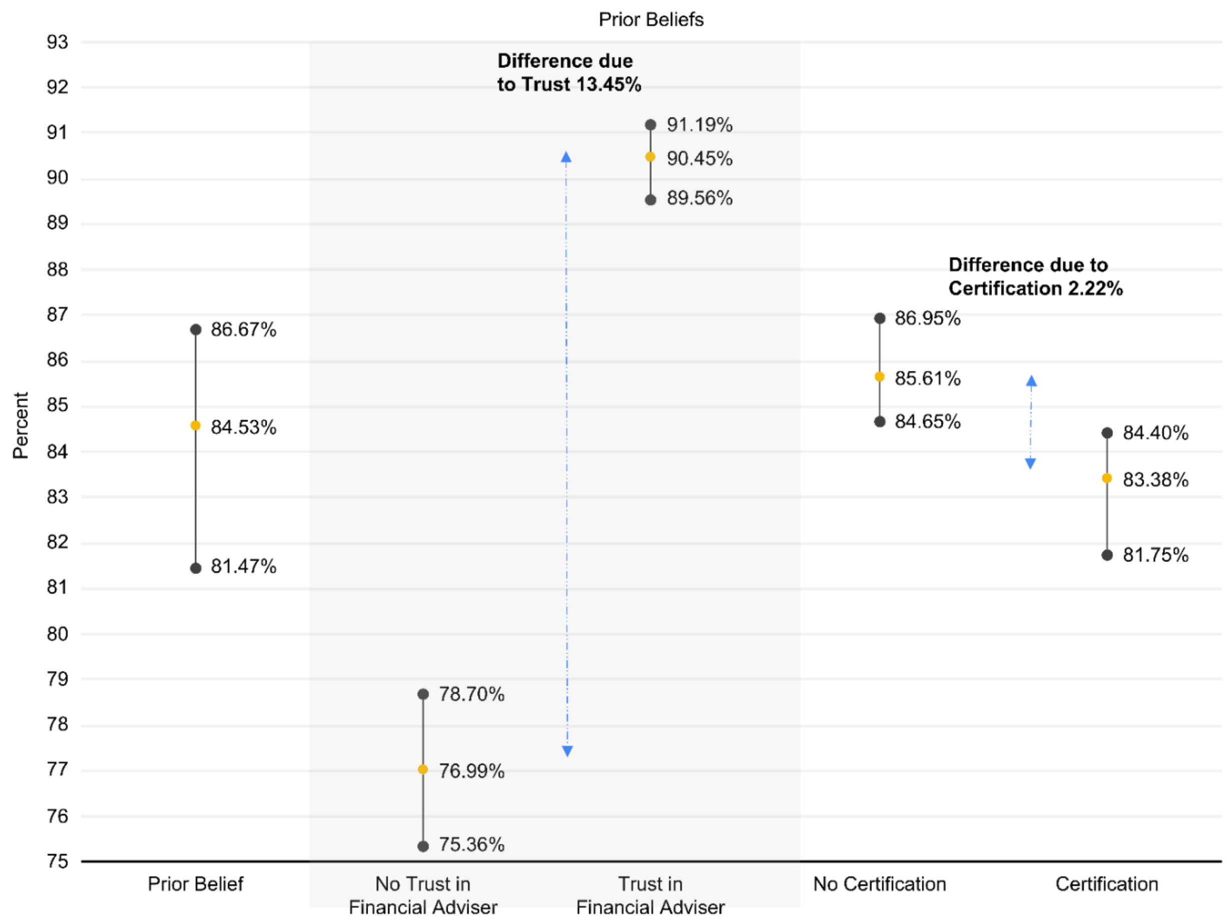

Figure 3. Factors Influencing Prior Beliefs that the Financial Adviser is Good

This figure displays the probabilities and associated 95 percent CIs affecting participants' prior beliefs given different factors. The blue arrows display the difference between the probabilities reflecting the marginal influence of each factor. Rounding may result in the displayed difference being slightly different than the calculated. Blue arrows are displayed when the factor CIs do not overlap and the parameters from the CIs found in Table IV exclude zero.

