Is There a Tipping Point: Objective and Subjective Measures of Debt and Retirees' Wellbeing

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ABSTRACT: We examine the relationship between objective financial positions and subjective experiences of over-indebtedness in later life, using data from the Health and Retirement Study. We employ nonparametric and probit analyses, followed by Fairlie decomposition and calibration using Youden's J statistic to identify differences in debt sentiments and debt experiences across groups. Contrary to expectations, we find that older individuals report significantly less debt distress and greater tolerance for higher debt-to-assets than younger adults. By estimating group-specific tipping points in debt-to-asset ratios, we provide new insights into when debt becomes genuinely burdensome.

(91 words)

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*The opinions expressed here are the authors' and do not necessarily reflect the views of the Investment Company Institute, its staff or members.

1.0 Introduction

Many have considered the topics of debt and debt burdens. Debt supports many productive undertakings, such as buying a home (a home mortgage), durables (e.g., car loans), the smoothing of consumption (credit card debt), education (student loans), and medical care (medical debt).

Debt comes with costs—both explicit and implicit (emotional stress). Zinman (2014) aims to judge whether consumer credit markets tend to produce too much or too little debt and concludes that the answer is unclear. We approach this question from the perspective of the household as borrowers, examining how individuals experience the debt they hold. Specifically, we investigate whether there are amounts of debt at which individuals feel that they have "too much debt."

Many researchers have documented the rising incidence and level of debt among older US households, often using data from the Federal Reserve Board's Survey of Consumer Finances (SCF).[1] These data show that debt incidence among households aged 65 to 74 rose from 50% in 1989 to 65% in 2022, and median debt amounts rose from $11,530 to $45,000 (2022 dollars).[2] Over this same time period, incidence and amounts of debt for households aged 75 or older rose more dramatically.[3]

[1] For example, see Chiang and Dueholm (2024); Chen et al. (2023); US Government Accountability Office (2021); and Yilmazer and DeVaney (2005). Additionally, these trends can be explored using the Interactive Chartbook at US Federal Reserve Board (2025).

[2] See "Debt" by household age at US Federal Reserve Board (2025). For discussion of the 2022 SCF, see Aladangady (2023).

[3] Debt incidence among households aged 75 or older rose from 21% in 1989 to 53% in 2022, as median debt amounts rose from $6,800 to $36,000 (2022 dollars). The increases were much more subdued across all US households. See US Federal Reserve Board (2025).

Roughly 20 years ago, Yilmazer and DeVaney (2005) concluded that "although the popular press has speculated that older households accumulate excessive amounts of mortgage debt and credit card balances, our results do not support this claim." This is consistent with the idea that debt levels below some threshold may not be harmful and may be preferred to reductions in consumption or sales of assets when interest rates are low. Since then, Pottow 2012 and Zhong 2025 have noted rising debt payment delinquency rates among older populations. Chen et al. (2023) document rising incidence and amounts of debt among older households and use a variety of debt measures to identify higher-risk households, noting heterogeneity even within that group.

Turning to economic theory, buffer-stock and lifecycle models suggest households work to smooth consumption.[4] As a result, younger households will borrow, in middle-age debts are paid down, and thus, older households consume out of assets and their returns, once retired. Adding transitory shocks to income and consumption further explains intertemporal smoothing over shorter time frames.[5] Adding income uncertainty, bankruptcy, illiquidity, and present bias to a lifecycle model, results in a prediction of greater and longer-lived unsecured debt.[6] More recent work finds smoothing and credit constraints impact different segments of the population differently, revealing a "model of mental accounting."[7] Finally, Fulford and Low (2024) find that while people over age 61 are less likely to experience an expense shock, when they do, it tends to be large. They conclude that "the precautionary motive in retirement may be even more important than typically modeled." All of this work is helpful for understanding why some

[4] See Ando and Modigliani (1963), Carroll (1997), Deaton (1991), and Gourinchas and Parker (2002).

[5] See Friedman (1957).

[6] See Laibson et al. (2000).

[7] See Baugh et al. (2021).

households reach retirement with debt balances despite holding substantial assets. None of the various iterations of lifecycle models provides estimates of the amount of debt any given household will have at any point in time or a metric by which to evaluate whether households have excessive debt.

2.0 Data

To analyze why individuals feel they have "too much debt," we turn to data from the Health and Retirement Study (HRS).[8] Specifically, we combine the RAND Longitudinal Data file (V2 2020),[9] DC pension balances from several RAND Fat Files, and HRS 2018 Module 2: Understanding Debt.[10] The debt module surveyed 1,336 respondents spanning AHEAD through Late Baby Boomers cohorts.[11] Our analysis focuses on the 2018 cross-section respondents who answered the debt module questions.[12]

2.1 Dependent variables

[8] The HRS (Health and Retirement Study) is sponsored by the National Institute on Aging (grant number NIA U01AG009740) and is conducted by the University of Michigan. Our work with these data builds on efforts described in Holden and Seligman (2023), and Holden and Seligman (2025).

[9] The RAND HRS Longitudinal File is an easy-to-use panel dataset based on the HRS core data. The RAND HRS Fat Files take almost all the raw variables from the HRS survey and collapse them into a single respondent-level dataset for each wave. These files were developed at RAND with funding from the National Institute on Aging and the Social Security Administration.

[10] The survey questionnaire used for collecting these data can be found here: https://hrs.isr.umich.edu/sites/default/files/meta/2018/core/qnaire/online/Module2_2018B-A.pdf.

[11] For more on HRS birth cohorts, see Bugliari et al. (2024), or the reference chart "Longitudinal Cohort Sample Design," available at https://hrs.isr.umich.edu/documentation/survey-design.

[12] Although we focus on the 2018 cross-section, we incorporate variables from earlier waves where appropriate to construct stable measures and address missing data for those respondents in 2018.

Our dependent variable derives from the debt module question: "How strongly do you agree or disagree with the following statement? I have too much debt right now. Do you strongly disagree, disagree, neither agree nor disagree, agree, or strongly agree?" We report this as an ordinal variable, {1, .., 5} following response options above, but also code this to be a binary {0,1} variable, based on whether the respondents {agree/strongly agree, versus other responses}. The main focus of our analysis is on the binary variable.

2.2 Independent variables

We select independent variables theoretically motivated as contributors to financial stress, organized across the categories below.

Demographic and socioeconomic characteristics

We include standard demographic controls that prior research has linked to financial vulnerability. Age and income[13] are both included to capture a household's point along the lifecycle path. Gender captures documented differences in lifetime earnings trajectories and financial decision-making patterns.[14] Race accounts for well-established disparities in wealth accumulation and credit access (Shapiro, 2014). Education serves as a proxy for lifetime income, following the human capital framework.[15] Widowhood and an interaction term for female widows indicate loss of household income and heightened financial vulnerability, particularly among older adults.

Health and retirement shocks

[13] We define income as including both the RAND Longitudinal measures for total household income, and records of IRA withdrawals over the prior two years, annualized. For details on this method see both Hurd et al. (2018) and Bugliari et al. (2024) at pages 1234 –1238.

[14] For example, Hanna et al. (2021) analyze gender patterns of respondents to the Survey of Consumer Finances and find, "death or divorce may leave the less informed partner in a bad situation." Their "research shows that the wife is much less likely to be the financially more knowledgeable spouse in households with high net worth" (at page 9).

[15] We follow the Lusardi, Mitchell, and Oggero (2020a) specification and control for education with four dummy variables (less than high school is the omitted variable in the probit): college graduate or higher, some college, high school graduate, or less than high school (see Table 1).

