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Likert Scale Variables in Personal Finance Research: The Neutral Category Problem

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Abstract: Personal finance research often utilizes Likert-type items and Likert scales as dependent variables, frequently employing standard probit and ordered probit models. If inappropriately modeled, the "neutral" category of discrete dependent variables can bias estimates of the remaining categories. Through the utilization of hierarchical models, this paper demonstrates a methodology that accounts for the econometric issues of the neutral category. We then analyze the technique through an empirical exercise relevant to personal finance research using data from the National Financial Capability Study. We demonstrate that ignoring the "neutral" category bias can lead to incorrect inferences, hindering the progression of personal finance research. Our findings underscore the importance of refining statistical modeling techniques when dealing with Likert-type data. By accounting for the neutral category, we can enhance the reliability of personal finance research outcomes, fostering improved decision-relevant insights.

Keywords: financial planning; Likert scales; National Financial Capability Study; personal finance; statistical modeling

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1. Introduction

Personal finance and financial planning researchers analyze data to garner insights across a broad range of subjects. Likert-type items and Likert scales have emerged as popular tools, allowing researchers to capture quantitative data through convenient ordinal responses. Moreover, many datasets commonly utilized by U.S. personal finance researchers contain Likert-type items and Likert scales, such as the Survey of Consumer Finances (SCF), Panel Study of Income Dynamics (PSID), Health and Retirement Study (HRS), and the National Financial Capability Study (NFCS). For example, the NFCS has utilized Likert-type items to examine a broad range of personal finance and financial planning topics, such as financial literacy (Lusardi and Mitchell 2011), the use of mobile and web financial services (Pearson 2021, 2022), financial satisfaction (Fan and Henager 2022; Woodyard and Robb 2016), perceptions of financial planner use (Wann and Burke-Smalley 2021), and investment risk tolerance (Liu et al. 2023; Moreland 2018; Said and Powell 2020). To note, more than 29% and 15% of the articles published in the *Journal of Financial Counseling and Planning* between 2010–2019 utilized data collected from the SCF and NFCS, respectively (Xiao et al. 2020). However, the seemingly straightforward interpretation of these instruments often masks a hidden challenge: the enigmatic "neutral" category.

Although numerous personal finance and financial planning studies have employed the use of Likert methods since their introduction by Rensis Likert (1932), very few studies attempt to address the potentially biased estimates that result from the inclusion of a "neutral" category in econometric models with discrete outcome variables. A neutral category is a middle option in odd-numbered Likert-type items, which can also be presented as "undecided", "unsure", or "impartial". Armstrong (1987) shows that the differences among the nomenclature utilized for the middle category are negligible.

Kaptein et al. (2010) suggested that the definition of Likert-type items and Likert scales should be recognized. Likert-type items are measurement tools for assessing individual response items, while Likert scales are derived from linked associations (i.e., as used in personality scale development). In other words, a Likert scale is a specific type of scale used to measure attitudes, opinions, or perceptions, while Likert-type responses are a broader category that encompass any type of response scale (e.g., rating scales and semantic differential scales). This paper will attempt to match the definitions provided by Kaptein et al. (2010).

When considering item response theory, several statistical models have been suggested to account for a response item and proficiency of response in matching its intended measurement. For instance, item response trees that use ordinal scale only (Böckenholt and Meiser 2017; Meiser et al. 2019) and mixed models for Likert-type items (Tijmstra et al. 2018) have been offered by the literature. Van der Linden (2016) and Pliakos et al. (2019) provide a detailed overview of the proposed models for ordinal responses. While item response theory aims to assess latent traits, we focus on the effects of independent variables.

In the text that follows, we relax the assumption of ordinal scale and assume a multinomial approach to account for the data's discreteness. As Tutz (2021) suggested, if neutral category preferences vary across respondents, ordinal models may yield biased estimates. Consequently, this requires the creation of two new dependent variables, which will be separately modeled. We then demonstrate the use of the recoding algorithm through an NFCS exercise, shedding light on the nuances of our approach and its implications for personal finance and financial planning research. We conclude by showing how this approach offers several advantages over traditional methods, particularly in addressing the challenges of ordinal data and accounting for individual differences in response styles.