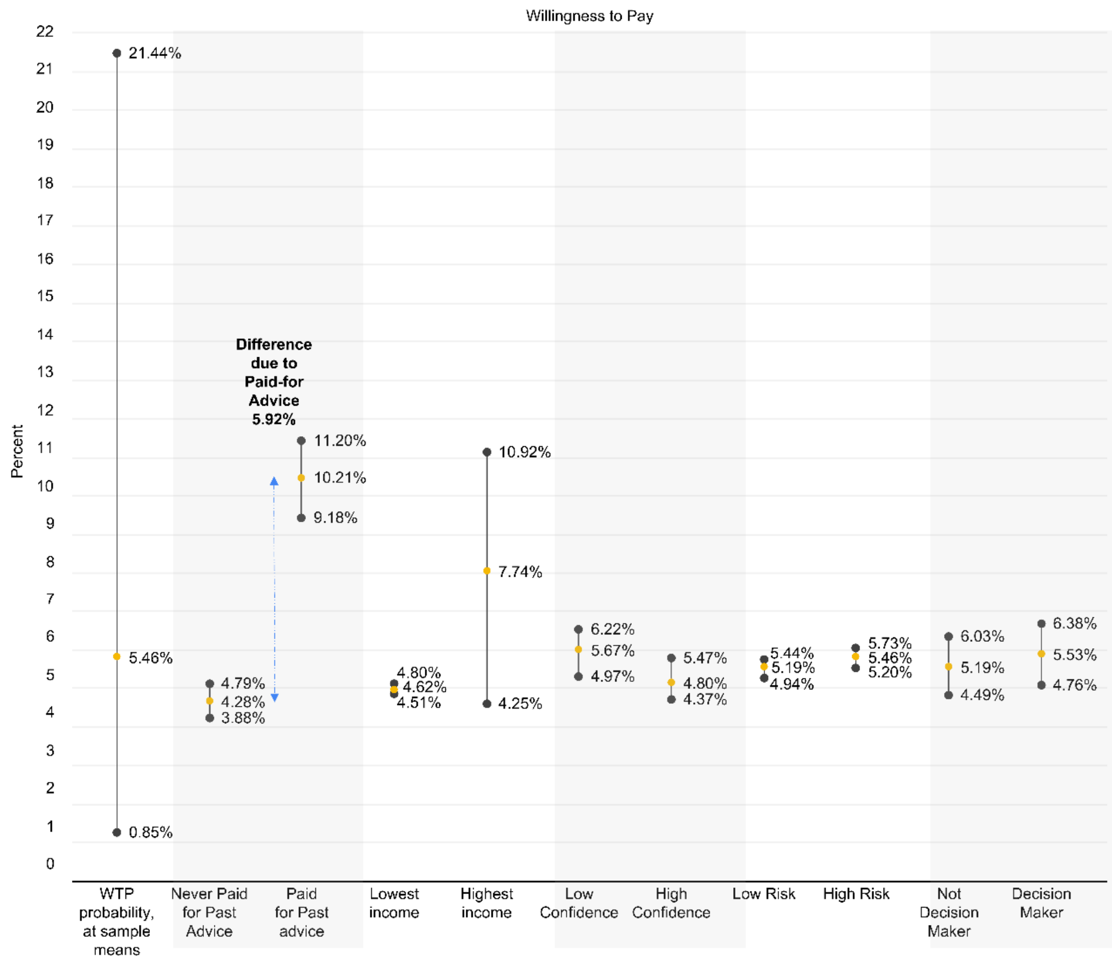

Figure 4. Factors Affecting Willingness-to-Pay for the Adviser

This figure displays the probabilities and associated 95 percent CIs affecting participants' willingness-to-pay given different factors. The blue arrows display the difference between the probabilities reflecting the marginal influence of each factor. Rounding may result in the displayed difference being slightly different than the calculated. Blue arrows are displayed when the factor CIs do not overlap and the parameters from the CIs found in Table IV exclude zero.

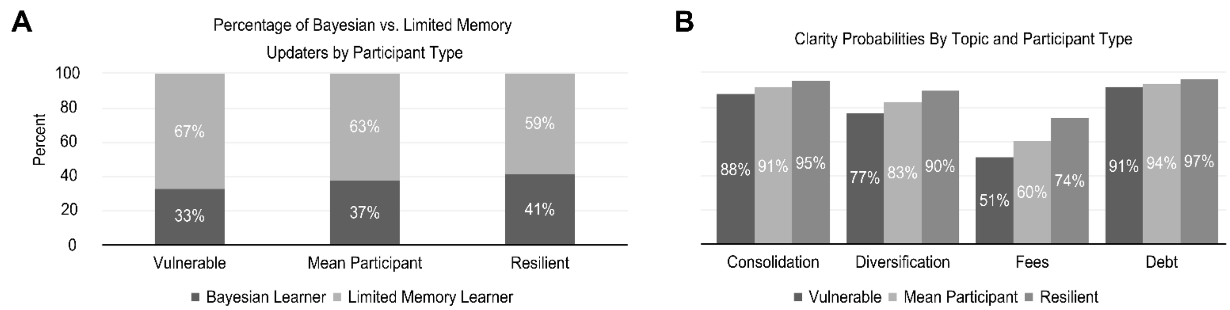

Figure 5. Breakdown of Bayesian and Limited Memory Updaters

Panel A reports the simulated percentage of Bayesian versus limited memory updaters for each type of participant (vulnerable, mean and resilient). Panel B reports the simulated probabilities that the different types of participants perceive each advice topic as clear.

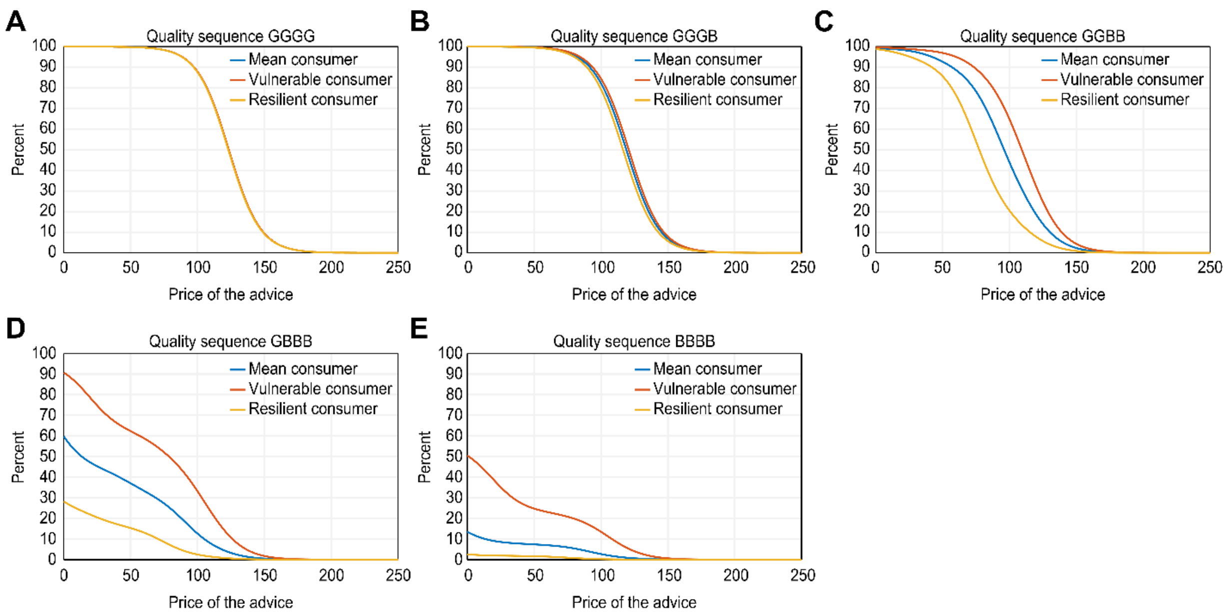

Figure 6. Willingness-to-Pay from a "Best-Case World" to a "Worst-Case World" by Participant Type

These figures plot the simulated probability distribution of each group's willingness-to-pay various adviser fees for different sequences of good versus bad advice. The "Best-Case World" is where all the advice given is good (Panel A- Quality Sequence GGGG) and the "Worst-Case World" is where all the advice given is bad (Panel E- Quality Sequence BBBB).