We include measures of health status and retirement shocks that can precipitate financial distress. Depression history captures mental health conditions that affect both financial management capacity and stress perception (Ryu and Fan, 2023). Poor health status reflects elevated medical expenses and reduced earning capacity (Smith, 1999). Involuntary retirement (sometimes related to health) indicates unexpected permanent income loss,[16] which prior research shows is associated with increased financial strain among exiting workers (Coile and Levine, 2011; Seligman, 2014; Holden and Seligman, 2025).[17]

Financial experiences, preferences, and planning

We include variables that capture individual differences in financial behavior and preferences. Risk tolerance (measured on a 1–10 scale) reflects willingness to carry debt and accept financial risk. Whether the respondent has ever tried to figure out how much to save for retirement provides focus on long-term goals. The 2018 Debt Module contains one financial literacy question, documenting whether the individual could correctly answer a compound interest question—this proxies for the ability to understand and manage debt obligations effectively. Financial planning horizons serve as a proxy for discount rates and intertemporal preferences, which influence borrowing decisions.

Debt characteristics

We include several variables that signal financial difficulties or describe individual debt profiles, including the household's debt in absolute and relative terms. Absolute debt levels capture the magnitude of obligations.[18] The debt-to-asset ratio provides a comprehensive measure of

[16] Here, we take advantage of the longitudinal design of the HRS, controlling for any record of involuntary retirement across every survey wave record, through 2018.

[17] Also considering events around retirement, Butrica and Karamcheva (2018), as well as, Lusardi et al. (2020b), consider the impact of debt when approaching retirement decisions.

[18] In this analysis, gross debt sums mortgages, other home loans, and other debt (credit card, medical debts, life insurance policy loans, auto loans, loans from relatives etc.). We are unable to unpack other debt, which we simply describe as "non-mortgage debt."

leverage.[19] The debt-to-income ratio serves as a proxy for debt service burden and payment capacity.[20]

Additionally, we construct ratios of types of debt to total debt, to test whether higher proportions of non-mortgage debt are more stressful, holding total debt constant. The non-mortgage debt share aims to capture differences in interest rates, amortization schedules, and debt service burdens.

We include three variables that could signal that the individual is having difficulty managing their debts. First, debts that were unexpected or greater than expected 10 years earlier,[21] are related to both (weak) planning and unexpected shocks.[22] Contact from debt collectors may indicate severe payment difficulties, triggering agreement that the respondent has too much debt. Finally, including self-reports of a bad credit score may further speak to an individual's concerns about their debt, ability to manage it, or constrained credit access and higher borrowing costs. In some cases, it may speak to pent up demand for credit (Fulford, 2015).

Table 1 describes the sample data employed in baseline probit[23] and subsequent analysis. We also present the characteristics of the full HRS sample weighted to the US population as of 2018 and our regression sample to see how our regression sample compares to the relevant population.[24] Focusing on our dependent variable, in our probit regression sample, 28% of respondents either strongly agree or agree that they have too much debt (Table 1).

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[19] In this analysis, assets sums the gross value of primary residence, second home, other real estate, transportation, businesses, IRAs, stock, checking/savings, CDs/T-bills, bonds, other assets, and DC balances from all current and prior jobs. The DC balance includes estimates described in Holden and Seligman (2025). We do not include the present value of Social Security, defined benefit (DB) pensions, or annuities, as we take these as being related to income streams.

[20] The HRS does not contain robust and consistent data on debt service, across all types of debts.

[21] The specific question is: "As of ten years ago, did you think you would have about the amount of debt that you have at this point in your life?" Our binary variable equals one if the respondent answered that they didn't think about future debt, or they thought they'd have less debt.

[22] For discussion of the variety of ways households manage expense shocks, see Lusardi et al. (2011) and Fulford and Low (2024).

[23] Appendix Table A.1 presents results from our baseline probit analysis.

[24] While the Full HRS contains many more observations than are in the 2018 Debt Module, the final regression sample represents roughly 7.7 million older Americans, when weighted.

<Table 1 here>

3. Methods and Results

3.1 Raw cross tabs/summary stats for feelings of over-indebtedness by groups

We start by documenting the prevalence of over-indebtedness across the full sample and within demographic groups. This descriptive approach provides a clear baseline for how debt strain is distributed across our sample. Observed group differences also serve as a benchmark for evaluating model performance: By comparing predicted outcomes from the regression to actual group-level outcomes, we can assess how well the model captures the underlying patterns in the data.

We observe that younger individuals, those with lower-household income, and those with higher relative and absolute debt levels are more likely to self-report over-indebtedness (Figure 1).[25] This alignment validates the quality of the self-reported sentiments—when people agree that they have "too much debt," they appear to be considering their income, assets, and debt levels.

<Figure 1 here>

While Figure 1 highlights large differences in feelings of over-indebtedness across groups, Table 2 reveals that these groups differ in many other ways too. For example, lower-income individuals don't just have less income; they also tend to have higher debt-to-asset ratios, more experience with mental depression, and worse credit scores. Table 2 allows us to consider how factors co-

[25] See Ryu and Fan (2023) who examine the association between financial worries and psychological distress among US adults and include a review of the literature on mental depression and financial worries. Their analysis finds that higher financial worries were significantly associated with higher psychological distress.

vary across the panels, which occurs in a variety of ways. For example, when the sample is grouped by income quintile (second panel), average gross debt rises across the income quintiles, as debt-to-assets falls, and the share reporting unexpected or greater-than-expected debt falls. In contrast, average debt-to-income is highest for the third and fourth income quintiles and lowest for the second income quintile. When the sample is grouped by debt-to-assets quintile (fourth panel), the third quintile has the highest average income.

Figure 1 illustrates patterns of debt sentiments and documents how well our probit model predicts the likelihood of reporting having "too much debt" by a variety of factors. Table 2 places covarying factors related to having "too much debt" in context. For example, reports of unexpected or greater-than-expected debt vary across quintiles across the panels (Table 2). This measure falls with age (first panel) and falls with income (second panel). It follows a hump-shaped pattern across debt quintiles, with the highest percentage of reports in the middle debt quintile (third panel); is relatively flat across the first two debt-to-assets quintiles, then rising in quintiles three, four, and five (fourth panel); and rises to essentially level out for the third, fourth, and fifth debt-to-income quintiles (fifth panel).

<Table 2 here>

3.2 Probit

To disentangle these relationships, we estimate a probit regression model for our binary dependent variable {agrees/strongly agrees = 1}. This model assesses how well household balance-sheet variables, subjective assessments, and demographic characteristics predict reported over-indebtedness, while controlling for each other and other regressors.

The specification is:

$$\Pr(Y_i = 1 | X_i) = \Phi(\alpha + X_i' \cdot \boldsymbol{\beta})$$

where Y_i is the observed binary indicator, X_i is a vector of covariates, Φ is the standard normal cumulative distribution function with $\varepsilon_i \sim N(0,1)$ a standard normal error term. Our primary specification includes Y_i and X_i outlined in Section 3.1 and summarized in Table 1.

Nonparametric analyses revealed non-linear relationships between several continuous variables and perceived over-indebtedness (our dependent variable)(e.g., see Table 1, Figure 1, and Table 2). To accommodate these non-linearities, we tested alternative specifications including squared terms and spline functions. We ultimately adopt a spline specification for continuous variables for two reasons. First, splines yielded the highest pseudo R-squared in our probit models, which undergird prediction of thresholds for debt sentiments. Second, splines offer a practical advantage for our threshold analysis: they allow identification of inflection points where the marginal effect of debt burden shifts. In contrast, quadratic specifications require solving for the roots of a quadratic equation, which can sometimes yield no real-number solution or solutions outside the economically meaningful range of the data.