2. Likert Scale Correction

The recent literature on Likert-type items and Likert scales highlights the econometric concerns with the so-called "neutral" category (Dykema et al. 2022; Pimentel 2019; Shafiq et al. 2020; Vonk 2022). This growing awareness underscores the necessity of methodological advancements to address the challenges posed by the neutral category, forming the foundation for the approach presented in this paper. The technique to correct for the neutral category bias showcased in this paper is straightforward and relatively undemanding to implement. Its simplicity enhances its practical utility, making it accessible to a wide range of researchers in personal finance studies and other broader microeconomic and social fields. The technique involves the separate estimation of the neutral category and the remaining categories. This separation allows for a more nuanced understanding of the distinct impact that the neutral category can have on estimates, contributing to a more accurate representation of personal finance preferences and responses in Likert scales. In the following explanation, we utilize the notation of Tutz (2021).

The process of modeling the neutral category starts with identifying the neutral category. This initial step is critical in establishing a clear foundation for subsequent analyses, emphasizing the importance of correctly identifying and isolating the neutral category within the Likert scale. In our empirical examples, we use a 7-item Likert scale. Thus, the neutral category would be the fourth category, or responses labeled as "4". Other Likert scaling can also be corrected if the neutral category can be identified, which is normally the case.

Mathematically, the neutral or "middle" category can be represented as $m = \left(\frac{k+1}{2}\right)$, where m is the middle category and k is the total number of Likert scale categories. Given the middle category, we let $Y_i^{(n)}$ represent a binary coding of the original dependent variable Y^i as follows:

$$Y_i^{(n)} = \begin{cases} 1 & Y_i \neq m \\ 0 & Y_i = m \end{cases} \tag{1}$$

Equation (1) provides a clear encoding strategy for handling the neutral category in Likert scales. This equation states that we should encode our original Likert scale dependent variable into the new variable $Y_i^{(n)}$ so that the neutral or middle categories are coded as 0 and the other Likert scale values are coded as a 1. Thus, we take the original dependent variable and create a new dependent variable to separately model the neutral category. In this case, one would use a standard probit model, as we have two categories: the neutral category (coded as a 1) and the remaining categories (coded as 0), using the existing explanatory variables. This modeling choice enables a systematic exploration of the factors influencing responses in the neutral category, enhancing the precision of the subsequent analysis.

The second step in correcting for potential bias in the neutral category requires another recoded dependent variable. Let $Y_i^{(a)}$ represent the remaining categories without the neutral category included. Now, only categories $1, \ldots, m-1, m+1, \ldots k$ can occur. Let $Y_i^{(a)}$ take values according to the following formula:

$$Y_i^{(a)} = \begin{cases} Y_i & Y_i \leq m-1 \\ Y_i - 1 & Y_i \geq m+1 \end{cases} \tag{2}$$

Equation (2) is a rescaling of the remaining categories, and an ordered probit model can be used to estimate a model where $Y_i^{(a)}$ is the new dependent variable and the same explanatory variables are used from the original model. This application ensures that the ordinal nature of Likert scale responses is preserved, allowing for an in-depth examination of the remaining categories.

Table 1 shows the recoding algorithm for a hypothetical Likert scale-type dependent variable. In this example, we have a 5-item Likert scale, which makes the middle category a 3. The first column represents the original Likert scaling of the dependent variable, offering a clear depiction of the initial responses collected. The second column represents the binary (either/or) recoding of the dependent variable, where 0 represents the middle category and 1 represents all other categories. This binary representation simplifies the encoding process, emphasizing the isolation of the neutral category for precise modeling. The third column shows the original coding without the inclusion of the neutral coding, providing a comparison to the binary recoding. This step underscores the necessity of explicitly accounting for the neutral category in Likert scales, as excluding it can lead to biased estimates. The last column shows the rescaled version, illustrating the adjustments made to the original coding. By excluding the middle category and reassigning values, this rescaled version ensures a more accurate representation of the remaining categories, facilitating unbiased estimation. One additional note is that the sample size for each of the two separate regression models will not be the same. This observation highlights the consequence of excluding the neutral category in the rescaled version, leading to a reduction in the number of observations available for analysis.

Table 1. Recoding algorithm for Likert scale dependent variable.

Original Likert Scale Dependent Variable	Binary Coded	Original Excluding Middle Category	Rescaled Original
5	1	5	4
3	0	N/A	exclude
4	1	4	3
1	1	1	1
3	0	N/A	exclude
2	1	2	2
Sample Size:	6	4	4

Data collected from the 2018 National Financial Capability Study State-by-State Survey—Tracking Dataset are utilized. n = 26,757.