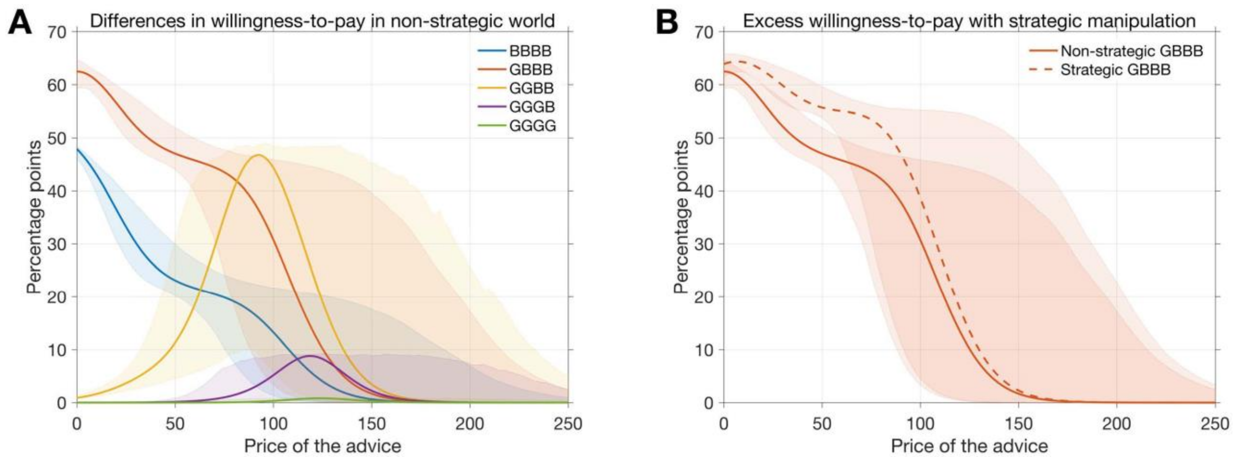

Figure 7. Statistical Difference between Vulnerable and Resilient Clients' Willingness-to-Pay

Panel A plots for each quality sequence shown in Figure 6 the differences between the vulnerable and resilient participants' probability lines. Advisers are not strategically manipulating advice. The shaded areas provide the CIs. If the shaded areas representing the CIs do not overlap the horizontal axis, the differences between the two groups are considered different from zero at the 95 percent level or more. Panel B compares the differences between when there is no strategic manipulation for the quality sequence GBBB (The line is the same as is shown in Panel A for that quality sequence) and when there is strategic manipulation of the topics for that same quality sequence. In the strategic case, the adviser provides advice topics in the following order to take advantage of a strong first impression: debt, consolidation, diversification, and fees. The shaded areas provide the CI.

IRB approval

THIS PROJECT WAS APPROVED BY THE COLLEGE OF WILLIAM AND MARY PROTECTION OF HUMAN SUBJECTS COMMITTEE (Phone 757-221-3966) ON 2017-03-20 AND EXPIRES ON 2018-03-20. (Note this project's first approval was on 2013-03-08. Once data collection was completed in 2014 renewal of approval was not necessary, but we continued to renew the IRB until 2018. The last statement of approval we received is above.)

Conflict-of-interest disclosure statement

Julie Agnew
I occasionally give presentations or serve on award selection committees for which I receive compensation and/or travel reimbursement. I am a TIAA Institute Fellow, an Associate Investigator for the ARC Centre of Excellence in Population Ageing Research (CEPAR), an affiliated researcher of Boston College's Center for Retirement Research, a member of Wharton's Pension Research Council's Advisory Board, a member of the Defined Contribution Institutional Investment Association (DCIIA) Academic Advisory Council and Retirement Income Institute (RII) Scholars Advisory Group. At times, I have received travel reimbursement and or compensation for work completed associated with these groups. In 2017, I received grant funding of $75,000 from TIAA for a research project. During the past three years, I have received compensation and stock exceeding $10,000 serving on the Board of Directors at C&F Bank. C&F Bank and my other affiliations may or may not have an interest in the research in this paper. This research project is generously funded by an Australian Research Council grant [Grant DP1093842]. I have no other potential conflicts of interest to disclose.

Hazel Bateman
I occasionally give presentations for which I receive compensation and/or travel reimbursement. I am a Chief Investigator of the ARC Centre of Excellence in Population Ageing Research (CEPAR) supported by an Australian Research Council grant [Grant CE17010005], a member of the Executive Committee (and President) of the International Pension Research Association, a

member (and Chair) of the Scientific Council of the Dutch Network for Research in Pensions, Ageing and Retirement (Netspar), a member of the Steering Committee of the Mercer CFA Institute Global Pensions Index, an academic representative on the UniSuper Consultative Committee, a member of the Advisory Board of the Conexus Institute and a member of the Advisory Board of MyHomeStream Pty Ltd. During the past three years, I have received research funding exceeding $10,000 and data from Cbus Superannuation Fund. Cbus may or may not have an interest in the research in this paper. This research project is generously funded by an Australian Research Council grant [Grant DP1093842]. I have no other potential conflicts of interest to disclose.

Christine Eckert
This research project is generously funded by an Australian Research Council grant [Grant DP1093842]. I have nothing further to disclose.

Fedor Iskhakov
I occasionally give presentations for which I receive compensation and/or travel reimbursement. This research project is generously funded by an Australian Research Council grant [Grant DP1093842]. I have nothing else to disclose.

Jordan Louviere
I'm a member of the Research Team for Smart WA, which aims to understand, model and forecast consumers' likely response to Covid initiatives that small businesses could take to enhance visitations. I also am C.O.O. of Choiceflows, LLC, headquartered in Chapel Hill, NC, USA, a consulting company focused on choice modelling and data analytics. I do not think any of these activities conflict with my research role in this paper. As a now-retired academic, I no longer make presentations or attend meetings. This research project is generously funded by an Australian Research Council grant [Grant DP1093842].

Susan Thorp

I occasionally give presentations for which I receive compensation and/or travel reimbursement. I am an Associate Investigator for the ARC Centre of Excellence in Population Ageing Research (CEPAR), a member of the OECD-International Network on Financial Education Research Committee, the Steering Committee of the Melbourne-Mercer Global Pensions Index, the Australian Securities and Exchange Commission (ASIC) Consultative Committee, and am a Director of Super Consumers Australia, a not-for-profit advocacy organization for Australian pension plan participants. During the past three years, I have received research funding exceeding $10,000 from the financial regulator ASIC and research funding exceeding $10,000 and data from Cbus Superannuation Fund. ASIC and Cbus may or may not have an interest in the research in this paper. This research project is generously funded by an Australian Research Council grant [Grant DP1093842]. I have no other potential conflicts of interest to disclose.

