## Question 1 – Descriptive statistics.

1. **Why is Assessing the Quality of Financial Advice Difficult?**

**Theoretical (Conceptual) Challenges in Assessing Financial Advice Quality**

Assessing financial advice quality is challenging due to the subjective nature of financial goals and risk tolerance. "High-quality" advice varies widely, as advisors must align recommendations with unique client objectives and risk preferences, making standardization difficult. For instance, low-risk advice may suit conservative clients but be suboptimal for those with high-risk tolerance and long-term goals (d'Astous et al., 2024).

Additionally, conflicts of interest can arise when advisors recommend products based on their compensation structure, for example including commissions, even if it is not optimal for the client. Indeed, advisors may recommend an underperforming fund if it offers higher compensation, as long as they are not limited by regulations or the risk of losing future business. Expecting advisors to act solely in the client’s best interest is often neither practical nor economically efficient (Finke, 2013). Such biases are difficult to detect and control in observational data (Inderst & Ottaviani, 2012).

Advisor familiarity with certain products can also bias recommendations, leading advisors to favor products they know well, such as mutual funds, even if these choices may not align with the client's best interests. Studies indicate that this familiarity bias can result in over-recommending specific products based on advisor preference rather than client welfare (Foerster et al., 2017).

Finally, client involvement complicates assessment. Clients who inquire about specific products can influence advisors to recommend those, regardless of better options, which may distort the perceived quality of advice (d'Astous et al., 2024). This variability makes it hard to evaluate advice in a consistent, objective manner.

**Econometric Challenges in Assessing Financial Advice Quality**

Self-selection bias poses a major econometric challenge, as clients seeking advice often differ in financial literacy and motivation. It has been demonstrated that older, wealthier, risk averse, and female investors are more inclined to seek advice (Montmarquette et al., 2015). Those who could benefit most from financial advice—typically less financially literate clients—often do not seek it (Reyers, 2016). This limits generalizability, as observational data may not represent the broader population effectively. Additionally, observational datasets often lack detailed information on client preferences and advisor interactions. The lack of random assignment in real-world data also prevents controlled assessment, as clients have unique, non-random inquiries and preferences that affect recommendations. Mullainathan et al. (2012) suggest that audit studies, where "mystery shoppers" are used to simulate client interactions with financial advisors, offer an alternative method, but these are challenging to scale and ethically complex to implement.

Endogeneity further complicates analysis, as client traits like wealth or education may influence outcomes independently of advice quality, making it difficult to isolate the advisor’s impact (Foerster et al., 2017). Establishing causality requires counterfactuals—knowing what a client would do without advice. This is essential for evaluating advice quality since an effective assessment would ideally compare outcomes with and without advisor intervention. Chalmers and Reuter (2020) argue that without a clear counterfactual, it is challenging to isolate the advisor's influence on client outcomes from other external factors. However, observational studies rarely provide this, complicating efforts to determine whether advice directly influences outcomes.

Ethical and legal constraints limit data collection, particularly in direct client-advisor interactions, further complicating the measurement of advice quality (Huber & Kirchler, 2023).

Longitudinal data is needed to measure long-term effects, but tracking clients over time is challenging due to advisor changes and evolving client goals. Without it, studies risk focusing on short-term outcomes, which may not reflect the true quality of advice. Long-term studies are therefore essential for evaluating advice effectiveness, especially for outcomes like retirement savings. (Linnainmaa et al., 2021; Huber & Kirchler, 2023).

1. **What is the purpose of an experiment in this context and how does it help address the difficulty you pointed out in question a.?**

**Purpose of an Experiment in Assessing Financial Advice Quality**

Experiments provide a controlled setting that allows researchers to manipulate and isolate variables like client characteristics, advisor incentives and product features, moving beyond correlation to identify causation. This controlled environment addresses complexities that observational studies cannot, offering clearer insights into the factors influencing financial advice quality.

**How Experiments Address These Challenges**

Vignettes to Address Subjective Financial Goals

The experiment addresses the variability in financial goals by using standardized vignettes representing different client objectives, like retirement or long-term care (d'Astous et al., 2024). While this method controls for specific financial goals and risk profiles, it cannot capture the full range of individualized objectives present in real-life advisory settings, offering only a partial view of how well advisors align with diverse client needs.

Randomization to Isolate Influences and Measure Biases

By randomizing client characteristics and advisor incentives, experiments reduce biases inherent in observational data, enabling researchers to isolate each factor's impact on recommendations. For example, randomized commission structures reveal if advisors promote certain products due to compensation incentives (Chalmers & Reuter, 2020). Experiments can also test advisor biases, like preference for familiar products, by presenting advisors with both familiar and unfamiliar options, which helps measure the extent to which familiarity shapes recommendations (Hackethal et al., 2018). This controlled approach helps reveal the behaviors and contexts that influence financial advice quality, which are often hard to disentangle in observational data.

Avoiding Self-Selection Bias

Self-selection bias skews observational studies because clients who seek advice often differ in financial literacy and motivation. Experiments counter this by using standardized scenarios for advisors, ensuring results reflect a consistent client profile rather than a self-selected subset. This approach makes findings more generalizable and applicable to a broader population by capturing advice quality in a controlled environment (Mullainathan et al., 2012).

Establishing Counterfactuals to Measure Causal Impact

Experiments simulate counterfactuals by varying conditions like product information or compensation structures, allowing researchers to infer causation by observing how recommendations change under different scenarios. Although experiments cannot fully replicate a “no-advice” situation, they help reveal causal effects by showing how specific factors, such as client prompts, shape advisor behavior (Foerster et al., 2017).

Ethical Constraints

To navigate ethical limitations, the study uses hypothetical client scenarios instead of actual client interactions, maintaining privacy and avoiding consent issues. The study therefor respects confidentiality requirements and ethical standards, providing a structured view of advisor responses without risking personal data exposure or privacy concerns.

**Practical Applications of Experimental Insights**

Experimental findings have practical implications for the financial advice industry. By identifying specific factors that influence advice quality, financial firms and regulators can design better compensation models and training programs. For example, if experiments show that commission-based compensation biases recommendations, firms may adopt fee-based models to better align advisor incentives with client interests (Inderst & Ottaviani, 2012).

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## Annexe: Replication of Table 2 (descriptive statistics) from the paper



