

# Factors Shaping Financial Well-Being: Examining Demographics, Psychological Elements, and Financial Knowledge\*

Psychological Distress and Financial Health: Measuring the Relationship

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This paper examines factors affecting financial well-being using the Consumer Financial Protection Bureau's National Financial Well-Being Survey. Through regression analysis of over 6,000 respondents, we found that psychological distress showed the strongest negative connection to financial well-being, with highly stressed individuals scoring 16.5 points lower on the financial well-being scale. People with higher income and those in older age groups reported better financial outcomes, while education demonstrated small positive effects. These results indicate that financial education programs would benefit from including mental health support, especially for people facing financial challenges.

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\*Code and data are available at: [https://github.com/xgao28/financial\\_well\\_being\\_analysis](https://github.com/xgao28/financial_well_being_analysis).

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## 1 Introduction

Financial well-being forms a core objective for individuals and households navigating modern economic conditions. The concept encompasses meeting present and future financial obligations, influenced by financial literacy, demographics, and psychological factors. Understanding these relationships informs policy design and programs to enhance financial outcomes across populations.

The Consumer Financial Protection Bureau (CFPB) created the Financial Well-Being Scale (FWBscore), a 10-item questionnaire measuring four components: control over daily finances, ability to handle financial emergencies, progress on financial objectives, and freedom to make life choices. Researchers have developed several tools to evaluate financial knowledge. The Lusardi and Mitchell financial knowledge scale (LMscore) by Lusardi and Mitchell (2008) uses three items to measure basic financial concepts. The Knoll and Houts financial knowledge

scale (KHscore) by Knoll and Houts (2012) employs a 10-item assessment based on item response theory. The CFPB Financial Skill Scale (FSscore) by Bureau (2015) measures practical financial abilities using IRT methods.

Research has studied how financial literacy affects economic outcomes. However, questions remain about how demographics and psychological factors combine with financial knowledge to shape financial well-being. Understanding these relationships could better explain differences in financial outcomes across population groups.

Our study examines how changes in demographic and psychological characteristics relate to financial well-being scores, while controlling for other variables. This analysis identifies which factors most strongly influence financial well-being, helping guide policy decisions.

The results show psychological distress has the strongest negative link to financial well-being (-16.5 points). Higher income (\$150,000+) shows the largest positive relationship (+12.6 points). Age over 75 years and excellent health status also predict better outcomes (+9.4 and +7.7 points respectively). Financial knowledge measures show smaller effects than these psychological and demographic factors, suggesting new approaches to financial education may be needed.

The paper continues as follows: Section 2 describes our data and methods. Section 3 explains our modeling approach. Section 4 presents our findings. Section 5 examines implications and concludes. Section 6.1 details survey methods and Section 6.2 lists acknowledgements.

## 2 Data

### 2.1 Overview of the Dataset

The National Financial Well-Being Survey Public Use File (PUF) by Consumer Financial Protection Bureau (2017) provides the data for this study. The dataset contains 217 variables measuring financial, demographic, and psychological factors from a representative U.S. population sample. It records financial knowledge, skills, behaviors, and well-being.

GfK KnowledgePanel collected the survey data using an online probability-based panel representing U.S. adults. The panel forms through random household selection and invitation. GfK provides computers and internet service to households lacking access, ensuring representation across U.S. demographic groups. The dataset includes contextual variables like county-level poverty rates, providing environmental context for financial well-being assessments. While other datasets like the Survey of Consumer Finances and Panel Study of Income Dynamics contain financial information, they lack the standardized FWBscore measure, making this CFPB dataset particularly suitable.

## **2.2 Variables of Interest**

### **2.2.1 Primary Outcome Variable**

Financial Well-Being Score (FWBscore): This 10-item CFPB scale measures four areas: control over day-to-day finances, capacity to handle financial emergencies, progress toward financial goals, and freedom of financial choices. Scores range from 0 to 100, with higher scores showing better financial well-being.

### **2.2.2 Independent Variables**

The data comes from self-reported questionnaire responses:

Age (agecat): Groups include 18–24, 25–34, 35–44, 45–54, 55–64, and 65+.