Table 1 shows that our hypothetical example shows six observations and that all observations are preserved in the binary-coded dependent variable. In contrast, the rescaled original dependent variable, which excluded the middle category, now only has four observations to accommodate the correction. This reduction in sample size underlines the impact of isolating the neutral category on the available data for analysis.

In summary, the algorithm to correct for the possible bias of the neutral category requires the creation of two new dependent variables: one to recode the dependent variable for the presence or absence of the middle category and another dependent variable that completely removes the dependent variable and reassigns values to the dependent variable. The first model can be estimated via a standard probit or logit model, and the second model can be estimated via an ordered probit or logit model. This dual-model approach ensures a comprehensive correction for potential bias and provides a better understanding of how the neutral category influences Likert scale responses.

3. Likert Scale Correction—An NFCS Exercise

Using the 2018 wave of the National Financial Capability Study (NFCS), we demonstrate an application of the Likert scale correction to a 7-item Likert scale. This practical application serves to showcase the adaptability of the methodology to different Likert scales and its relevance to real-world data. The dependent variable of interest is subjective personal financial ability, and the example's explanatory variables of interest are the variables gender, race, education, marriage, age, and income. STATA 17 is utilized to conduct the analyses.

The exercise's dependent variables are obtained from the NFCS question: "How strongly do you agree or disagree with the following statements?—I am good at dealing with day-to-day financial matters, such as checking accounts, credit and debit cards, and tracking expenses". This specific question aligns with the subjective personal financial ability, offering a focused lens on respondents' self-assessment of their financial capabilities. Respondents have the option to answer 1 (Strongly Disagree), 2, 3, 4 (Neither Agree nor Disagree), 5, 6, and 7 (Strongly Agree). Respondents also have the option of answering 98 (Don't know) and 99 (Prefer not to say). For this exercise, 98 and 99 responses are dropped. The sample size is (n = 26,757).

In this exercise, the neutral category would be the fourth category, or responses labeled as "4 (Neither Agree nor Disagree)". This identification is crucial as it forms the basis for the subsequent application of the Likert scale correction methodology. It ensures a targeted correction for potential biases associated with the neutral category in the analysis. Given the middle category, we now let $Y_i^{(n)}$ represent a binary coding of the original dependent variable Y^i as follows:

$$Y_i^{(n)} = \begin{cases} 0 & Y_i \neq 4 \\ 1 & Y_i = 4 \end{cases}$$

This binary coding aligns with the Likert scale correction methodology, facilitating the isolation and separate modeling of the neutral category. This step-by-step explanation enhances the transparency of the methodology for researchers and readers.

Table 2 provides the summary statistics of the neutral category dependent variable and explanatory variables. This summary serves as a comprehensive overview, offering insights into the distribution and variability of key variables in the analysis. The explanatory variables are coded as follows: Gender, race, education, and married are coded as a "1" if the respondent is male, white, has at least a 4-year bachelor's degree, and is married, respectively. A "0" is coded otherwise. Income and education are categorical measures. These variable codings simplify the interpretation of results, allowing for a clearer understanding of the impact of different factors on subjective personal financial ability.

Table 2. Example's summary statistics.

	Frequency	**Std. Dev.**
Subjective Personal Financial Ability (Non-Neutral Response = 1)	23,386 (87.40%)	0.3318
Gender (Male = 1)	11,794 (44.08%)	0.4965
Race (White = 1)	19,887 (74.32%)	0.4369
Education (Bachelor's Degree or Higher = 1)	9372 (35.03%)	0.4771
Marriage (Married = 1)	14,312 (53.49%)	0.4988
Age		
18–24	2728 (10.20%)	0.3026
25–34	4585 (17.14%)	0.3768
35–44	4457 (16.66%)	0.3726
45–54	4618 (17.26%)	0.3779
55–64	4876 (18.22%)	0.3860
65+	5493 (20.53%)	0.4039
Income		
Income < \$15,000	2949 (11.02%)	0.3132
\$15,000 ≤ Income < \$25,000	2759 (10.31%)	0.3041
\$25,000 ≤ Income < \$35,000	2894 (10.82%)	0.3106
\$35,000 ≤ Income < \$50,000	3887 (14.53%)	0.3524
\$50,000 ≤ Income < \$75,000	5215 (19.49%)	0.3961
\$75,000 ≤ Income < \$100,000	3819 (14.27%)	0.3498
\$100,000 ≤ Income < \$150,000	3413 (12.76%)	0.3336
Income ≥ \$150,000	1821 (6.81%)	0.2518

Data collected from the 2018 National Financial Capability Study State-by-State Survey—Tracking Dataset are utilized. n = 26,757.