INTERNET APPENDICES

Internet Appendix A. Demographics: Survey Sample and Australian population (18-79 years), 2011 Census

This table presents the demographics of a sample of 2003 participants drawn from a nationally representative online panel by email invitation in 2014 with 2011 (most recent at time of experiment) Australian census.

	Survey Participant Sample	18-79 yrs Australian Population		Survey Participant Sample	18-79 yrs Australian Population
Gender			**Marital Status**		
Male	50%	49%	Never Married	26%	30%
Female	50%	51%	Divorced/ Separated	10%	13%
Age			Widowed	2%	3%
18-24 years	8%	10%	Married or long-term relationship	62%	54%
25-29 years	8%	10%	**Personal Income**		
30-34 years	12%	10%	$1-$20,799 (i.e., less than $399 a week)	24%	25%
35-39 years	12%	10%	$20,800-$51,999 (i.e., $400-$999 a week)	35%	32%
40-44 years	12%	10%	$52,000-$103,999 (i.e., $1,000-$1,999 a week)	25%	23%
45-49 years	9%	10%	$101,000 (i.e. ,$2,000 a week) or more	7%	7%
50-54 years	12%	10%	Negative or nil Income	9%	6%
55-59 years	12%	9%	Not stated	0%	7%
60-64 years	13%	8%	**Highest Level of Education**		
65-69 years	2%	6%	High school or less	26%	40%
70-79 years	0%	8%	Vocational/Technical certificate	21%	20%
Work Status			Tertiary diploma	11%	9%
Employed	62%	63%	Bachelor degree	23%	15%
Unemployed	8%	3%	Graduate certificate, diploma or degree	19%	6%
Not in the labor force	18%	29%	Not stated	0%	10%
Retired	12%	not broken out			
Not stated	0%	5%			

Internet Appendix B. Sequential Adaptive Bayesian Learning Estimation

The discontinuities in the likelihood function of our model cause implementation problems due to the inherent computational difficulty for maximum likelihood estimators (see also Chernozhukov and Hong(2004)). We overcome these difficulties with Bayesian estimation methods. More specifically, we use sequential adaptive Bayesian learning (SABL) proposed by Durham and Geweke (2014). SABL is an extension of sequential Monte Carlo methods that additionally exploits the benefits of parallel computing environments. SABL does not require the modeler to specify conjugate priors and it is also robust to multimodal posteriors, which can arise in high dimensional problems (Jasra, Stephens, and Holmes (2007)) such as ours. When used for Bayesian inference, SABL is a posterior simulator.

As with any Bayesian estimation approach, SABL requires the user to specify the likelihood function as well as prior distributions for the parameters to be estimated. We chose uninformative priors. We assumed that the prior for each parameter of interest is independent normal with a mean of zero and a standard deviation of five. We evaluated the sensitivity of prior influence by a careful visual examination of the posterior distribution against the prior distribution.

The advantage of using SABL (or a Bayesian approach in general) is that the posterior distribution of draws can help in assessing the identification of the model parameters (see also discussion in the previous section). More specifically, a high correlation between the posterior draws of two parameters may suggest that these are not separately identified by the choice data. In addition to including different covariates in the different model parts (see also discussion in

Section 4) and specifying different uninformative priors, we used this correlation matrix check to further assess the identification of our model.[1]

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Chernozhukov, Victor and Han Hong, 2004 , Likelihood estimation and inference in a class of nonregular econometric models, *Econometrica* 72, 1445-1480.

Durham, Garland and John Geweke, 2014, Adaptive sequential posterior simulators for massively parallel computing environments, in *Bayesian Model Comparison*: Emerald Group Publishing Limited.

Geweke, John, 2016, Sequentially adaptive Bayesian learning for a nonlinear model of the secular and cyclical behavior of US real GDP, *Econometrics* 4, 10.

Jasra, Ajay, David A Stephens, and Christopher C Holmes, 2007, On population-based simulation for static inference, *Statistics and Computing* 17, 263-279.

[1] We run SABL using its MATLAB interface. A detailed explanation of SABL and its implementation in the SABL software can be found in Geweke (2016). SABL itself can be downloaded from http://www.quantosanalytics.org/garland/mp-sps_1.1.zip . The time to estimate our model using SABL is approximately 60 minutes.

Internet Appendix C – Copy of Survey Instrument

Note this survey requires Flash Player which as of December 31, 2021 is no longer supported by Adobe. The Microsoft Edge browser may allow you to view the videos and other flash features in the survey as they were seen by participants. This link provides instructions https://support.microsoft.com/en-us/microsoft-edge/turn-on-adobe-flash-in-microsoft-edge-565dd3e2-50e7-201f-5b6d-ce602f74f7df to enable Flash on the Edge Browser. In case this does not work, we have included screen shots from the survey AND a link to one of the video conditions from our earlier 2018 Management Science paper.

Link to live survey: http://survey.us.confirmit.com/wix/p3070864270.aspx

Screen Shots of Survey

Thank you for agreeing to participate in this survey about financial advice. The survey will take approximately **25** minutes to complete. Please take as much time as you need to answer the questions. Most questions only require you to tick a box. All your answers to the questions are strictly anonymous – that is no one involved in this study can identify you personally, no one will contact you after the survey and no sales solicitation is involved. Your answers will be used for academic and industry research purposes only.

This study is being conducted by researchers at the Institute for Choice, University of South Australia, the University of Technology Sydney, the University of New South Wales and the College of William and Mary (Virginia, USA). The purpose is to learn more about financial advice. Your answers will be used to suggest ways to improve the way financial advice is given. If you are interested, the final research report analysing the survey results will be available on the Institute for Choice's website accessible through the following link:

http://www.unisa.edu.au/Research/Institute-for-Choice/Publications/Working-papers/

As part of this survey, you will view video recommendations from two different financial advisors relating to four financial scenarios, some of which you may have already experienced. For each scenario, we will ask you which advice you would be most likely to follow if you were in this situation. Following that we have a few questions for you to complete in an online survey. We gratefully acknowledge permission to use risk questions designed and copyrighted by FinaMetrica in this survey.