Education (PPEDUC): Categories range from less than high school to graduate degrees.

Household Income (PPINCIMP): Groups span from <\$20,000 to higher brackets like \$20,000–\$39,999 and \$40,000–\$59,999.

Marital Status (PPMARIT): Includes single, married, divorced, widowed, and other.

Health (HEALTH): Self-reported rating from 1 (Poor) to 5 (Excellent).

Stress (DISTRESS): Self-reported rating from 1 (Not at all) to 5 (Extremely).

Using categories for continuous variables like age and income helps interpret results across demographic groups, enables statistical group comparisons, and matches policy planning needs. This grouping also protects respondent privacy while maintaining analytical detail. The standard categories allow comparison with other demographic research.

### **2.2.3 Additional Variables**

Lusardi and Mitchell Financial Knowledge Scale Score (LMscore): Three items measuring financial literacy in planning and decision-making.

Knoll and Houts Financial Knowledge Scale Score (KHscore): Ten items using IRT methods to assess financial knowledge.

Financial Skill Scale Score (FSscore): CFPB-developed IRT measure of practical financial skills including budgeting, debt management, and saving.

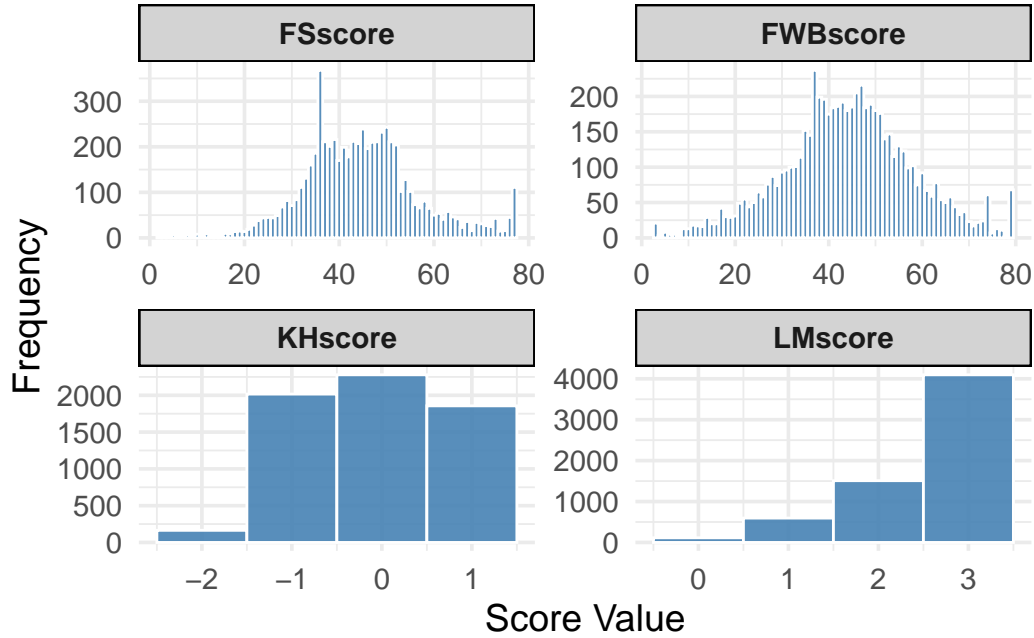


Figure 1: Histograms of Financial Scores

## 2.3 Variable Summary

Figure 1 displays distributions of four financial measures: FScore, FWBScore, KHscore, and LMScore. The FScore and FWBScore follow roughly bell-shaped patterns. FScore spans 0-80, peaking between 40-50, while FWBScore shows a more balanced distribution centered at 45-50. KHscore plots across four points (-2 to 1), with the highest frequency at 0 and similar frequencies at -1 and 1. LMScore ranges from 0 to 3, with most responses concentrated at 3. These patterns indicate that financial well-being and financial situations distribute evenly through the population, while most respondents score high on basic financial literacy.