Table 3 provides the recoding algorithm for the 7-item Likert scale dependent variable. Given the dependent variable is a 7-item Likert scale, the middle category is 4. This identification is pivotal for the recoding process, as it designates the neutral category that requires targeted correction. The emphasis on the middle category sets the stage for the subsequent binary recoding and rescaling steps. The first column represents the original Likert scaling of the dependent variable. This column offers a clear view of respondents' initial Likert scale responses, providing the raw data for the subsequent recoding process. The second column represents the binary recoding of the dependent variable, where 0 represents the middle category, and 1 represents all other categories. This binary representation simplifies the encoding process, enabling the isolation and focused modeling of the neutral category. The third column shows the original coding without the inclusion of the neutral coding. This column serves as a point of comparison, highlighting the impact of excluding the neutral category in the recoding process. It underscores the importance of the Likert scale correction methodology in addressing potential biases associated with the neutral category. The last column shows the rescaled version, providing a visual representation of the adjustments made to the original coding. This rescaled version ensures a more accurate representation of the remaining categories, contributing to unbiased estimation in subsequent analyses.

Table 4 shows the parameter estimates from fitting the probit model, as observed in the column *Probit Model, Separated Fits*, on variables ending with *Nuet*, which refer to the choice of the neutral category (e.g., *GenderNuet*). This specialized probit model focuses on variables related to the selection of the neutral category, shedding light on factors influencing respondents' decisions to choose the "Neither Agree nor Disagree" option in the Likert scale. The variables *EducationNuet*, *AgeNuet*, and *IncomeNuet* have an effect

($p < 0.001$) on the choice of the subjective personal financial ability neutral category. The statistical significance of these variables underscores their relevance in understanding the determinants of opting for the neutral category. Education, age, and income emerge as influential factors, providing valuable insights into how demographic and socioeconomic characteristics impact the likelihood of selecting the neutral option. The results from the probit model shows that many of the explanatory variables are associated with choosing the neutral category in the Likert scale dependent variable, which can result in biased estimates of the parameter estimates if the neutral category is included in an ordered probit model. This observation highlights the potential bias introduced when the neutral category is not explicitly addressed in the modeling process. The significance of these associations emphasizes the importance of applying the Likert scale correction methodology to avoid skewed parameter estimates in subsequent analyses.

Table 3. Recoding algorithm for subjective personal financial ability Likert dependent variable.

Original Likert Scale Dependent Variable	Binary Coded	Original Excluding Middle Category	Rescaled Original
7	0	7	6
6	0	6	5
4	1	N/A	Exclude
5	0	5	4
3	0	3	3
4	1	N/A	Exclude
2	0	2	2
1	0	1	1
Sample Size:	8	6	6

Data collected from the 2018 National Financial Capability Study State-by-State Survey—Tracking Dataset are utilized. n = 26,757.

Table 4. Modeling subjective personal financial ability—neutral results.

	Probit Model, Separated Fits (*Nuet*)	
	Estimate	**Std. Err.**
GenderNuet	−0.0024	0.0208
RaceNuet	−0.0559	0.0229
EducationNuet	−0.2504	0.0245
MarriageNuet	0.0321	0.0231
AgeNuet (18–24 as reference)		
25–34	−0.0665	0.0364
35–44	−0.0432	0.0370
45–54	−0.1396 ***	0.0373
55–64	−0.3416 ***	0.0387
65+	−0.6114 ***	0.0408
IncomeNuet (<$15,000 as reference)		
$15,000 ≤ IncomeNuet < $25,000	−0.1508 ***	0.0383
$25,000 ≤ IncomeNuet < $35,000	−0.2097 ***	0.0388
$35,000 ≤ IncomeNuet < $50,000	−0.3640 ***	0.0378
$50,000 ≤ IncomeNuet < $75,000	−0.4155 ***	0.0369
$75,000 ≤ IncomeNuet < $100,000	−0.5812 ***	0.0426
$100,000 ≤ IncomeNuet < $150,000	−0.5976 ***	0.0457
IncomeNuet ≥ $150,000	−0.6615 ***	0.0591

Age 18–24 and Income < $15,000 serve as the reference categories to which their other respective categories are compared. Data collected from the 2018 National Financial Capability Study State-by-State Survey—Tracking Dataset are utilized. Significance is defined as follows: *** significant at $p < 0.001$. n = 26,757.