We use a spline with a single knot at the 75th percentile of each of our continuous variables. This placement roughly captures a point where financial stress tends to accelerate—most households remain below this threshold, while those above this threshold often exhibit meaningfully different relationships between debt metrics and perceived burden. When compared with a linear or quadratic specification, this specification balances model flexibility with interpretability. With this empirical specification in hand, we estimate parameters $\hat{\alpha}$ and $\widehat{\boldsymbol{\beta}}$ in the equation above.

The key advantage of this multivariate prediction framework is twofold. First, it enables meaningful decomposition of group differences in over-indebtedness into components

attributable to differences in observable characteristics (e.g., younger households hold more debt) versus differences in how those characteristics relate to debt distress (e.g., younger households report more distress at similar debt levels). Second, it allows us to back out empirical tipping points in debt burden metrics—the thresholds at which increases in debt begin to substantially elevate the probability of feeling over-indebted—while holding other factors constant.

While our focus is not on the marginal effects of each covariate on feelings of over-indebtedness, we report raw probit coefficients to facilitate interpretation. We provide the full probit model output in Appendix Table A.1.

3.3 Average predicted probabilities by groups

In the next step of our analysis, we use the model to calculate the predicted probabilities for each individual within a given group and report the average of their predicted probabilities by group (Figure 1). Specifically, we calculate for each individual: "What likelihood of feeling one has "too much debt" does the model predict for the individual, using their actual data?" We then average those individual predications across the group to produce the "average predicted probability."

Figure 1 shows that group differences in predicted feelings of over-indebtedness remain largely intact—an indication that the model fits well. Put another way, given that the group differences of actual reports of feelings of over-indebtedness match the group differences of predicted feelings of over-indebtedness, the model is doing a good job of predicting feelings of over-indebtedness based on the included covariates.

However, even though the model explains the patterns by groups well, it does not tell us which variables are doing the explaining. To unpack this further, we turn to the next step of the analysis, a Fairlie decomposition, which quantifies how much of the observed group-level gap in over-indebtedness can be explained by differences in observable characteristics (i.e., group composition).

3.4 Fairlie decompositions

A Fairlie decomposition quantifies how much of the gap in a binary outcome—such as perceived over-indebtedness-between two groups, is due to differences in observable characteristics versus differences in how those characteristics relate to the outcome and other unobservable differences.[26] More specifically, after estimating our probit model, the method generates counterfactuals by substituting one of the two group's covariate distribution into the other's, holding estimated probit coefficients fixed. The portion of the gap explained by this substitution reflects effects specific to the group's characteristics (compositional effects); the remainder captures differences in coefficients or unobserved factors. A Fairlie decomposition hence allows us to assess whether group differences in the likelihood of feeling over-indebted stem from structural factors, i.e., differences in how characteristics relate to over-indebtedness, or from group-level differences in those characteristics themselves (e.g., lower-income individuals also tending to have higher debt burdens).

For ease of interpretation, we simplify the analysis by moving from quintile-based comparisons to binary groupings—comparing individuals above versus below the median (e.g., for income), or across natural binary categories (e.g., gender).

[26] See Fairlie (2005) for detail on the method and Schwiebert (2015) for a critique of the Fairlie decomposition method.

We report Fairlie decompositions for a wide range of binary comparisons in Table 3, focusing on several key groupings below: demographics (age, income, race, gender), health status (mental depression and self-assessed health), and debt characteristics (credit score, unexpected debt, debt-to-asset ratio).

Demographics

Younger respondents are 16 percentage points more likely to report feeling over-indebted than older respondents (Table 3). Most of this gap (81%) can be explained by observable differences in financial characteristics between the two groups. Younger individuals are more likely to have poorer credit scores, hold larger total debt balances, have been contacted by debt collectors, and carry a higher share of non-mortgage debt—all factors associated with higher predicted over-indebtedness. These differences suggest that the age gradient in debt distress largely reflects differences in financial position and credit experience rather than age itself.

Those with below-median income are 8 percentage points more likely to feel over-indebted than those with higher income, with 40% of this difference is explained by observed characteristics (Table 3). Lower-income households are more likely to report having unplanned debt, poorer credit scores, higher non-mortgage debt shares, and more debt-collection contact – all of which are strongly linked to higher predicted over-indebtedness. These findings point to income-related differences in both borrowing conditions and the capacity to manage debt obligations.

Non-white respondents are 17 percentage points more likely to report feeling over-indebted than white respondents (Table 3). The vast majority of this difference (76%) is explained by observable characteristics. Non-white individuals in the sample are more likely to have poorer credit scores, hold unplanned debt, have experienced debt-collection contact, be younger, and

have a higher share of non-mortgage debt. These factors, all positively associated with debt distress, account for most of the racial gap in perceived over-indebtedness. These findings suggest that racial disparities in perceived over-indebtedness primarily reflect differences in access to credit, financial stability, and demographic characteristics rather than race itself.

Women are 4 percentage points more likely to report feeling over-indebted than men, but less than one-third of this difference (31%) is explained by observed characteristics (Table 3). Female respondents tend to have lower incomes, higher non-mortgage debt shares, poorer health and credit outcomes, and a higher prevalence of experience with mental depression—all factors that are linked to marginally greater debt concern in the model. The relatively small, explained share suggests that identification might be challenging for our model. This suggests other factors might drive gender differences (though small).

Health

Individuals reporting fair-or-poor health are 12 percentage points more likely to feel over-indebted than those reporting better health (Table 3). Nearly three-quarters (73%) of this gap is explained by observable differences. Those in fair-or-poor health are estimated to be more likely to have lower credit scores and income, more debt-collection contact, a higher non-mortgage debt share, and some experience with mental depression—all factors linked to higher predicted over-indebtedness in the model.

Individuals who have experienced mental depression are 13 percentage points more likely to report feeling over-indebted compared to those who have not (Table 3). Nearly half (45%) of this difference is accounted for by differences in observed characteristics between the two groups. Specifically, individuals with some experience with mental depression are more likely to report

contact from debt collectors, to be in fair-or-poor health, to have lower credit scores, to hold a larger share of non-mortgage debt, and to be widowed. These characteristics are, on average, associated with a higher probability of reporting over-indebtedness and help explain almost half of the observed gap. This suggests that the link between experience with mental depression and debt distress operates partly through observable financial and demographic channels, though substantial unexplained differences remain.

Debt characteristics

Respondents above the median debt-to-asset ratio are 25 percentage points more likely to report over-indebtedness than those below (0.41 vs. 0.16) (Table 3). This is one of the most explained gaps given our specification: 84% is accounted for by observed differences. The key contributors are higher debt-to-income ratios (49%), larger non-mortgage debt shares (24%), worse credit scores (11%), more debt-collection contact (6%), and more unexpected debt (4%).

The debt-to-assets ratio stands out as a particularly powerful and comprehensive marker of financial fragility, capturing multiple dimensions of households' balance sheet risk linked to perceived over-indebtedness.

Individuals whose debt was unexpected or greater than expected are 22 percentage points more likely to feel over-indebted than those whose debt was expected (0.37 vs. 0.15) (Table 3). About 44% of this difference is explained by observed characteristics. The main contributors are a higher prevalence of poor credit scores (26%), more debt-collection contact (17%), widowhood (15%), higher debt balances (10%), and larger non-mortgage debt shares (10%). Unexpected borrowing thus aligns strongly with a broader profile of financial vulnerability.

Respondents with self-reported bad credit scores are 35 percentage points more likely to report feeling over-indebted than those with good credit scores (0.57 vs. 0.21) (Table 3). More than half (53%) of this gap is explained by observed characteristics. The largest contributions come from greater exposure to debt-collection contact (27%), higher non-mortgage debt share (26%), more unexpected debt (14%), lower income (9%), and worse health (8%). These factors account for much of the difference between credit score groups. Poor credit thus appears to be both a consequence and a signal of broader financial distress.