Figure 2 presents a correlation matrix heatmap comparing FWBScore, FScore, LMScore, and KHscore. LMScore and KHscore show the strongest relationship (0.6), followed by FWBScore and FScore (0.49). FWBScore pairs with LMScore (0.23) and KHscore (0.33), showing smaller positive relationships. FScore has the smallest relationships with LMScore (0.11) and KHscore (0.19). The positive values indicate that scores tend to move in the same direction. Each measure's correlation with itself equals 1.0 on the diagonal.

Figure 3 presents the demographic patterns of survey participants. Age groups 25-34, 45-54, and 62-69 have the highest numbers of respondents, while age groups 18-24 and 70-74 show lower participation. In education, "Some college/Associate" and "High school degree/GED" form the largest groups, with "Less than high school" having the smallest representation. Income groups distribute evenly, with a slight peak in the \$100,000-\$149,999 range. Married respondents make up the largest portion of marital status categories. For health status, most

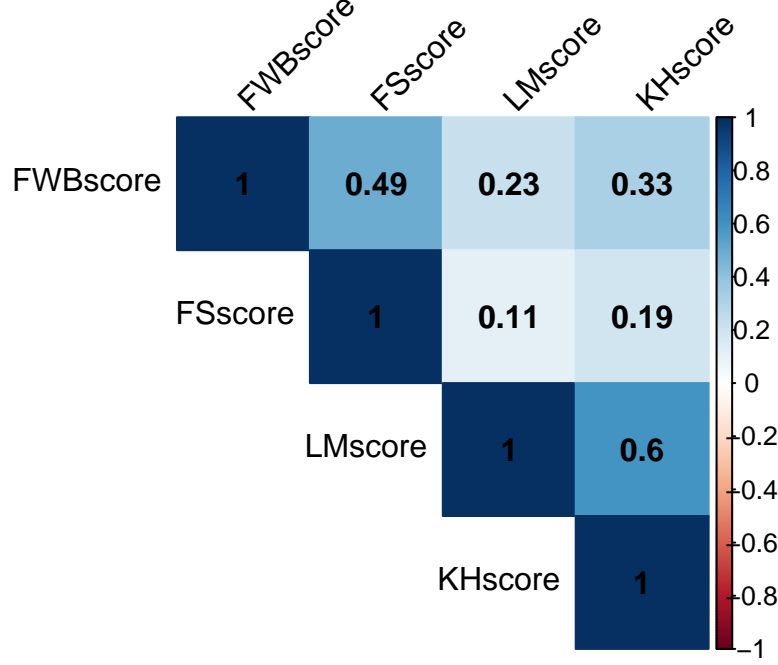


Figure 2: Correlation Plot of Continuous Financial Measures

people report “Very good” or “Good” health, with few selecting “Poor.” Psychological distress responses center between “Neither agree nor disagree” and “Agree,” tapering at both ends.

### 3 Model

We use two regression models to study financial well-being: one examining demographic and psychological factors, and another focusing on financial knowledge and skills.

#### 3.1 Primary Model

The primary model takes this form:

$$\text{FWB}_i = \beta_0 + \beta_1 \text{Age}_i + \beta_2 \text{Education}_i + \beta_3 \text{Income}_i + \beta_4 \text{Marital}_i + \beta_5 \text{Health}_i + \beta_6 \text{Distress}_i + \epsilon_i$$

where  $\epsilon_i \sim \mathcal{N}(0, \sigma^2)$

The variables represent: -  $\text{FWB}_i$ : Financial Well-Being score for individual  $i$  - Age: Categories with 18-24 as baseline - Education: Levels starting at “Less than high school” as baseline - Income: Categories beginning with “Less than \$20,000” as baseline - Marital status: Using “Married” as baseline - Health status: From “Poor” (baseline) to “Excellent” - Psychological distress: From “Strongly disagree” (baseline) to “Strongly agree”