Table 5 shows the parameter estimates from fitting the ordered probit model on the algometric recoded subjective personal financial ability variable, as observed in the left column *Ordinal Model*, *Separated Fits*. Comparatively, the right column, *Ordinal Model*

All Categories, provides the parameter estimates from the ordinal model with the neutral category treated as one of the ordered categories. The results indicate that the parameter estimates differ from the probit model estimates. This divergence emphasizes the significance of appropriately addressing the neutral category in the modeling process. The distinct parameter estimates highlight the importance of considering the refinement introduced by the neutral category, revealing potential biases when excluded or treated indifferently.

Table 5. Modeling subjective personal financial ability—non-neutral results.

	Ordinal Model, Separated Fits		**Ordinal Model All Categories**	
	Estimate	**Std. Err.**	**Estimate**	**Std. Err.**
Gender	0.0185	0.0152	0.0196	0.0139
Race	0.0458 **	0.0175	0.0623 ***	0.0158
Education	0.0483 **	0.0168	0.1189 ***	0.0155
Marriage	−0.0121	0.0171	−0.0179	0.0155
Age (18–24 as reference)				
25–34	0.1070 ***	0.0296	0.1002 ***	0.0261
35–44	0.1682 ***	0.0301	0.1422 ***	0.0266
45–54	0.3085 ***	0.0300	0.2810 ***	0.0266
55–64	0.5984 ***	0.0303	0.5769 ***	0.0270
65+	0.8346 ***	0.0302	0.8453 ***	0.0272
Income (<\$15,000 as reference)				
\$15,000 $\leq$ Income < \$25,000	0.0922 **	0.0326	0.1276 ***	0.0283
\$25,000 $\leq$ Income < \$35,000	0.2059 ***	0.0325	0.2376 ***	0.0284
\$35,000 $\leq$ Income < \$50,000	0.3301 ***	0.0309	0.3818 ***	0.0271
\$50,000 $\leq$ Income < \$75,000	0.3846 ***	0.0301	0.4428 ***	0.0264
\$75,000 $\leq$ Income < \$100,000	0.5587 ***	0.0329	0.6277 ***	0.0292
\$100,000 $\leq$ Income < \$150,000	0.5863 ***	0.0345	0.6560 ***	0.0308
Income $\geq$ \$150,000	0.7746 ***	0.0415	0.8230 ***	0.0377

Age 18–24 and Income < \$15,000 serve as the reference categories to which their other respective categories are compared. Data collected from the 2018 National Financial Capability Study State-by-State Survey—Tracking Dataset are utilized. Significance is defined as follows: ** significant at $p < 0.01$; *** significant at $p < 0.001$. $n = 26{,}757$.

Comparison of Marginal Effects

Table 6 provides the estimated average marginal effects from the ordered probit regression results on the algometric recoded subjective personal financial ability variable, while Table 7 provides the average marginal effects on the unaltered subjective personal financial ability variable. The differences in the parameter estimates from the two regression models (i.e., the neutral excluded vs. neutral included) can be quite large. For example, in the ordered probit model with the unaltered dependent variable, the coefficient on the Education variable for the first category is −0.0076, while in the neutral category corrected results, the coefficient on the Education variable for the first category is −0.0034, which is 2.23 times smaller. This highlights how the correction strategy significantly influences the estimated effects of individual variables. Given the sheer number of results in the table, we do not illustrate all of the differences, but similar differences exist between the corrected and the uncorrected results across the Education and other variables. This suggests a persistent impact of the correction approach on the interpretation of the relationships between explanatory variables and Likert scale responses.

Table 6. Comparison of average marginal effects on subjective personal financial ability—neutral category excluded.

