## Question 3 – Using the domain selected in the previous question, along with all the available data from the dataset, conduct a new analysis of the data.

1. **Formulate a new research question or hypothesis that can be answered using the data available in the survey.**

Our study aimed to examine how personal financial characteristics of financial analysts influence their risk recommendations. Specifically, we focused on two main variables:

Debt-to-Income Ratio (DIR): Calculated as the ratio of an analyst’s total debt to their income, representing the relative financial pressure they may face.

Absolute Debt Level: The total debt amount, which serves as a measure of the absolute financial burden without considering income.

In addition, we analyzed other demographic and professional factors such as age, education level, and work experience, to understand their potential roles in shaping risk recommendation tendencies. Our hypothesis is that the accumulation of debt levels creates some degree of ‘financial anxiety’ for analysts, or a preference for leveraged and risky products. Although advisors should act in the best interests of their clients, they are often constrained by their own incentives to intentionally mislead clients. This bias is difficult for clients to detect, as they generally lack the necessary financial literacy and sophistication.

**b.) Develop a conceptual or theoretical framework to address the question. Back your predictions with work from the literature and knowledge from the field.**

The aim of this study is to explore the impact of financial advisors' level of personal debt (Debt-to-Income Ratio) on their financial product recommendation behaviour. By analysing the Debt-to-Income Ratio (DIR) and Direct Debt of financial advisors, we seek to understand how these variables affect their product selection tendencies in different contexts. The data contains a variety of variables such as age, education level, work experience, income and other control variables to ensure a comprehensive examination of the factors influencing advisor recommendation behaviour. A multinomial logistic regression (MNLogit) model is used to analyse advisers' choices for each option to quantify the effect of debt level on recommendation behaviour and identify the significant effect of debt burden on financial product recommendation preferences.

Drawing inspiration from Gerrans and Hershey's (2017)[3] exploration of financial advisor anxiety and behavior, we incorporate advisors’ personal financial conditions as a key factor impacting their recommendations. Using a multinomial logit (MNLogit) model, as seen in recent work by d’Astous et al. (2024)[5] on the quality of financial advice, we examine how debt levels and other controls (age, education, income, and work experience) affect advisors' preferences across various financial products. The inclusion of DIR as a variable is informed by the framework established in the study on certification in private debt markets (2024), which emphasizes the relevance of personal debt burden in professional financial decisions. Furthermore, insights from Vijayakumar and Daniels (2006)[4] on the behavior of financial advisors in municipal bond markets guide our approach to analyzing advisor behavior. Together, these sources provide a comprehensive foundation for understanding the role of personal debt in shaping financial advisors' product recommendations.

**c.) For your main new empirical analysis, present your results in a table. Explain your methods (e.g., OLS, Probit, etc) and justify why they are applicable here (e.g Probit for binary data, OLS for continuous, etc). Additionally, the mean and standard deviation of all variables used in your analysis must be presented in one descriptive statistics table.** & **d. )Interpret your results, explaining the significance of the estimated effects and whether they verify your hypothesis. Discuss possible explanations if the hypothesis is not verified.**

Why MNLogit is applicable here

MNLogit allows for the analysis of multiple unordered categories of dependent variables that do not have a natural order and therefore cannot be handled by methods such as OLS or Probit. In addition, MNLogit is suitable for contexts with multiple independent variables, both continuous and categorical. It is able to estimate the relative impact of each independent variable on different choices, which has high explanatory power for our research objective (analysing advisers' recommendation preferences at different debt levels). In this study, the dependent variable is the product categories (e.g. RRSPs, TFSAs, ETFs, Seg funds, etc.) recommended by financial advisors in different contexts, which are disorganised and varied and cannot be reasonably modelled by linear regression or Probit models. So here we choose to use MNLogit model for our analysis.