Keep in mind that the information presented in the following videos and the accompanying online survey is for research purposes only and should NOT under any circumstances be understood to be actual financial advice being provided by the University of South Australia, The University of Technology Sydney, the University of New South Wales (UNSW) and the College of William and Mary, nor by any staff or student affiliated with these organizations. We encourage you to please seek the advice of a professional financial planner when making your own personal financial decisions.

When taking the survey, please DO NOT USE the “back” and “forward” buttons in your browser, please use the buttons at the bottom of each screen. If you would like to pause the survey to return to it later, simply close the window and click on the original link in the invitation, it will return you to the last point of entry in the survey.

Please click on " >> " button to proceed.

>>

Please note that due to the nature of this survey you will be asked questions about your personal information such as your income and your housing situation. You have the right to refuse to answer any question. Your answers to these questions are confidential, and cannot be used to identify you personally. They will be used only to make comparisons of different types of people, such as younger and older people, males and females, high and low income people, etc.

Finally, please be aware that you may terminate participation in the survey at any time. However, only completed surveys will be given full compensation for participation.

Will you participate in this survey?

- ○ Yes
- ○ No

THIS PROJECT WAS APPROVED BY THE COLLEGE OF WILLIAM AND MARY PROTECTION OF HUMAN SUBJECTS COMMITTEE (Phone 0011-1-757-221-3966) ON 2014-03-11 AND EXPIRES ON 2015-03-11.

<< >>

Some questions in this survey require certain features to be available in your browser (Flash Player etc.). To test them, simply click on the "Test Features" button if you can see it in the embedded Flash interface. If you cannot see it, please select "I cannot see this button".

To test whether you have required features in this browser for this survey, please click on the button below.

Test Features

I cannot see this button

To which age group do you belong?

- Under 18 years
- 18-24 years
- 25-29 years
- 30-34 years
- 35-39 years
- 40-44 years
- 45-49 years
- 50-54 years
- 55-59 years
- 60-64 years
- 65-69 years
- 70-74 years
- 75 years and over

Are you?

- Male
- Female

<< >>

The following questions measure your general financial competence and numeracy skills. Please answer the questions without using a calculator.

Suppose you had $100 in a savings account and the interest rate was 2% per year. After 5 years, how much do you think you would have in the account if you left the money to grow?

- ○ More than $102
- ○ Exactly $102
- ○ Less than $102
- ○ Do not know

Imagine that the interest rate on your savings account was 1% per year and inflation was 2% per year. After 1 year, how much would you be able to buy with the money in this account?

- ○ More than today
- ○ Exactly the same
- ○ Less than today
- ○ Do not know

Buying shares in a single company usually provides a safer return than buying units in a managed share fund.

- ○ True
- ○ False
- ○ Do not know

Suppose you had $100 in a savings account and the interest rate is 20% per year and you never withdraw money or interest payments. After 5 years, how much would you have in this account in total?

- ○ More than $200
- ○ Exactly $200
- ○ Less than $200
- ○ Do not know

<< >>

Suppose you had a $2,000 credit card debt, but you also want to save for a holiday. You should:

- Save for your holiday first
- Pay off your credit card debt
- Do not know

Suppose you have recently changed jobs. You are now trying to decide whether or not to move your superannuation to your new employer's superannuation fund. You should:

- Consolidate your superannuation accounts in one fund
- Keep two superannuation accounts in different funds
- Do not know

Suppose you want to invest in the share market. You should:

- Buy shares in one blue chip company
- Spread your money across a variety of shares in different companies
- Do not know

<< >>

An equity index fund...

Please choose the correct statement below

- Buys and sells a portfolio of equities to outperform an index such as the S&P200
- Buys and sells equities, bonds and cash to outperform an index such as the S&P200
- Buys a portfolio of equities that mimic an index such as the S&P200
- Buys a portfolio of equities, bonds and cash that mimic an index such as the S&P200
- Buys a portfolio of equities that generate a return that is no worse than an index such as the S&P200
- Buys a portfolio of equities, bonds and cash that generate a return that is no worse than an index such as the S&P200

Two statements below describe equity index funds. Please tell us whether you think each statement is true or false.

1) *All equity index funds that follow the same index offer the same product, so an investor should choose a fund with low fees.*

- True
- False

2) *Some equity index funds have better reputations than others, so an investor should avoid a low-fee fund.*

- True
- False

<< >>

Imagine that we rolled a fair, six-sided die 1,000 times. Out of 1,000 rolls, how many times do you think the die would come up even?

Please enter a number between 0 to 1000 in the box.

[ ] times

In a lottery, the chance of winning a $500 prize is 1%. What is your best guess of how many people would win the prize if 1,000 people each buy a single ticket in the lottery?

Please enter a number between 0 to 1000 in the box.

[ ] people

In a raffle, the chance of winning a car is 1 in 1,000. What per cent of tickets in the raffle win a car?

Please enter a percentage.

[___._] %

<< >>

The following questions are designed to help us learn more about your understanding and use of financial products.

Which, if any, of the following financial products do you have or have you used in the past?

Please select all that apply.

- ☐ Mortgages (home loans)
- ☐ Life insurance policies
- ☐ Credit cards
- ☐ Personal loans
- ☐ Bank accounts
- ☐ Index funds
- ☐ Superannuation accounts
- ☐ Shares (stocks)
- ☐ Bonds (corporate or government issued)
- ○ None of the above

<< >>

Tick the products which you know enough about to explain them to a friend or colleague.

Tick only the boxes that apply to you personally

- ☐ Mortgages (home loans)
- ☐ Life insurance policies
- ☐ Credit cards
- ☐ Personal loans
- ☐ Bank accounts
- ☐ Index funds
- ☐ Superannuation accounts
- ☐ Shares (stocks)
- ☐ Bonds (corporate or government issued)

<< >>

Tick the products you personally consider useful or valuable.

Tick only the boxes that apply to you personally

- ☐ Mortgages (home loans)
- ☐ Life insurance policies
- ☐ Credit cards
- ☐ Personal loans
- ☐ Bank accounts
- ☐ Index funds
- ☐ Superannuation accounts
- ☐ Shares (stocks)
- ☐ Bonds (corporate or government issued)

<< >>

Tick the products you would NOT choose due to personal circumstances such as you can't afford it, you would have to learn new knowledge or skills to use it, your friends or colleagues would think badly of you if they knew you used it, or some other barrier or constraint to your choosing.