<Table 3 here>

3.5 Debt tipping points

In the final step of our analysis, we use our probit model to estimate tipping points—threshold values of key variables above which individuals are more likely to report feeling over-indebted.

The Fairlie results guide threshold identification by revealing which grouping variables best distinguish between those who feel over-indebted and those who do not. The debt-to-assets ratio emerges as the strongest marker on two criteria. First, economically, the debt-to-assets ratio captures household leverage and buffer capacity, so large jumps across its bins indicate that moving from low to high leverage materially changes expected sense of over-indebtedness. Second, this ratio produces a large spread in predicted over-indebtedness (Table 3). In a well-specified model, large, monotonic differences in predicted probabilities across bins of a single variable indicate strong discrimination power: put differently, the variable alone partitions the sample into groups with substantially different expected outcomes. Statistically, this reflects high between-group variance relative to within-group variance in predicted risk.

Third, 84% of the gap between high and low debt-to-assets groups is explained by observable balance sheet characteristics—primarily total debt levels, debt composition, and credit worthiness (Table 3). This suggests households with high debt-to-assets ratios likely feel over-indebted because they have riskier financial positions.

Together, these properties make debt-to-assets particularly valuable for threshold identification: it both discriminates between outcomes and encapsulates the core economic drivers of debt strain in a single, interpretable measure. And it varies across groups, triggering at different levels for different types of people.

We use our estimated probit model in order to tease out debt-to-assets tipping points. Specifically, consider the estimated model below:

$$\hat{p}_i = \Phi\left(\hat{\alpha} + \hat{\beta} D2AR_i + \hat{\gamma} Z_i\right)$$

where Z_i is the matrix of covariates for person i of all other variables except debt-to-assets, $D2AR_i$ is the debt-to-assets ratio for person i, and $\hat{\alpha}$, $\hat{\beta}$, and $\hat{\gamma}$ are estimated coefficients.

We next classify individuals as predicted to feel over-indebted if $\hat{p}_i > p^*$ for some threshold p^*.

We choose p^* using Youden's J statistic, which is the threshold probability p^* that maximizes sensitivity (true positive rate) + specificity (true negative rate) - 1. We choose Youden's J since it is a neutral approach that treats catching true positives (feeling over-indebted) and true negatives (not feeling over-indebted) equally (Youden, 1950).[27]

[27] Appendix Table A.2 provides sensitivity analysis across different p^*values. Appendix Table A.3 contains supporting confusion matrices.

Note that with a threshold $p^* = 0$, we would find all true positives, but many false negatives (1-specificity). Hence there is a trade-off: as p^* rises, we find more true positives at the expense of capturing more false negatives. The Youden's J statistic finds the optimal p^* in this trade-off and is equivalent to maximizing the vertical distance from the Receiver Operating Characteristic (ROC) curve to the 45 degree line.

Using our Youden's J statistical value of p^* we then find the $D2AR^*$ that solves the following:

$$D2AR^* = \frac{\Phi^{-1}(p^*) - \hat{\alpha} - \hat{\gamma}\bar{Z}}{\hat{\beta}}$$

Specifically, we multiply estimated coefficients $\hat{\gamma}$ by the sample mean of each corresponding covariate to find a sample-wide debt-to-assets ratio tipping point $D2AR^*$. The idea is that when debt-to-assets is greater than $D2AR^*$, the person is more likely to feel over-indebted (be classified as feeling over-indebted according to our model).

Additionally, we can calculate $D2AR_g^*$ for specific groups in the sample, by instead averaging all covariates for specific groups $\bar{Z}_g$. Using this method, we can interpret the calculated threshold as the point above which an individual in that group—holding all other covariates at their sample means[28]—is more likely to feel over-indebted.

[28] In other words, to interpret these thresholds, we are assuming that the person is otherwise average—as described by the covariate sample means.

Using the Youden's J index to select the classification threshold (p* = 0.267, which correctly identifies 76% of all reported instances of over-indebtedness), we estimate a debt-to-assets threshold of 0.21 for the full sample (Figure 2). This represents the point at which the likelihood of being correctly classified as feeling over-indebted rises, holding other factors at their means.

However, we find considerable heterogeneity across groups, revealing that debt tolerance varies systematically with individual characteristics and circumstances. These group-specific thresholds demonstrate that no single benchmark adequately captures when debt becomes burdensome.

Demographic differences

Age differences in debt tolerance are very pronounced (Figure 2) and as expected given the cross tabs of the raw data (Table 2). Older adults exhibit substantial debt tolerance, with an estimated debt-to-assets threshold of 0.56, whereas younger adults show essentially no capacity to hold debt at this classification threshold and evaluated at group means (Figure 2). When we apply more stringent classification criteria (a higher p^*), younger adults consistently tolerate significantly less leverage than their older counterparts, all else equal (Appendix Table A.2). Income follows a similar pattern as age, with lower-income individuals showing lower tolerance for debt than higher income (Figure 2). Gender also emerges as a strong predictor of debt tolerance. Women are likely to feel over-indebted at an estimated debt-to-assets ratio of 0.12, while men can tolerate ratios up to 0.33—nearly three times higher—holding all else equal.

Health

Individuals who report they have never experienced mental depression exhibit substantial debt tolerance, with an estimated debt-to-assets threshold of 0.34, whereas those who have ever

experienced mental depression show essentially no capacity to hold debt at this classification threshold and evaluated at group means (Figure 2).

Financial experiences

Individuals who correctly answer the compound interest financial literacy question tolerate an estimated debt-to-assets ratio of 0.26, compared with 0.18 for those who answer incorrectly (Figure 2).

Debt characteristics

The nature and quality of debt matter substantially. When the respondent reports unexpected or greater-than-expected debt, they tolerate significantly less leverage (Figure 2), reflecting the association between unexpected borrowing and financial distress. Credit quality similarly shows through as individuals with self-reported bad credit scores show essentially no tolerance to hold debt at this classification threshold and evaluated at group means, while those without credit problems can tolerate higher debt-to-assets ratios.

These findings underscore that over-indebtedness cannot be captured by a single debt-to-assets threshold applicable to all households. Debt tolerance depends critically on demographic characteristics, financial resources, and the circumstances surrounding borrowing. Factors such as bad credit scores or unexpected debt dramatically reduce the amount of leverage individuals can sustain without experiencing financial distress, even holding balance sheet positions constant.

<Figure 2 here>

4.0 Summary and Conclusions

Some have raised concern that debt incidence and debt levels have been rising over time across US households. Economic theory alone does not help us determine any single level that might cause concern for those holding debts at older ages. The literature has generally noted increases in levels of debt among older Americans, but while some have expressed alarm, others have been more sanguine about the situation. The broad evolution of lifecycle and related income and consumption theories has increasingly considered and accommodated more transitory shocks, as well as mental accounting. We turn to an empirical analysis that links objective measures of debt to individuals reporting that they judge themselves as having too much debt.

We document substantial heterogeneity in perceived over-indebtedness across the population and estimate a probit model linking demographics; health and financial experiences; and debt characteristics to respondents' self-assessment of whether they have too much debt. Our probit model specification's average predicted probabilities match observed heterogeneity. The probit model enables us to apply a Fairlie decomposition to differences in predicted likelihood of feeling over-indebted across groups, revealing how much variation in debt distress stems from observable characteristics. The debt-to-assets ratio emerges as a powerful grouping variable: 84% of the gap between high and low debt-to-assets groups is explained by observable characteristics.