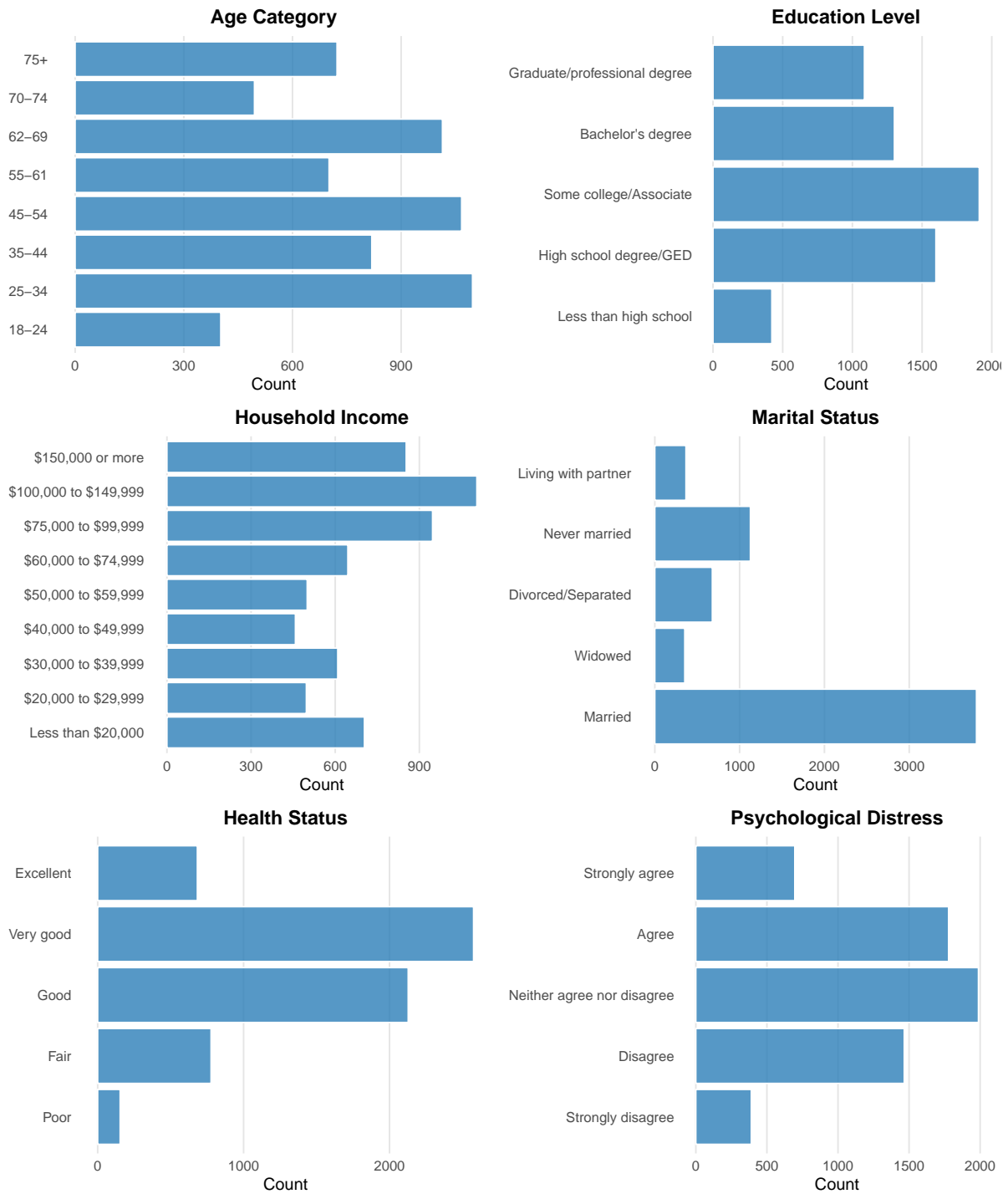


Figure 3: Bar Plots of Categorical Variables

### 3.2 Supplementary Model

This model examines how financial literacy relates to well-being:

$$\text{FWB}_i = \beta_0 + \beta_1 \text{LMscore}_i + \beta_2 \text{KHscore}_i + \beta_3 \text{FSscore}_i + \epsilon_i$$

where each score represents a standardized measure of financial knowledge and skills.