Tick only the boxes that apply to you personally

- ☐ Mortgages (home loans)
- ☐ Life insurance policies
- ☐ Credit cards
- ☐ Personal loans
- ☐ Bank accounts
- ☐ Index funds
- ☐ Superannuation accounts
- ☐ Shares (stocks)
- ☐ Bonds (corporate or government issued)

<< >>

Suppose you had $100 in a savings account and the interest rate is 20% per year and you never withdraw money or interest payments. After 5 years, how much would you have in this account in total?

- ○ More than $200
- ○ Exactly $200
- ○ Less than $200
- ○ Do not know

Suppose you want to invest in the share market. You should:

- ○ Buy shares in one blue chip company
- ○ Spread your money across a variety of shares in different companies
- ○ Do not know

Have you seen these questions previously in this survey?

- ○ Yes
- ○ No

<< >>

The following questions will assess your experience with and attitudes towards financial advisors.

Please read each of the 4 statements below, and then rank them from 1 to 4 in order of the statement that best describes how you feel about financial advisors (=1) to the statement that least describes how you feel about financial advisors (=4).

Please use drag-n-drop to rank the following statements.

Statements	Rank	
Generally, financial advisors do what is best for their customers	1	
For the most part, financial advisors are trustworthy	2	
Financial advisors tend to have their own interests in mind	3	
Potential commissions influence the advice a financial advisor gives to his/her clients	4	

<< >>

Who would you go to for financial advice if you needed it?

Please select all that apply.

- ☐ Employer
- ☐ Private banker/investment banker
- ☐ Fund manager
- ☐ Superannuation fund representative
- ☐ Full service stockbroker
- ☐ Bank relationship manager (including personal banker)
- ☐ Bank branch staff or manager
- ☐ Mortgage broker
- ☐ Accountant
- ☐ Financial planner/advisor
- ☐ Friends or family
- ☐ Other (please specify) ______

Have you ever paid for professional financial advice?

- ○ Yes
- ○ No

<< >>

IF Paid for Professional Financial Advice = NO

Why have you never paid for professional advice?

Please select all that apply.

- ☐ I have no need for financial advice
- ☐ I do not have enough money to make it worthwhile
- ☐ Financial advice is too expensive
- ☐ I can do it myself
- ☐ If I need advice I ask family or friends
- ☐ I like to be in control of my finances
- ☐ I do not know where to find a good financial advisor
- ☐ I do not trust financial planners or the advice industry
- ☐ I am not interested in financial matters
- ☐ I do not want to disclose my financial situation
- ☐ I do not feel confident talking about financial matters
- ☐ Other (please specify) ______

<< >>

IF Paid for Professional Financial Advice = YES

Why did you pay for professional financial advice?

Please select all that apply.

- ☐ Key life event, such as marriage, birth of child, divorce, redundancy, retirement, inheritance
- ☐ To address a particular financial goal, such as saving for a house or saving for retirement
- ☐ Wanted advice about budgeting and debt management
- ☐ Wanted a review of my financial situation
- ☐ To learn about financial matters to be able to make my own financial decisions
- ☐ To increase the chance that I would stick to a financial plan
- ☐ The tax and regulations affecting financial products are complicated
- ☐ Wanted to start a Self-managed Superannuation Fund
- ☐ Other (please specify) ________

What was this advice for?

- ○ A comprehensive financial plan

A specific issue (or issues)

- ☐ Superannuation
- ☐ Property investment
- ☐ Financial investment (for example, shares, managed funds)
- ☐ Insurance
- ☐ Estate planning
- ☐ Social security
- ☐ Tax minimisation
- ☐ Self-managed Superannuation Fund
- ☐ Other (please specify) ________

<< >>

[VIDEO TASK: See Table 2 for experimental design. For an example of the videos, please refer to this link (https://drive.google.com/file/d/0B-1NMLVfExG1ZzFhZWlrRWlsR2s/preview)that shows one condition from the 2018 Management Science paper
]

Now that you've experienced the two financial advisors, we'd like to know what you think about them.

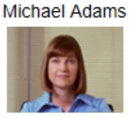
Please select the advisor that MOST displays this characteristic:

	 Elizabeth Turner	Both the same	 Michael Adams
Trustworthiness	○	○	○
Competence	○	○	○
Attractiveness	○	○	○
Understanding	○	○	○
Professionalism	○	○	○
Genuineness	○	○	○
Persuasiveness	○	○	○

<< >>

Thinking about the 2 advisors you saw, which one of them do you think is most like you?

○ 
Michael Adams

○ 
Elizabeth Turner

<< >>

The last question has to do with paying for financial advice. Both advisors charge $100 for a one hour session. Now that you've experienced both of them, what would you be most likely to do?

Advisor A	Advisor B
 Elizabeth Turner	 Michael Adams

- ○ I would pay both Advisor A and Advisor B to give me financial advice
- ○ I would only pay Advisor A for financial advice
- ○ I would only pay Advisor B for financial advice
- ○ I would not pay Advisor A or Advisor B for financial advice

<< >>

This following questions are to see where you fit in the Australian population.

What is your marital status?

- ○ Never married and not living in a long term (de facto) relationship
- ○ Widowed
- ○ Divorced
- ○ Separated but not divorced
- ○ Married
- ○ Living in long term relationship (de facto)

Who is most responsible for the major financial decisions in your household?

- ○ I am
- ○ Someone else
- ○ Someone else and I are equally responsible

How many people in your household do you fully or partially support financially?

- ○ 1 (myself)
- ○ 2
- ○ 3
- ○ 4 or more

<< >>

What is the highest level of school you have completed?

- ◯ Year 12 or equivalent
- ◯ Year 11 or equivalent
- ◯ Year 10 or equivalent
- ◯ Year 9 or equivalent
- ◯ Year 8 or equivalent
- ◯ Year 7 or equivalent
- ◯ Year 6 or below
- ◯ Did not go to school

What is the highest post school qualification you have?