	1	2	3	4	5	6
	Estimate (Std. Err.)	**Estimate (Std. Err.)**	**Estimate (Std. Err.)**	**Estimate (Std. Err.)**	**Estimate (Std. Err.)**	**Estimate (Std. Err.)**
Gender	−0.0013 (0.0011)	−0.0006 (0.0005)	−0.0009 (0.0008)	−0.0025 (0.0021)	−0.0015 (0.0013)	0.0069 (0.0056)
Race	−0.0032 ** (0.0012)	−0.0014 ** (0.0005)	−0.0023 ** (0.0009)	−0.0062 ** (0.0024)	−0.0038 ** (0.0015)	0.0169 ** (0.0065)
Education	−0.0034 ** (0.0012)	−0.0015 ** (0.0005)	−0.0025 ** (0.0009)	−0.0065 ** (0.0023)	−0.004 ** (0.0014)	0.0179 ** (0.0062)
Marriage	0.0008 (0.0012)	0.0004 (0.0005)	0.0006 (0.0009)	0.0016 (0.0023)	0.001 (0.0014)	−0.0045 (0.0063)
Age (18–24 as reference)						
25–34	−0.0119 *** (0.0034)	−0.0045 *** (0.0013)	−0.007 *** (0.002)	−0.0147 *** (0.004)	−0.0018 ** (0.0005)	0.0399 *** (0.011)
35–44	−0.0179 *** (0.0034)	−0.0069 *** (0.0013)	−0.0108 *** (0.002)	−0.0234 *** (0.0042)	−0.0041 *** (0.0008)	0.0632 *** (0.0112)
45–54	−0.0294 *** (0.0032)	−0.012 *** (0.0013)	−0.0191 *** (0.002)	−0.0441 *** (0.0043)	−0.0128 *** (0.0014)	0.1174 *** (0.0113)
55–64	−0.0457 *** (0.0031)	−0.0201 *** (0.0014)	−0.0336 *** (0.0021)	−0.0863 *** (0.0044)	−0.0435 *** (0.0024)	0.2291 *** (0.0113)
65+	−0.0534 *** (0.0032)	−0.0247 *** (0.0015)	−0.0424 *** (0.0021)	−0.1173 *** (0.0044)	−0.0774 *** (0.0029)	0.3151 *** (0.011)
Income (< \$15,000 as reference)						
\$15,000 ≤ Income > \$25,000	−0.0104 ** (0.0037)	−0.0038 ** (0.0014)	−0.0058 ** (0.0021)	−0.0122 ** (0.0043)	−0.0017 (0.0007)	0.0338 ** (0.012)
\$25,000 ≤ Income < \$35,000	−0.0213 *** (0.0035)	−0.0082 *** (0.0014)	−0.0127 *** (0.0021)	−0.0279 *** (0.0044)	−0.0064 *** (0.0013)	0.0765 *** (0.012)
\$35,000 ≤ Income < \$50,000	−0.031 *** (0.0033)	−0.0124 *** (0.0013)	−0.0198 *** (0.002)	−0.0456 *** (0.0042)	−0.0149 *** (0.0016)	0.1237 *** (0.0114)
\$50,000 ≤ Income < \$75,000	−0.0347 *** (0.0032)	−0.0141 *** (0.0013)	−0.0226 *** (0.002)	−0.0534 *** (0.0041)	−0.0196 *** (0.0016)	0.1445 *** (0.0111)
\$75,000 ≤ Income < \$100,000	−0.0442 *** (0.0033)	−0.0188 *** (0.0015)	−0.031 *** (0.0021)	−0.078 *** (0.0046)	−0.0382 *** (0.0025)	0.2102 *** (0.0121)
\$100,000 ≤ Income < \$150,000	−0.0454 *** (0.0033)	−0.0195 *** (0.0015)	−0.0322 *** (0.0022)	−0.0818 *** (0.0048)	−0.0415 *** (0.0028)	0.2205 *** (0.0127)
Income ≥ \$150,000	−0.0522 *** (0.0033)	−0.0233 *** (0.0016)	−0.0394 *** (0.0023)	−0.1063 *** (0.0055)	−0.067 *** (0.0047)	0.2884 *** (0.0148)

Age 18–24 and Income < \$15,000 serve as the reference categories to which their other respective categories are compared. Data collected from the 2018 National Financial Capability Study State-by-State Survey—Tracking Dataset are utilized. Significance is defined as follows: ** significant at $p < 0.01$; *** significant at $p < 0.001$. n = 26,757.