### 3.3 Model Diagnostics

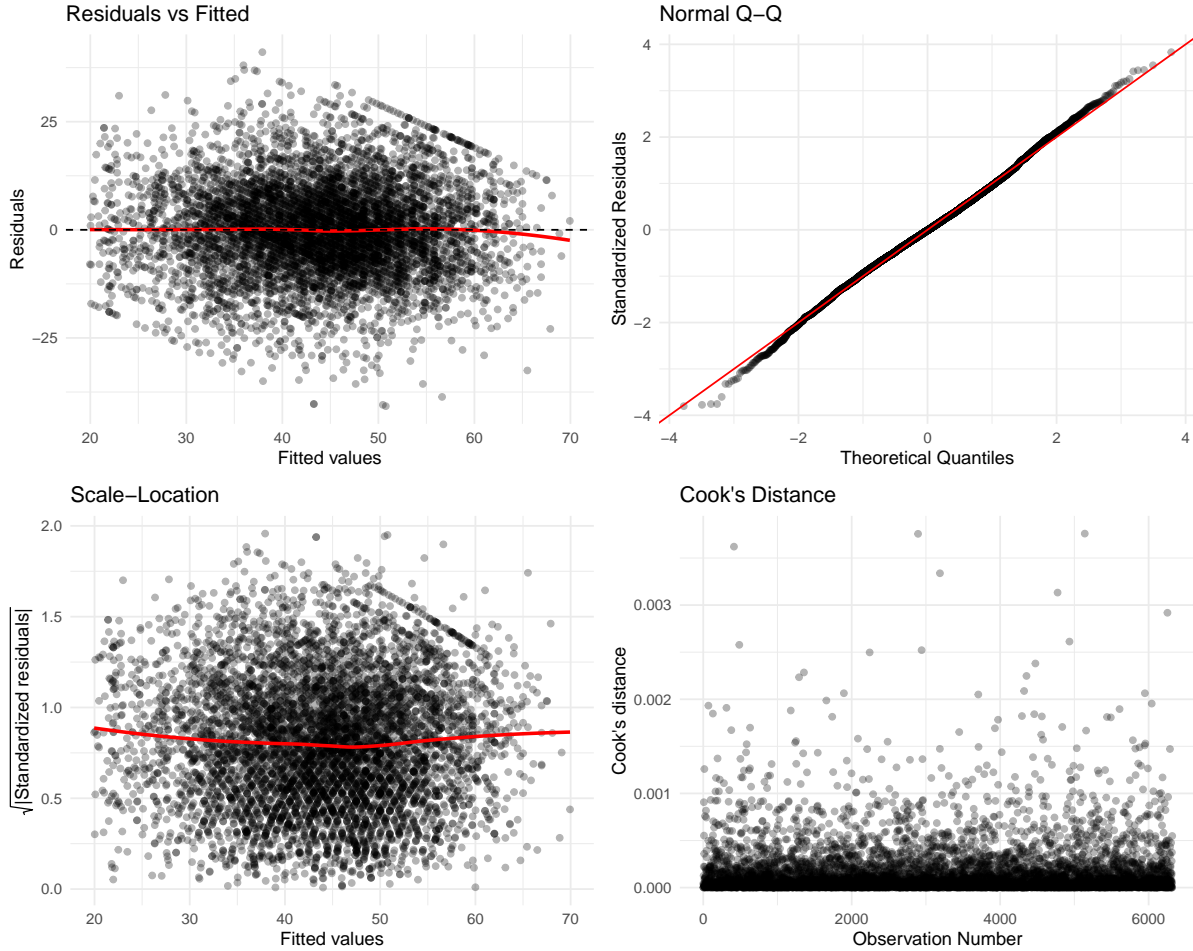


Figure 4: Model Diagnostic Plots

The model checks in Figure 4 support our statistical assumptions. The residual plots show consistent error variance and maintain linear patterns. The Q-Q plot confirms mostly normal residuals, with slight tail variations. The Cook's distance measurements indicate no single observation unduly affects our results.