- ◯ PhD
- ◯ Master Degree or equivalent
- ◯ Graduate Diploma and Graduate Certificate from university or equivalent
- ◯ Bachelor Degree or equivalent
- ◯ Advanced Diploma and Diploma from university/TAFE or equivalent
- ◯ Certificate or equivalent from TAFE or equivalent
- ◯ None of the above

What was the main field of study for your highest qualification completed?
For example: plumbing, history, economics, primary school teaching, hairdressing, greenkeeping, finance, etc.

Please type in the box below.

[ ]

Which of the following best describes your current work status?

- ◯ Employed full time
- ◯ Employed part time
- ◯ Unemployed
- ◯ Not in the labour force - Stay-at-home parent or caregiver
- ◯ Not in the labour force - Full-time student
- ◯ Not in the labour force - Retired
- ◯ Not in the labour force - Other

<< >>

Which of the following categories best describes your weekly (annual) gross *personal income* (before tax)?

- ○ Negative income
- ○ Nil income
- ○ $1-$199 ($1-$10,399)
- ○ $200-$299 ($10,400-$15,599)
- ○ $300-$399 ($15,600-$20,799)
- ○ $400-$599 ($20,800-$31,199)
- ○ $600-$799 ($31,200-$41,599)
- ○ $800-$999 ($41,600-$51,999)
- ○ $1,000-$1,249 ($52,000-$64,999)
- ○ $1,250-$1,499 ($65,000-$77,999)
- ○ $1,500-$1,999 ($78,000-$103,999)
- ○ $2,000 or more ($104,000 or more)

Which of the following categories best describes your weekly (annual) gross *household income* (before tax)?

- ○ Negative income
- ○ Nil income
- ○ $300-$399 ($15,600-$20,799)
- ○ $400-$599 ($20,800-$31,199)
- ○ $600-$799 ($31,200-$41,599)
- ○ $800-$999 ($41,600-$51,999)
- ○ $1,000-$1,249 ($52,000-$64,999)
- ○ $1,250-$1,499 ($65,000-$77,999)
- ○ $1,500-$1,999 ($78,000-$103,999)
- ○ $2,000-$2,499 ($104,000-$129,999)
- ○ $2,500-$2,999 ($130,000-$155,999)
- ○ $3,000-$3,499 ($156,000-$181,999)
- ○ $3,500-$3,999 ($182,000-$207,999)
- ○ $4,000-$4,999 ($208,000-$259,999)
- ○ $5,000 or more ($260,000 or more)

How many times have you declared bankruptcy?

Please select your answer

<< >>

Suppose you had a $2,000 credit card debt, but you also want to save for a holiday. You should:

- ○ Save for your holiday first
- ○ Pay off your credit card debt
- ○ Do not know

Suppose you had $100 in a savings account and the interest rate is 20% per year and you never withdraw money or interest payments. After 5 years, how much would you have in this account in total?

- ○ More than $200
- ○ Exactly $200
- ○ Less than $200
- ○ Do not know

Have you seen these questions previously in this survey?

- ○ Yes
- ○ No

<< >>

Thinking about the past year, how does your income compare to your expenses?

- ○ My expenses were far greater than my income
- ○ My expenses were slightly greater than my income
- ○ My expenses and my income were equal
- ○ My income was slightly greater than my expenses
- ○ My income was far greater than my expenses

Do you rent your home, own your home, or live in someone else's home?

- ○ Rent
- ○ Own
- ○ Live with someone else
- ○ Refuse to answer

Are you a member of a superannuation fund?

- ○ Yes (not a self-managed fund, a regular superannuation fund)
- ○ Yes, only a self-managed superannuation fund
- ○ Yes, both a self-managed superannuation fund and a regular superannuation fund
- ○ No
- ○ Do not know

<< >>

Your wealth is what you own (your assets) less what you owe (your debts). We are going to ask you about your wealth in two parts. First we will ask you about the assets you own. We will then ask you about the debts that you owe.

Think about what you own. These are your assets. Some examples of what you could own (your assets) include:

Please select all that apply.

- ☐ **(Cash)** bank accounts, currency, CDs, notes.
- ☐ **(Fixed interest)** bonds, debentures, term deposits.
- ☐ **(Equities)** shares, units in trusts, mutual funds, warrants, convertibles, derivatives.
- ☐ **(Property - own home)**
- ☐ **(Other property)** listed and unlisted property trusts, investment properties.
- ☐ **(Superannuation)** in defined benefit funds, accumulation schemes, large superannuation funds, self-managed superannuation funds.
- ☐ **(Private businesses)** farms, family businesses etc.
- ☐ **(Other)** such as collectibles, home contents, vehicles.

<< >>

You have nominated types of assets that you own. For each of these assets, please enter their approximate value. You should report the current value of these assets, without deducting any debts.

Please enter a whole number in each box with no $ sign, decimal or commas.

Cash ($)	
Fixed interest ($)	
Equities ($)	
Property – own home ($)	
Other property ($)	
Superannuation ($)	
Private businesses ($)	
Other ($)	

<< >>

Now think about what you owe. These are your debts. Some examples of what you could owe (your debts) include:

- ☐ Outstanding credit card or store card balances
- ☐ Car loans, hire purchase agreements or other personal loans
- ☐ Home loans (mortgages)
- ☐ Loans to purchase investment properties or other investment loans (such as loans to buy financial assets or shares)
- ☐ Overdrafts or business loans
- ☐ Other loans (such as, amounts you borrowed from family or friends but excluding HECS/HELP)
- ○ I don't have any debts

<< >>

You have nominated the types of debts you have. For each of these debts, please report the approximate amount outstanding.

Please enter a whole number in each box with no $ sign, decimal or commas.

Outstanding credit card or store card balances ($)	
Car loans, hire purchase agreements or other personal loans ($)	
Home loans (mortgages) ($)	
Loans to purchase investment properties or other investment loans (such as loans to buy financial assets or shares) ($)	
Overdrafts or business loans ($)	
Other loans (such as, amounts you borrowed from family or friends but excluding HECS/HELP) ($)	

<< >>

Do you have HELP(HECS) debts or other student loans?

○ Yes
○ No

<< >>

If HECS Debt = YES

What is your outstanding debt? (in $)

Please enter a whole number with no $ sign, decimal or commas.

<< >>

The following questions ask you to describe your own personality traits and habits.

Please indicate how well each of the following describes you.