Next, we use the model to identify empirical thresholds by mapping predicted probabilities to estimated debt-to-asset ratios where households become likely to feel over-indebted. These thresholds vary systematically across groups, revealing substantial differences in debt tolerance by age, income, whether the group had self-reported poor credit scores, and whether the group had unexpected or greater-than-expected debt.

Our findings demonstrate that over-indebtedness cannot be defined by a single threshold. With regard to the question of retirees' debt and well-being, we find strong evidence that older individuals are less concerned about a given level of debt, after controlling for other contributing factors. While our data and research here are cross-sectional, these findings suggest that people generally manage to get their debts organized in their later careers and continue to improve their financial positions and outlook about their indebtedness in retirement.

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Table 1: Summary Statistics

	Weighted HRS sample						Regression sample				
	N	**Weighted N**	**Mean**	**Std. dev.**	**Min**	**Max**	**N**	**Mean**	**Std. dev.**	**Min**	**Max**
Dependent variables											
* Too much debt {1: strongly disagree; 3: neutral; 5: strongly agree}	1,255	7,994,472	2.44	1.36	1	5	1,263	2.51	1.38	1	5
* Agrees or strongly agrees they have too much debt {0, 1}	1,255	7,994,472	0.26	0.44	0	1	1,263	0.28	0.45	0	1
Demographic and Socioeconomic Characteristics											
Age (years | in 2018)	16,132	103,633,596	66.29	9.86	52	103	1,263	66.87	11.26	35	97
Gross income (in dollars)	16,132	103,633,596	$101,877	$172,863	$0	$5,381,149	1,336	$79,642	$156,786	$0	$4,333,118
Race: White/Caucasian {0, 1}	16,132	103,633,596	0.80	0.40	0	1	1,263	0.70	0.46	0	1
Gender: Female {0, 1}	16,132	103,633,596	0.54	0.50	0	1	1,263	0.59	0.49	0	1
Widowed {0, 1}	16,132	103,633,596	0.16	0.36	0	1	1,263	0.19	0.39	0	1
- Female & widowed {0, 1}	16,132	103,633,596	0.12	0.32	0	1	1,263	0.14	0.35	0	1
- Level of Education											
Less than high school diploma or GED {0,1}	16,129	103,625,445	0.11	0.32	0	1	1,263	0.15	0.35	0	1
High school graguate {0, 1}	16,129	103,625,445	0.30	0.46	0	1	1,263	0.32	0.47	0	1
Some college {0, 1}	16,129	103,625,445	0.28	0.45	0	1	1,263	0.26	0.44	0	1
College graduate or beyond {0, 1}	16,129	103,625,445	0.31	0.46	0	1	1,263	0.28	0.45	0	1
Health and Retirement Shocks											
- Health											
Fair-or-poor health (2018)	16,132	103,633,596	0.25	0.43	0	1	1,263	0.30	0.46	0	1
- Decline in health to fair-or-poor, from better health in 2016	16,132	103,633,596	0.09	0.29	0	1	1,263	0.11	0.31	0	1
Mental depression (ever depressed) {0, 1}	16,112	103,480,918	0.27	0.44	0	1	1,263	0.25	0.44	0	1
- Retirement											
Reports retirement was forced in full or part {0, 1}	16,132	103,633,596	0.04	0.20	0	1	1,263	0.04	0.19	0	1
Financial Experiences, Preferences, and Planning											
Above average willingness to take risk {0, 1}	15,468	99,950,575	0.58	0.49	0	1	1,263	0.56	0.50	0	1
* Whether ever tried to figure out how much to save for retirement {0, 1}	1,257	8,006,023	0.43	0.50	0	1	1,263	0.38	0.49	0	1
* Whether correctly answering a compound interest question {0, 1}	1,269	8,069,998	0.35	0.48	0	1	1,263	0.33	0.47	0	1
Financial planning horizon of longer than 10 years {0, 1}	15,862	102,033,629	0.16	0.36	0	1	1,263	0.14	0.35	0	1
Debt Characteristics											
Gross debt (in dollars)	15,974	102,036,186	$58,851	$93,169	$0	$511,650	1,258	$47,621	$85,329	$0	$452,460
- Debt-to-asset ratio (0, ..., >0)	16,132	103,633,596	0.21	0.33	0	15.50	1,263	0.51	2.03	0	15.50
- Non-mortgage debt-to-total debt ratio (0, ..., 1)	15,969	102,649,536	0.72	2.72	0	1.00	1,263	0.23	0.34	0	1.00
- Debt-to-income ratio (0, ..., >0)	15,989	102,824,971	0.78	1.33	0	9.64	1,259	0.65	1.14	0	9.12
* Debts unexpected or greater than expected 10 years earlier {0, 1}	1,225	7,781,077	0.56	0.50	0	1	1,228	0.63	0.48	0	1
* Self-reported credit score being fair or poor {0, 1}	1,257	8,015,147	0.17	0.38	0	1	1,263	0.21	0.40	0	1
* Collection agency contact over the past 12 months {0, 1}	1,261	8,006,946	0.13	0.34	0	1	1,263	0.14	0.35	0	1

Source: Authors' calculations from RAND HRS Longitudinal Data File 2020 (V2), RAND HRS Fat File. 2016, and RAND HRS Fat File. 2018.

*: Variable is derived from 2018 Debt Module (Lusardi, Mitchell, and Oggero)

Table 2: Variation in the Characteristics of the Sample by Quintile

Age Quintiles	Q1	Q2	Q3	Q4	Q5
Age (in years)	**53**	**60**	**66**	**74**	**84**
Gross income (in dollars)	$103,000	$81,122	$73,130	$83,261	$53,401
Gross debt (in dollars)	$71,673	$52,374	$55,365	$38,275	$19,874
Debt-to-asset ratio (0, ..., >0)	0.99	0.77	0.54	0.24	0.30
Debt-to-income ratio (0, ..., >0)	0.94	0.76	0.68	0.64	0.37
Debts unexpected or greater than expected 10 years earlier {0, 1}	73%	65%	63%	58%	57%
Agrees or strongly agrees they have too much debt {0, 1}	*46%*	*33%*	*29%*	*23%*	*12%*

Income Quintiles	Q1	Q2	Q3	Q4	Q5
Age (in years)	67	70	68	65	64
Gross income (in dollars)	**$12,080**	**$27,256**	**$48,392**	**$82,982**	**$228,000**
Gross debt (in dollars)	$11,825	$20,003	$38,573	$61,636	$111,000
Debt-to-asset ratio (0, ..., >0)	1.46	0.63	0.35	0.28	0.17
Debt-to-income ratio (0, ..., >0)	0.62	0.56	0.79	0.78	0.69
Debts unexpected or greater than expected 10 years earlier {0, 1}	*80%*	*70%*	*64%*	*55%*	*49%*
Agrees or strongly agrees they have too much debt {0, 1}	*35%*	*31%*	*30%*	*30%*	*20%*

Debt Quintiles	Q1	Q2	Q3	Q4	Q5
Age (in years)	70	68	65	64	62
Gross income (in dollars)	$61,965	$46,161	$67,918	$78,485	$162,000
Gross debt (in dollars)	**$0**	**$2,002**	**$17,481**	**$67,057**	**$218,000**
Debt-to-asset ratio	0.00	1.26	1.09	0.69	0.55
Debt-to-income ratio	0.00	0.09	0.60	1.40	2.17
Debts unexpected or greater than expected 10 years earlier {0, 1}	*62%*	*64%*	*69%*	*65%*	*61%*
Agrees or strongly agrees they have too much debt {0, 1}	*16%*	*28%*	*42%*	*39%*	*35%*