Table 8 provides the Akaike information criterion (AIC) and the Bayesian information criterion (BIC) across the estimated models, which are widely used as model selection criteria. The AIC results for the unaltered model and the neutral category excluded model are 76,537.29 and 57,300.22, respectively. The BIC results for the unaltered model and the neutral category excluded model are 76,717.57 and 57,469.47, respectively. The AIC is dependent on an asymptotic approximation, and the BIC is dependent on the assumption that the model errors are normally distributed and independent. Generally, the BIC is more effective in selecting a correct model, and the AIC is appropriate for finding the best model for predicting future observations. Lower values of both AIC and BIC indicate a better model fit, and our results indicate that the model that excludes the neutral category is the preferred model, demonstrating superior predictive and explanatory power.

Table 7. Comparison of average marginal effects on subjective personal financial ability—unaltered dependent variable.

	1	2	3	4	5	6	7
	Estimate (Std. Err.)	**Estimate (Std. Err.)**	**Estimate (Std. Err.)**	**Estimate (Std. Err.)**	**Estimate (Std. Err.)**	**Estimate (Std. Err.)**	**Estimate (Std. Err.)**
Gender	−0.0012 (0.0009)	−0.0005 (0.0004)	−0.0009 (0.0006)	−0.0024 (0.0017)	−0.0014 (0.001)	−0.0006 (0.0004)	0.0071 (0.005)
Race	−0.004 *** (0.001)	−0.0017 *** (0.0004)	−0.0028 *** (0.0007)	−0.0077 *** (0.002)	−0.0046 *** (0.0012)	−0.0019 *** (0.0005)	0.0226 *** (0.0057)
Education	−0.0076 *** (0.001)	−0.0032 *** (0.0004)	−0.0054 *** (0.0007)	−0.0148 *** (0.0019)	−0.0087 *** (0.0011)	−0.0036 *** (0.0005)	0.0432 *** (0.0056)
Marriage	0.0011 (0.001)	0.0005 (0.0004)	0.0008 (0.0007)	0.0022 (0.0019)	0.0013 (0.0011)	0.0005 (0.0005)	−0.0065 (0.0056)
Age (18–24 as reference)							
25–34	−0.0097 *** (0.0026)	−0.0037 *** (0.001)	−0.0059 *** (0.0016)	−0.0135 *** (0.0035)	−0.0053 *** (0.0013)	0.003 ** (0.0009)	0.0352 *** (0.0091)
35–44	−0.0133 *** (0.0026)	−0.0052 *** (0.001)	−0.0082 *** (0.0016)	−0.0193 *** (0.0036)	−0.0078 *** (0.0014)	0.0037 *** (0.0009)	0.0503 *** (0.0093)
45–54	−0.0236 *** (0.0025)	−0.0097 *** (0.001)	−0.0156 *** (0.0016)	−0.0385 *** (0.0037)	−0.0176 *** (0.0016)	0.0032 *** (0.0009)	0.1017 *** (0.0095)
55–64	−0.0384 *** (0.0024)	−0.0169 *** (0.0012)	−0.0285 *** (0.0017)	−0.0774 *** (0.0037)	−0.0433 *** (0.002)	−0.0107 *** (0.0015)	0.2152 *** (0.0098)
65+	−0.0458 *** (0.0025)	−0.0212 *** (0.0013)	−0.0368 *** (0.0018)	−0.1075 *** (0.0037)	−0.0688 *** (0.0023)	−0.0361 *** (0.0021)	0.3162 *** (0.0097)
Income (< $15,000 as reference)							
$15,000 ≤ Income < $25,000	−0.0133 *** (0.003)	−0.0049 *** (0.0011)	−0.0075 *** (0.0017)	−0.0166 *** (0.0037)	−0.0059 *** (0.0013)	0.0046 *** (0.0011)	0.0436 *** (0.0097)
$25,000 ≤ Income < $35,000	−0.0227 *** (0.0028)	−0.0087 *** (0.0011)	−0.0136 *** (0.0017)	−0.0313 *** (0.0038)	−0.0125 *** (0.0015)	0.0059 *** (0.001)	0.0829 *** (0.0099)
$35,000 ≤ Income < $50,000	−0.0327 *** (0.0027)	−0.0131 *** (0.0011)	−0.0209 *** (0.0016)	−0.0508 *** (0.0036)	−0.0229 *** (0.0017)	0.0041 *** (0.0012)	0.1363 *** (0.0095)
$50,000 ≤ Income < $75,000	−0.0362 *** (0.0026)	−0.0147 *** (0.0011)	−0.0237 *** (0.0016)	−0.0589 *** (0.0036)	−0.0279 *** (0.0016)	0.0021 (0.0012)	0.1593 *** (0.0092)
$75,000 ≤ Income < $100,000	−0.0445 *** (0.0027)	−0.0189 *** (0.0013)	−0.0313 *** (0.0018)	−0.0824 *** (0.0039)	−0.044 *** (0.0021)	−0.0082 *** (0.0017)	0.2294 *** (0.0104)
$100,000 ≤ Income < $150,000	−0.0456 *** (0.0027)	−0.0195 *** (0.0013)	−0.0323 *** (0.0018)	−0.0858 *** (0.0041)	−0.0466 *** (0.0023)	−0.0103 *** (0.0018)	0.2401 *** (0.011)
Income ≥ $150,000	−0.0505 *** (0.0028)	−0.0223 *** (0.0014)	−0.0377 *** (0.002)	−0.1047 *** (0.0046)	−0.0622 *** (0.0032)	−0.0251 *** (0.0031)	0.3025 *** (0.0135)