The mean and standard deviation of all variables used

|  |  |  |
| --- | --- | --- |
| **Variable** | **Mean** | **Std Dev** |
| Debt\_Impute | 333,673.76 | 333,293.78 |
| Age | 47.8 | 11.72 |
| Educ\_Level | 5.63 | 1.31 |
| Work\_Experience | 15.22 | 9.62 |
| Income\_Impute | 174,819.69 | 146,061.98 |
| Log\_DIR | 0.28 | 1.59 |

Table 3-1 mean and standard deviation



Table.3-2 MNLogit results

The data for this study are all derived from the dataset clean\_all.csv, which aggregates the analyst Q&A information from section2 and extracts their choices in different contexts as the core object of analysis. By constructing a multinomial logistic regression model (MNLogit), we relate analysts' recommendation behaviour to a number of key independent variables, including individual debt level ( debt ), age, education level ( educ\_level ), predicted income ( income\_impute ), and logarithmic value of debt-to-income ratio ( log\_DIR ).

In the regression analysis, we focus on the effect of the debt variable on different recommendation options and identify the financial products that analysts tend to recommend at high debt levels. The regression results show that debt is statistically significant on the recommendation behaviour of ETFs, Seg Funds, RRSPs, TFSAs and Repay Debt. Specifically, the positive effect of debt level on ETFs and Seg Funds suggests that analysts are more inclined to recommend these types of more flexible investment products as debt increases, while the negative effect on RRSPs, TFSAs, and Repay Debt implies that analysts are less likely to recommend these products under high debt conditions. This result supports our hypothesis that analysts' debt burden significantly affects their recommendation preferences and that higher debt levels favour more short-term liquid options.

As we can see from table 3.2, the coefficient of 0.15 (p < 0.05) for debt in the recommendation of ETFs suggests that analysts tend to recommend this type of more flexible investment product in high debt situations. Similarly, the positive coefficient of 0.08 (p < 0.05) for debt in the selection of Seg Funds further supports this behavioural tendency. In addition, the negative effect of debt on RRSP and Repay Debt is -0.15 (p < 0.05) and -0.05 (p < 0.10), respectively, suggesting that analysts are more inclined to avoid long term lock-up or repayment type of options in the context of high debt.

An additional point to discuss is that log\_DIR does not show significance across all options, which may be related to the introduction of an income variable in its calculation. As income is often difficult to fully control by individuals, its explanatory power in behavioural decisions may be weak, which somewhat diminishes the impact of log\_DIR. Meanwhile, debt level, as a more directly autonomous variable, is more reflective of analysts' personal preferences and behavioural patterns in financial management. This phenomenon suggests that analysts' debt propensity may provide clearer clues about their decision-making behaviour, whereas the effect of income, due to its lack of autonomy, may not be sufficient to significantly influence recommendation behaviour.

图表, 箱线图

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Figure 3- 3

As we see in Figure 3-3, there are significant differences in the impact of debt levels on recommendations of different financial products. Specifically, the coefficients on debt for ETFs, Seg funds, and MFs are positive and statistically significant, suggesting that advisors are more inclined to recommend these highly liquid or flexible investment products in high debt scenarios. This phenomenon may reflect the existence of a preference for these more liquid and volatile products among advisors with a higher propensity for debt. In contrast, the negative debt coefficients for products such as IL-GIC, RRSP, and TFSA indicate that advisors are not inclined to recommend these more robust, but relatively illiquid, long-term investment products in high-debt scenarios. This behaviour may stem from advisers' reservations about longer-term commitments in a high debt state, and thus a greater tendency to avoid these options with some constraints on liquidity and to pursue products that are more risky and liquid.

The advisor's incentive structure is not perfectly aligned with the client's goals, and this incentive structure significantly affects the advisor's recommendation outcomes. Specifically, advisors tend to receive higher commissions for selling higher-priced products that typically generate lower risk-adjusted returns for clients. Our research suggests that these external incentives interact with advisors' own financial pressures to exacerbate their propensity to recommend risky products, especially if their personal debt levels are high.

As we hypothesise, the accumulation of debt levels creates a degree of ‘financial anxiety’ for analysts, or a preference for leveraged and risky products that is clearly evidenced by the data. While advisors are supposed to act in the best interests of their clients, they are often under the impression that they are biased by their own factors and make biased recommendations. This bias is difficult for clients to detect, as they generally lack the necessary financial literacy and sophistication.

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## Annexe:

MNLogit Regression Results

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