Debt-to-Asset Quintiles	Q1	Q2	Q3	Q4	Q5
Age (in years)	71	69	65	63	63
Gross income (in dollars)	$67,697	$107,000	$112,000	$89,772	$54,034
Gross debt (in dollars)	$0	$13,182	$81,499	$116,000	$98,038
Debt-to-asset ratio (0, ..., >0)	**0.00**	**0.02**	**0.11**	**0.31**	**3.19**
Debt-to-income ratio (0, ..., >0)	0.00	0.13	0.82	1.47	1.92
Debts unexpected or greater than expected 10 years earlier {0, 1}	*58%*	*52%*	*59%*	*68%*	*80%*
Agrees or strongly agrees they have too much debt {0, 1}	*14%*	*18%*	*31%*	*41%*	*54%*

Debt-to-Income Quintiles	Q1	Q2	Q3	Q4	Q5
Age (in years)	71	68	64	63	64
Gross income (in dollars)	$62,222	$105,000	$83,313	$105,000	$70,025
Gross debt (in dollars)	$0	$6,239	$28,511	$107,000	$159,000
Debt-to-asset ratio (0, ..., >0)	0.00	0.47	1.17	0.58	1.29
Debt-to-income ratio (0, ..., >0)	**0.00**	**0.05**	**0.34**	**1.01**	**2.93**
Debts unexpected or greater than expected 10 years earlier {0, 1}	*61%*	*57%*	*70%*	*64%*	*66%*
Agrees or strongly agrees they have too much debt {0, 1}	*16%*	*22%*	*41%*	*41%*	*41%*

Source: Authors' calculations using RAND HRS Longitudinal Data File 2020 (V2) and RAND HRS Fat Files.
All figures report nonparametric means by group-quintile.

Table 3: Fairlie Decomposition Highlights Roles of Contributing Factors

Age		Income		White / Caucasian	
Pr(over-indebted | below median age)	0.37	Pr(over-indebted | below median income)	0.33	Pr(over-indebted | not-white)	0.41
Pr(over-indebted | above median age)	0.21	Pr(over-indebted | above median income)	0.25	Pr(over-indebted | white)	0.24
Difference	**0.16**	Difference	**0.08**	Difference	**0.17**
Total explained	0.13	Total explained	0.03	Total explained	0.13
Percent explained	**81%**	Percent explained	**40%**	Percent explained	**76%**
Top five contributors:	71%	Top five contributors:	143%	Top five contributors:	75%
Poor credit score	23%	Unexpected debt	109%	Poor credit score	37%
Debt (dollarsl)	22%	Poor credit score	79%	Unexpected debt	24%
Contacted by loan collector	16%	Non-mortgage debt-to-total debt	72%	Contacted by loan collector	14%
Non-mortgage debt-to-total debt	14%	Female and widowed	49%	Age	13%
Race	13%	Contacted by loan collector	46%	Non-mortgage debt-to-total debt	10%
Female		**Fair-or-In fair-to-poor health**		**Depressed**	
Pr(over-Indebted | male)	0.27	Pr(over-indebted | not in fair-to-poor health)	0.25	Pr(over-indebted | never depressed)	0.26
Pr(over-Indebted | female)	0.31	Pr(over-Indebted | in fair-to-poor health)	0.37	Pr(over-indebted | ever depressed)	0.38
Difference	**0.04**	Difference	**0.12**	Difference	**0.13**
Total explained	0.01	Total explained	0.08	Total explained	0.06
Percent explained	**31%**	Percent explained	**73%**	Percent explained	**45%**
Top five contributors:	49%	Top five contributors:	94%	Top five contributors:	46%
Non-mortgage debt-to-total debt	51%	Poor credit score	34%	Contacted by loan collector	30%
Annual income (in dollars)	45%	Annual income (in dollars)	32%	In fair-to-poor health	24%
In fair-to-poor health	21%	Contacted by loan collector	27%	Poor credit score	21%
Poor credit score	21%	Non-mortgage debt-to-total debt	19%	Non-mortgage debt-to-total debt	19%
Mental depression (ever depressed) {0, 1}	19%	Mental depression (ever depressed) {0, 1}	16%	Widowed	8%
Debt-to-Assets		**Unexpected debt**		**Bad Credit Score**	
Pr(Over-Indebted | below median debt-to-asset	0.16	Pr(over-indebted | debt planned)	0.15	Pr(Over-Indebted | good credit score)	0.21
Pr(Over-Indebted | above median debt-to-asset	0.41	Pr(over-indebted | unexpected debt)	0.37	Pr(Over-indebted | bad credit score)	0.57
Difference	**0.25**	Difference	**0.22**	Difference	**0.35**
Total explained	0.21	Total explained	0.10	Total explained	0.19
Percent explained	**84%**	Percent explained	**44%**	Percent explained	**53%**
Top five contributors:	79%	Top five contributors:	35%	Top five contributors:	44%
Debt to Income Ratio	49%	Poor credit score	26%	Contacted by loan collector	27%
Non-mortgage debt-to-total debt	24%	Contacted by loan collector	17%	Non-mortgage debt-to-total debt	26%
Poor credit score	11%	Widowed	15%	Unexpected debt	14%
Contacted by loan collector	6%	Debt (in dollars)	10%	Annual income (in dollars)	9%
Unexpected debt	4%	Non-mortgage debt-to-total debt	10%	In fair-to-poor health	8%

Source: Authors' calculations employing Fairlie decompositions across groupings in variables, from a baseline probit (Table A.1) of RAND HRS Longitudinal Data File 2020 (V2) and RAND HRS Fat Files.

Figure 1: Predicted Likelihood of Agreement with *"I have too much debt right now."*