Age 18–24 and Income < $15,000 serve as the reference categories to which their other respective categories are compared. Data collected from the 2018 National Financial Capability Study State-by-State Survey—Tracking Dataset are utilized. Significance is defined as follows: ** significant at $p < 0.01$; *** significant at $p < 0.001$. n = 26,757.

Table 8. Akaike's information criterion and Bayesian information criterion across subjective financial ability models.

	N	11(Null)	ll(Model)	df	AIC	BIC
Unaltered DV	26,757	−40,088.87	−38,246.65	22	76,537.29	76,717.57
Neutral Category Excluded DV	23,386	−29,956.46	29,629.11	21	57,300.22	57,469.47

Age 18–24 and Income < $15,000 serve as the reference categories to which their other respective categories are compared. Data collected from the 2018 National Financial Capability Study State-by-State Survey—Tracking Dataset are utilized.

4. Conclusions

Likert scale dependent variables are ubiquitous in the personal finance and financial planning research literature. However, an issue arises due to the so-called neutral category bias, a challenge that may compromise the accuracy of statistical analyses and subsequent interpretations. By applying the methodology from Tutz (2021), we illustrate a relatively simple but effective technique for correcting for this bias by running separate models, one where the neutral category is recategorized into a standard probit model and one where the dependent variable is recoded to exclude the neutral category. It is important to determine whether neutral category bias exists, as using the incorrect model formulation can result in biased parameter estimates and incorrect inferences.

The findings of our study emphasize that neglecting the "neutral" category in Likert scale analyses can result in distorted parameter estimates and inaccurate conclusions. The dual-model approach, incorporating both recategorization of the neutral category and exclusion of the neutral category, proved to be an effective strategy for dealing with the issues associated with Likert scale variables. Moreover, the presented framework is flexible, allowing for the inclusion of various covariates and nonlinear effects. It can also be extended to handle more complex data structures, such as multi-dimensional scales or longitudinal data. Our results highlight the importance of refining statistical modeling techniques when working with personal finance research data to enhance the reliability and accuracy of outcomes.

The implications of our study extend across various disciplines that heavily rely on Likert scales to capture personal finance attitudes and preferences. The correction of neutral category bias is essential for improving the robustness of statistical analyses in fields such as marketing, finance, public policy, and healthcare. The study calls for a re-evaluation of conventional approaches to analyzing Likert-type data, urging researchers and practitioners to adopt more sophisticated techniques that account for the nuances introduced by the presence of a neutral category.

Furthermore, our findings have implications for the broader research community, emphasizing the importance of methodological advancements in addressing specific challenges associated with discrete dependent variables. As Likert scales are pervasive in personal finance research, adopting appropriate modeling techniques will contribute to more accurate and reliable insights into personal financial behaviors. Last, while our study offers a promising solution to the neutral category problem in personal finance research, researchers should be mindful of the limitations and carefully consider the appropriateness of the approach in the context of their specific study. Further research and validation across diverse datasets and domains are necessary to strengthen the generalizability and applicability of the proposed methodology.

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