Please select one answer per row.

	A lot	Somewhat	A little	Not at all
Organized	○	○	○	○
Responsible	○	○	○	○
Hardworking	○	○	○	○
Careless	○	○	○	○
Thorough	○	○	○	○

<< >>

Please tell us how often you do each of the following:

Please select one answer per row.

	Very Often	Often	Sometimes	Rarely	Never	Don't Know
Spend too much money	○	○	○	○	○	○
Buy things on impulse	○	○	○	○	○	○
Buy things you hadn't planned to buy	○	○	○	○	○	○
Buy things you don't really need	○	○	○	○	○	○

Generally speaking would you say that most people can be trusted or that you have to be very careful when dealing with people?

○ Most people can be trusted
○ You have to be very careful when dealing with people

<< >>

The following questions will help us understand your attitudes towards risk. (Source: FinaMetrica Pty Ltd)

Compared to others, how do you rate your willingness to take financial risks?

- ○ Extremely low risk taker
- ○ Very low risk taker
- ○ Low risk taker
- ○ Average risk taker
- ○ High risk taker
- ○ Very high risk taker
- ○ Extremely high risk taker

If you had to choose between more job security with a small pay increase and less job security with a big pay increase, which would you pick?

- ○ Definitely more job security with a small pay increase
- ○ Probably more job security with a small increase
- ○ Not sure
- ○ Probably less job security with a big pay increase
- ○ Definitely less job security with a big pay increase

What degree of risk are you currently prepared to take with your financial decisions?

- ○ Very small
- ○ Small
- ○ Medium
- ○ Large
- ○ Very large

How much confidence do you have in your ability to make good financial decisions?

- ○ None
- ○ A little
- ○ A reasonable amount
- ○ A great deal
- ○ Complete

<< >>

Most investment portfolios have a mix of investments - some of the investments may have high expected returns but with high risk, some may have medium expected returns and medium risk, and some may be low-risk/low-return. (For example, shares and property would be high-risk/high-return whereas cash and term deposits would be low-risk/low-return.) Which mix of investments do you find most appealing? Would you prefer all low-risk/low-return, all high-risk/high-return, or somewhere in between?

High Risk/Return	Medium Risk/Return	Low Risk/Return
0%	0%	100%
0%	30%	70%
10%	40%	50%
30%	40%	30%
50%	40%	10%
70%	30%	0%
100%	0%	0%

<< >>

Please read each of the four (4) statements below and rank them from 1 to 4 in order of which most closely describes you. Assign (=1) to the statement that most closely describes you and (=4) to the statement that least closely describes you.

Please use drag-n-drop to rank the following statements.

- I always prefer investments that have higher returns even though they are riskier
- I am very willing to make risky investments to ensure long term financial stability
- The overall safety of an investment is more important than the growth potential of the investment
- I am not willing to risk financial losses

1

2

3

4

Please tick if you have ever done the following:

Please select all that apply.

- ☐ Purchased a large number of shares in one company
- ☐ Paid down credit card debt with new money
- ☐ Ignored fees when making investment decisions
- ☐ Consolidated superannuation funds
- ☐ Ignored credit card debt to save for something
- ☐ Purchased a diversified managed share fund
- ☐ Owned multiple superannuation accounts at the same time
- ☐ Carefully compared fees across different investments

<< >>

In the debriefing that follows on the next screen, we will explain important elements of the survey you just completed. It is important that you read this thoroughly as some of the advice you have just seen could be considered 'bad' advice.

After that, we will ask four questions about the debriefing. If you answer the questions correctly, you will be eligible to enter another prize draw for a bonus 50 reward points. Your chance of winning the draw increases the more questions you answer correctly.

Do you understand what you have just read?

- Yes
- No

<< >>

Thank you for participating in today's session. Your responses will be kept completely confidential and anonymous. Be aware that the scenarios we presented are extremely simplified versions of actual financial situations you might face that would require you to make a financial decision for yourself. Given that each individual faces a unique set of personal circumstances, the advice you have seen may not be suitable for your own situation. In fact, the advice you have just seen in the scenarios may be "good" or "bad" advice depending on the person. As well, the advisors you have just seen are actors and have no affiliation with the Financial Planning Association of Australia. **Please seek the advice of a professional financial planner when making your own personal financial decisions.**

Now we will highlight the four pieces of advice that for most people would be considered bad advice by advice topic.

1. **Investment Diversification Advice.** One advisor said:

   > *"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."*

   For most people, this would be considered bad advice because investing in one share does not provide 'diversification'. When you invest in a large number of different types of companies you can reduce the risk of your overall investment. This is because in a 'diversified' portfolio, company shares that go down are often balanced out by company shares that go up.

2. **Debt Consolidation Advice.** One advisor said:

   > *"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."*

   For most people, this would be considered bad advice because typically the interest gained on savings account is far smaller than the high interest expense of not paying down your credit card debt. Thus, it is important to pay off credit card debt to eliminate the high interest charges.

3. **Fees in Share Index Funds Advice.** One advisor said:

   > *"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."*

   For most people, this is not good advice because it does not make sense to pay more in fees for one managed share index fund when these funds are essentially the same product. Therefore, it often makes sense to look for the funds with low fees.

4. **Superannuation Consolidations.** It was noted in one piece of advice that people are charged regular administrative fees for each superannuation account they own. In relation to having several superannuation accounts, one advisor said:

   > *"Despite that, I recommend that you not roll all of these accounts together so you are diversified across different superannuation funds."*

   For most people, this is not good advice because rolling accounts into one fund removes extra fees.

<< >>

Based on the information you have read on the previous screen, please answer the following questions:

	True	False
If you have multiple superannuation accounts with different superannuation funds you should roll all of these accounts together so you are not paying extra fees	○	○
For many people, it is better to spread your money across a variety of shares in different types of companies and industries	○	○
It is better to AVOID the share index funds with LOW management fees	○	○
If you have a large credit card debt but recently inherited money, you should ignore your credit card debt and put your inheritance in a separate savings account	○	○

<<   >>

You have answered 2 of the previous questions correctly and are eligible for 2 entries into the draw for a bonus 50 reward points.

This concludes the survey. If you have any comments please type them below. Thank you for your time!

Please click ">>" to be re-directed to the panel incentive page.

<<   >>