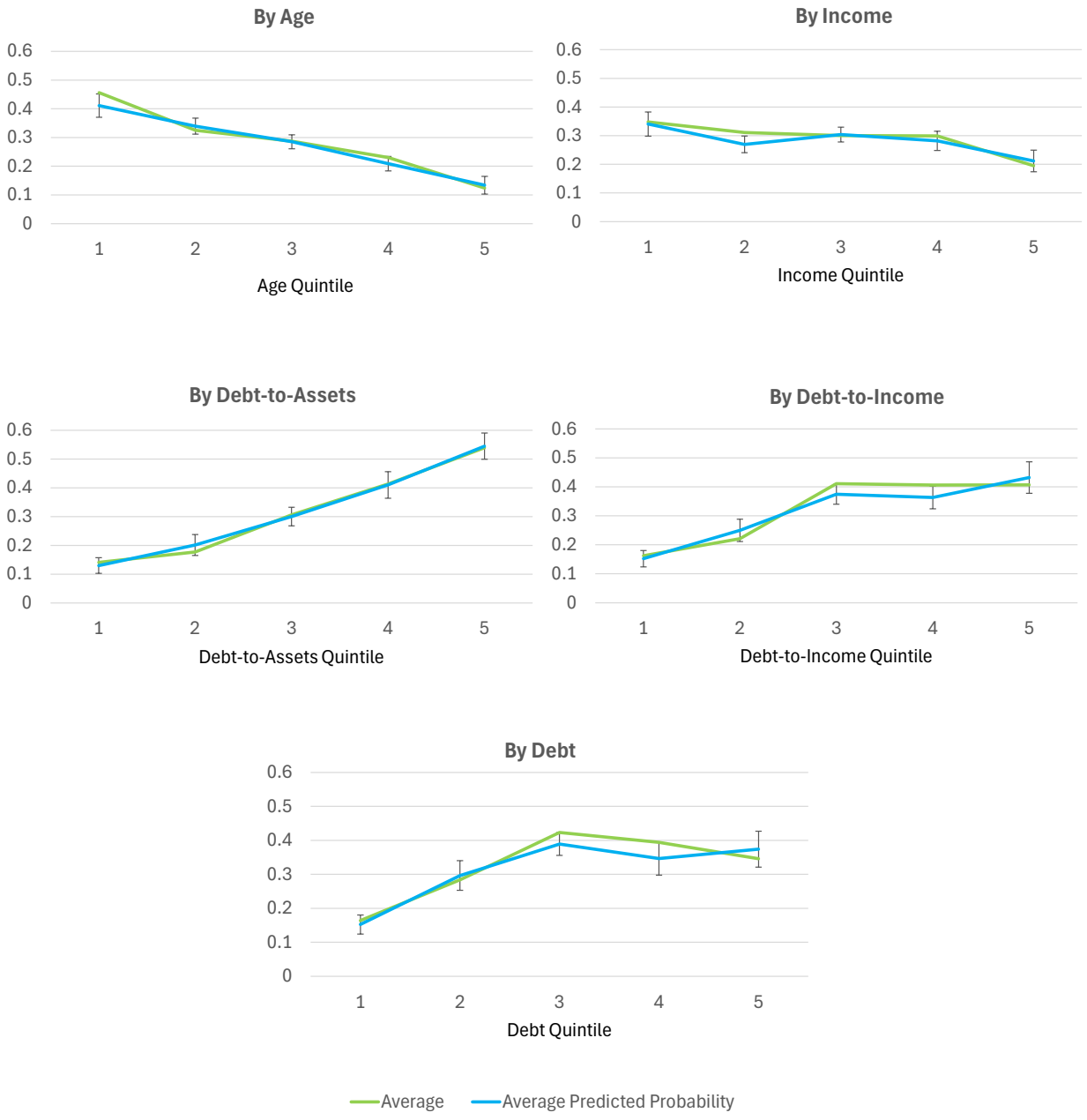
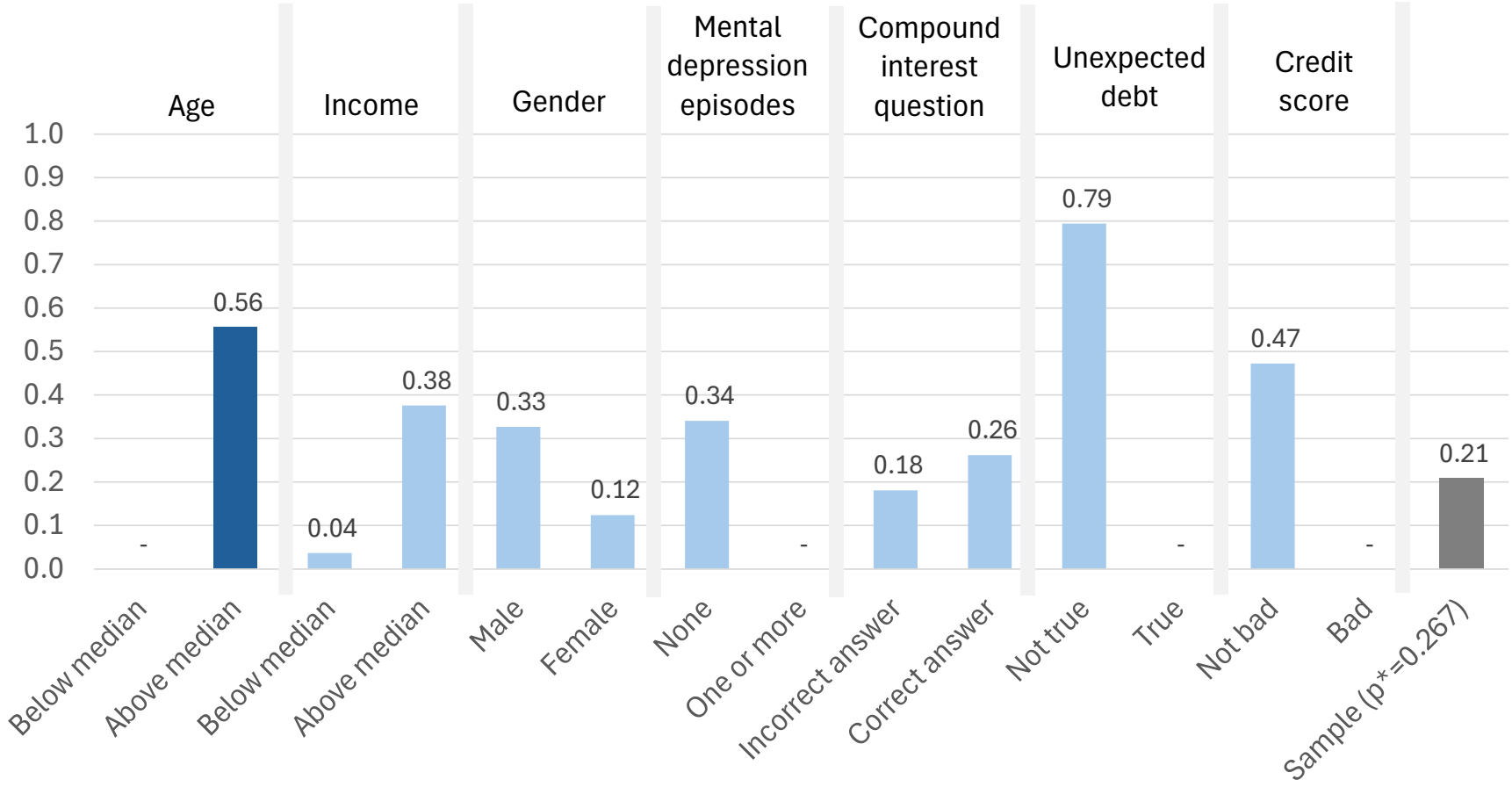


Figure 2: Tipping Points by Characteristic

Estimated debt-to-asset ratios at which people agree or strongly agree with the statement, "I have too much debt right now."



Source: Authors' calculations solving for debt-to-asset ratios at which groups are likely to feel they have too much debt, conditional on p^* that maximizes Youden's J-statistic for the regression sample (see Table 1 and Table A.1) of RAND HRS Longitudinal Data File 2020 (V2) and RAND HRS Fat Files.