## 4 Results

Table 1: Linear Model Output with Significant Variable and Levels

Variable	Value	estimate	std.error	statistic	p.value
Intercept	See footnote	38.334	1.348	28.436	0.000
agecat	55-61	1.764	0.753	2.343	0.019
agecat	62-69	6.354	0.732	8.675	0.000
agecat	70-74	7.509	0.823	9.122	0.000
agecat	75+	9.366	0.795	11.778	0.000
PPEDUC	Bachelor's degree	1.940	0.665	2.919	0.004
PPEDUC	Graduate/professional degree	2.921	0.692	4.224	0.000
PPINCIMP	\$30,000 to \$39,999	1.770	0.612	2.891	0.004
PPINCIMP	\$40,000 to \$49,999	3.779	0.669	5.652	0.000
PPINCIMP	\$50,000 to \$59,999	5.311	0.661	8.039	0.000
PPINCIMP	\$60,000 to \$74,999	6.166	0.626	9.852	0.000
PPINCIMP	\$75,000 to \$99,999	7.590	0.592	12.825	0.000
PPINCIMP	\$100,000 to \$149,999	9.163	0.594	15.419	0.000
PPINCIMP	\$150,000 or more	12.597	0.645	19.543	0.000
PPMARIT	Widowed	-1.313	0.641	-2.049	0.040
PPMARIT	Divorced/Separated	-1.905	0.464	-4.103	0.000
PPMARIT	Never married	-0.949	0.436	-2.179	0.029
PPMARIT	Living with partner	-1.842	0.624	-2.951	0.003
HEALTH	Good	3.372	0.924	3.648	0.000
HEALTH	Very good	5.635	0.932	6.049	0.000
HEALTH	Excellent	7.701	1.002	7.689	0.000
DISTRESS	Disagree	-3.845	0.620	-6.201	0.000
DISTRESS	Neither agree nor disagree	-7.674	0.608	-12.623	0.000
DISTRESS	Agree	-11.204	0.624	-17.949	0.000
DISTRESS	Strongly agree	-16.518	0.714	-23.142	0.000

Table 2: Summary of Supplementary Model

	estimate	std.error	statistic	p.value
(Intercept)	19.6183467	0.844	23.248	0
LMscore	0.8737951	0.248	3.527	0
KHscore	3.7484740	0.230	16.300	0
FSscore	0.5005944	0.012	41.524	0

Our analysis identifies clear patterns in financial well-being factors. Table 1 presents the primary model results.

## 4.1 Age Effects

Older adults report higher financial well-being compared to those aged 18-24. People aged 75+ score 9.37 points higher, followed by ages 70-74 (+7.51 points) and 62-69 (+6.35 points). Financial well-being improves with age, perhaps due to accumulated resources and experience.

## 4.2 Income and Education

Income shows the strongest positive link to financial well-being. People earning \$150,000+ score 12.60 points higher than those earning under \$20,000, with steady increases across income levels. Education also relates positively: graduate degree holders score 2.92 points higher than those without high school completion.

## 4.3 Health and Psychological Distress

Better health connects to higher financial well-being, while psychological distress shows the strongest negative relationship. People with excellent health score 7.70 points higher than those with poor health. High psychological distress relates to a 16.52-point decrease in financial well-being.

## 4.4 Financial Knowledge and Skills

Our supplementary model in Table 2 shows varying effects based on different measurement scales:

FSscore shows a positive relationship ( $\beta = 0.501$ ), measured on a normal distribution across the population.

KHscore has a larger coefficient ( $\beta = 3.748$ ), measured across four categories (-2 to 1).

LMscore shows a moderate effect ( $\beta = 0.874$ ), with most people scoring the maximum value of 3.

These measurements each relate positively to financial well-being, but their different scales affect interpretation. FScore provides the clearest measurement given its normal distribution. The effects of KHscore and LMscore need consideration alongside their measurement patterns. Better financial knowledge measures might help future studies capture population differences more precisely.

## **5 Discussion**

### **5.1 Overview**

This paper examines how psychological elements, especially mental distress, work with socioeconomic factors to shape financial well-being. Our analysis of the CFPB's National Financial Well-Being Survey shows that psychological distress affects financial well-being more strongly than income, education, or financial knowledge. This finding suggests we should broaden our approach beyond financial education alone.