Appendix Table A.1: Probit Specification Underlying Analyses

Agreement with sentiment: "I have too much debt right now."	*Probit { 0, 1 | agree or strongly agree }*					
	Coefficient	**Std. error**	**z-statistic**	**P>z**	**[95% conf.**	**interval]**
Demographic and Socioeconomic Characteristics						
Age (years | in 2018)	-0.01	0.00	**-2.06**	0.04	-0.02	0.00
* *Gross Income (in dollars)*						
- below 75th percentile	0.00	0.00	-0.43	0.67	0.00	0.00
- above "	0.00	0.00	-1.42	0.16	0.00	0.00
Race: White/Caucasian {0, 1}	-0.18	0.10	-1.83	0.07	-0.37	0.01
Gender: Female {0, 1}	0.03	0.10	0.29	0.77	-0.16	0.22
Widowed {0, 1}	-0.29	0.23	-1.24	0.22	-0.75	0.17
- Female & widowed {0, 1}	0.22	0.27	0.80	0.42	-0.32	0.75
- *Level of Education* [1]						
High school graguate {0, 1}	0.12	0.14	0.91	0.36	-0.14	0.39
Some college {0, 1}	-0.05	0.15	-0.33	0.75	-0.34	0.25
College graduate or beyond {0, 1}	-0.08	0.16	-0.48	0.63	-0.40	0.24
Health and Employment Shocks						
- *Health*						
Fair-or-poor health (2018)	0.23	0.12	1.91	0.06	-0.01	0.46
- Decline in health to fair-or-poor, from better health in 2016	-0.21	0.16	-1.29	0.20	-0.52	0.11
Experiences with mental depression {0, 1}	0.25	0.10	**2.51**	0.01	0.05	0.44
- *Employment*						
Reports retirement was forced in full or part {0, 1}	-0.20	0.22	-0.89	0.38	-0.63	0.24
Financial Experiences, Preferences, and Planning						
Above average willingness to take risk {0, 1}	-0.02	0.09	-0.21	0.84	-0.19	0.16
Whether ever tried to figure out how much to save for retirement {0,	-0.02	0.09	-0.21	0.83	-0.20	0.16
Whether correctly answering a compound interest question {0, 1}	-0.01	0.09	-0.13	0.90	-0.19	0.17
Financial planning horizon of longer than 10 years {0, 1}	-0.01	0.13	-0.08	0.93	-0.26	0.24
Debt Characteristics						
* *Gross debt (in dollars)*						
- below 75th percentile	0.00	0.00	0.88	0.38	0.00	0.00
- above "	0.00	0.00	1.62	0.11	0.00	0.00
* *Debt-to-asset ratio (0, ..., >0)*						
- below 75th percentile	0.87	0.75	1.15	0.25	-0.61	2.34
- above "	0.00	0.02	-0.08	0.93	-0.05	0.04
- Non-mortgage debt-to-total debt ratio (0, ..., 1)						
- below 75th percentile	0.30	0.25	1.19	0.24	-0.19	0.78
- above "	1.46	0.31	**4.73**	0.00	0.86	2.07
* *Debt-to-income ratio (0, ..., >0)*						
- below 75th percentile	0.30	0.38	0.80	0.42	-0.43	1.04
- above "	-0.06	0.06	-0.93	0.35	-0.18	0.06
Debts unexpected or greater than expected 10 years earlier {0, 1}	0.47	0.10	**4.61**	0.00	0.27	0.66
Self-reported credit score being fair or poor {0, 1}	0.50	0.11	**4.50**	0.00	0.28	0.72
Collection agency contact over the past 12 mo {0, 1}	0.46	0.12	**3.76**	0.00	0.22	0.71
Constant	-0.83	0.39	**-2.13**	0.03	-1.60	-0.07

Source: Authors' calculations from RAND HRS Longitudinal Data File 2020 (V2), RAND HRS Fat File. 2016, and RAND HRS Fat File. 2018.

z-statistic: **bold** at or above 95th level of confidence

*: Spline, fit at the 75th percentile across two groups {below, above}.

1: Level of education reference category is [Less than high school diploma or GED].

Appendix Table A.2: Sensitivity Analysis Related to Selection of p* Based on Youden's J Statistic

Debt-to-Asset Thresholds for {0,1} Classification

p:*	*0.15*	*0.2*	*0.25*	***0.267*** [†]	*0.3*	*0.4*	*0.5*
Below median age	-	-	-	-	-	0.30	0.59
Above median age	0.08	0.30	0.49	0.56	0.67	0.98	1.27
Below median income	-	-	-	0.04	0.15	0.46	0.75
Above median income	-	0.12	0.32	0.38	0.49	0.80	1.09
Male	-	0.07	0.27	0.33	0.44	0.75	1.05
Female	-	-	0.06	0.12	-	0.55	0.84
No mental depression episodes	-	0.09	0.28	0.34	0.45	0.77	1.06
One or more mental depression episodes	-	-	-	-	-	0.25	0.54
Compound interest question answered incorrecty	-	-	0.12	0.18	0.29	0.61	0.90
Compound interest question answered correctly	-	0.01	0.20	0.26	0.37	0.69	0.98
Debts as, or lower than, expected 10 years ago	0.32	0.54	0.73	0.79	0.91	1.22	1.51
Debts unexpected or greater than expected 10 years ago	-	-	-	-	-	0.28	0.58
Credit score is {good, ..., excellent}	-	0.22	0.41	0.47	0.59	0.69	1.19
Credit score Is {fair-or-poor}	-	-	-	-	-	-	-
Full sample	-	-	0.15	0.21	0.32	0.63	0.93
Sensitivity (true positive rate)	92.2%	84.5%	78.2%	76.4%	72.1%	57.2%	45.7%
Specificity (true negative rate)	49.4%	59.1%	68.8%	70.3%	73.5%	85.5%	91.6%
Percent correctly classified	61.6%	66.4%	71.5%	72.0%	73.1%	77.4%	78.5%
Youden's J statistic:	**41.6%**	**43.6%**	**46.9%**	**46.7%**	**45.6%**	**42.7%**	**37.3%**

Source: Authors' calculations employing Fairlie decompositions across groupings in variables, from a baseline probit (Table A.1)
RAND HRS Longitudinal Data File 2020 (V2) and RAND HRS Fat Files.
Measures: {true positive, true negative, percent correctly classified, and Youden J's statistic} based on postestimation output (**estat**) in Stata.
†: p *=0.267 forms the basis for Figure 2. Estimated in Stata, using: **cutpt ['too much debt' {0,1}] phat, youden**
A discrepancy in optimal p* by Youden J's statistic is likely due to differences in how the Stata **cutpt** command constructs the ROC curve.

Appendix Table A.3: Confusion Matrices for Different p^* Parameters

p*=0.15		Actual Outcome		
		1	0	Total
Predicted	1	**321**	441	762
	0	27	**430**	457
	Total	348	871	1,219

p*=0.15		Actual Outcome		
		1	0	Total
Predicted	1	**26.3%**	36.2%	62.5%
	0	2.2%	**35.3%**	37.5%
	Total	28.5%	71.5%	100.0%

p*=0.2		Actual Outcome		
		1	0	Total
Predicted	1	**294**	356	650
	0	54	**515**	569
	Total	348	871	1,219

p*=0.2		Actual Outcome		
		1	0	Total
Predicted	1	**24.1%**	29.2%	53.3%
	0	4.4%	**42.2%**	46.7%
	Total	28.5%	71.5%	100.0%

p*=0.25		Actual Outcome		
		1	0	Total
Predicted	1	**272**	272	544
	0	76	**599**	675
	Total	348	871	1,219

p*=0.25		Actual Outcome		
		1	0	Total
Predicted	1	**22.3%**	22.3%	44.6%
	0	6.2%	**49.1%**	55.4%
	Total	28.5%	71.5%	100.0%

p*=0.267		Actual Outcome		
		1	0	Total
Predicted	1	**266**	259	525
	0	82	**612**	694
	Total	348	871	1,219

p*=0.267		Actual Outcome		
		1	0	Total
Predicted	1	**21.8%**	21.2%	43.1%
	0	6.7%	**50.2%**	56.9%
	Total	28.5%	71.5%	100.0%

p*=0.3		Actual Outcome		
		1	0	Total
Predicted	1	**251**	231	482
	0	97	**640**	737
	Total	348	871	1,219

p*=0.3		Actual Outcome		
		1	0	Total
Predicted	1	**20.6%**	18.9%	39.5%
	0	8.0%	**52.5%**	60.5%
	Total	28.5%	71.5%	100.0%

p*=0.4		Actual Outcome		
		1	0	Total
Predicted	1	**199**	126	325
	0	149	**745**	894
	Total	348	871	1,219

p*=0.4		Actual Outcome		
		1	0	Total
Predicted	1	**16.3%**	10.3%	26.7%
	0	12.2%	**61.1%**	73.3%
	Total	28.5%	71.5%	100.0%

p*=0.5		Actual Outcome		
		1	0	Total
Predicted	1	**159**	73	232
	0	189	**798**	987
	Total	348	871	1,219

p*=0.5		Actual Outcome		
		1	0	Total
Predicted	1	**13.0%**	6.0%	19.0%
	0	15.5%	**65.5%**	81.0%
	Total	28.5%	71.5%	100.0%