### **5.2 Main Findings About Financial Well-Being**

#### **5.2.1 Psychological Factors' Role**

Psychological distress strongly influences financial well-being. Each point increase in psychological distress links to a 4.89-point decrease in financial well-being—three times the effect of one year of education. Mental health support might matter as much as financial education for improving financial outcomes.

#### **5.2.2 Financial Knowledge's Effect**

Financial knowledge shows smaller effects on financial well-being than psychological and demographic factors. While financial knowledge helps, it alone may not ensure financial well-being, especially when people face psychological challenges.

### **5.3 Study Limits**

Our study has several constraints. The data captures one point in time, so we cannot determine cause and effect. The connection between psychological distress and financial well-being likely works both ways—financial problems may increase distress, while distress may affect financial decisions.

Self-reported data on psychological distress and financial well-being may contain biases. People with financial difficulties might report more psychological distress.

While our sample represents the nation broadly, it might miss some groups' experiences, such as people without bank accounts or internet access.

## 5.4 Policy Suggestions and Next Steps

These findings point to several recommendations:

1. Financial wellness programs should include mental health components or screening.
2. Financial education initiatives should expand beyond teaching money concepts to include stress management skills.
3. Financial professionals should learn to recognize mental distress signs and connect people with mental health resources.

Future research should: - Track people over time to understand how psychological distress affects financial outcomes - Test programs that combine financial education with mental health support - Study how psychological distress affects different groups' financial well-being

In summary, improving financial well-being requires attention to both financial knowledge and psychological health. We should develop approaches that address financial and psychological aspects of money management.

## 6 Appendix

### 6.1 Survey Methodology

The CFPB Financial Well-Being Scale methodology warrants examination in three areas: sampling design, measurement validation, and methods.

#### 6.1.1 Sampling Framework and Implementation

The survey collected data through multiple rounds using a national survey provider. The first round tested 46 potential items with 4,500 respondents, split between ages 18-61 and 62+. This sample matched U.S. Census demographics for working-age and older adults, though it did not aim for full national representation. The survey included both self-administered and interviewer-administered formats to test how different groups responded to the questions.

The sampling had some limits. It may not fully represent people who move frequently or are hard to reach. The removal of 500 paper surveys due to data quality concerns shows differences between collection methods that might affect how widely the findings apply.

### 6.1.2 Measurement Development and Validation

The Financial Well-Being Scale development used item response theory (IRT), refining many initial items to create the final set. Analysis by Vector Psychometric Group supported using a bi-factor model that measures overall financial well-being while accounting for how questions were worded.

The scale showed strong internal consistency with 0.89 reliability, and the short version maintained 0.80 reliability. However, the study did not measure how stable scores remained over time. The small group of 19 people in cognitive interviews may not capture enough diverse perspectives.

Testing across demographic groups and survey types showed consistent scores in different settings. The scale distinguished between groups as expected and aligned with objective financial measures. However, limited testing with other datasets restricts how broadly we can apply these results.

### 6.1.3 Methods: Strengths and Limits

Using different survey formats helped assess how response methods affect results. Quality checks monitored attention and completion time, though the specific standards used remain unclear.

Key limitations:

1. Some groups may be underrepresented despite address-based sampling
2. Self-reported financial data may contain bias
3. We cannot tell if financial well-being scores stay stable over time

While response rates exceeded typical online surveys, we need more analysis of who did not respond. Multiple contact attempts and payments encouraged participation, but questions about response patterns remain.

The methods balance practical needs with survey design standards, following current research practices while noting common limitations in financial studies.

## 6.2 Acknowledgements

We would like to express our gratitude to the developers and contributors of R (R Core Team 2023) as well as several R packages that were essential for the analysis and visualization of the data in this report. The following R packages provided indispensable tools and functionalities:

- **tidyverse** (Wickham et al. 2019): A collection of R packages designed for data science, including `dplyr`, `ggplot2`, `readr`, `purrr`, and others, which greatly facilitated data manipulation, analysis, and visualization.
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