Online Appendix

This document contains additional material referenced in the text. Appendix A describes our data in greater detail. Appendix B contains details on our core microeconometric analysis from Section 4 and performs the robustness exercises referenced in Section 5. Appendix C provide additional information about the life-cycle model from Section 6. Appendix D describes the method for estimating the idiosyncratic volatilities and factor loadings on self-managed and robo portfolios in Section 6.2.1. Additional figures and tables are at the end of the appendix.

A Data Appendix

We provide additional details on the paper's two principal datasets: a weekly panel of deposit activity by robo participants (A.1); and a cross-section of portfolio snapshots for self-managed, non-robo portfolios (A.2). We also describe other datasets (A.3) and provide a catalog of the paper's key variables (A.4).

A.1 Deposits Dataset

Our first robo advising dataset contains a weekly time series of deposits with the robo advisor, Wealthfront. We obtain this information directly through a query of Wealthfront's internal server. Thus, we observe the same information as would an analyst working for the advisor. The query merges two internal subdatasets. The first subdataset includes demographic information about Wealthfront participants. The second subdataset contains the date and size of each deposit made by a Wealthfront participant from December 1, 2014 through February 29, 2016. The internal query then merges these two subdatasets together based on username and tax status of the portfolio associated with the username. Each merged observation defines a "robo participant". As implied by Table 1, the merged dataset includes information on 9,702 Wealthfront participants who made at least one deposit during the sample period, 4,366 of whom became participants before the July 2015 reduction and 5,336 of whom become participants afterward.[32]

Summarizing the discussion in the text, we observe the date and size of the deposit and whether the deposit comes from a new participant. In addition, we observe the participating investor's annual income, state of residence, liquid assets, recommended and selected risk tolerance score, and investor age. Per the language of the questionnaire, liquid assets are defined as "cash, savings accounts, certificates of deposit, mutual funds, IRAs, 401ks, and public stocks".

The risk tolerance score defines the portfolio allocation received by the participant, as shown in Table A2. The recommended risk tolerance score is a function of the investor's demographic information and answers to several questions about financial goals and response to market downturns. The selected risk tolerance score equals the recommended score for 64% of Wealthfront participants, and the remaining participants select a different score. We use this difference to calculate a measure of high risk aversion, denoted $\textit{Risk Averse}_i$ in the text. Only 3% of investors who select a different risk tolerance score deviate from their recommended score by more than 3 points, corresponding to a shift in CAPM beta of around 0.15.

We cross-referenced our robo advising dataset against publicly available SEC ADV filings. According to these filings, Wealthfront reported 18,800 participants (i.e., clients) in December 2014 and 61,000 participants in February 2016. As described in the text, the discrepancy between the SEC ADV filings and our dataset is explained by the SEC's filing requirements. Specifically, the SEC states: "The definition of

[32] The reduction technically occurs in the second week of July, and so, to be as precise as possible, we classify the first week of July as if it were still June in our regressions. This technicality has no bearing on the results.

’client’ for Form ADV states that advisors must count clients who do not compensate the advisor” (SEC 2017). Thus, the number of participants reported to the SEC by Wealthfront or any other robo advisor includes participants who did not make any deposits over the sample period as well as “participants” who created a username but never funded a Wealthfront account.

A.2 Portfolio Dataset

Our second robo advising dataset covers a subset of investors in the deposits dataset as well as a set of robo non-participants. It contains snapshots of investors’ portfolio holdings in an outside, traditional brokerage account. This information is paired with the portfolio holdings of the investor’s counterfactual robo portfolio, along with the same demographic information as in the deposits dataset. We also observe each portfolio’s advisory fees and tax status. The dataset was generated by a free online tool through which our data provider gave financial advice to candidate clients about their outside portfolio holdings.

Specifically, candidate clients would provide their log-in credentials for their outside brokerage account. Then, the robo advisor would take a snapshot of the account holdings and run an advice-generating algorithm on it. This produces a set of snapshots of investors’ non-robo accounts. While the advice algorithm ran, our data provider would ask the investor to answer its standard questionnaire, which is the source of our demographic variables. Finally, at the conclusion of the report, our data provider would tell the investor the portfolio she would receive as a client and give her the option to fund a robo portfolio. This produces a matched, counterfactual robo portfolio for each investor in the sample. Our sample contains 2,654 snapshots taken within a window of the reduction in account minimum.

Given that we use the dataset to calibrate self-managed portfolio characteristics, we filter this dataset to only include pairs of portfolios in which the non-robo portfolio has no advisory fee. The filtered dataset includes 1,913 portfolios, as shown in Table 4.

A.3 Auxiliary Datasets

A.3.1 Survey of Consumer Finances

The Survey of Consumer Finances (SCF) is a publicly available dataset administered by the Federal Reserve Board every three years, and we rely on the 2016 dataset. The SCF contains financial and demographic information about a representative cross-section of U.S. retail investors. The SCF is one of the most commonly used datasets in the literature, and Bricker et al. (2017) provide a thorough overview of it.

We use the SCF dataset to calculate quintiles of the overall U.S. distribution of liquid assets. To maximize comparability with our robo advising dataset, we define liquid assets in the SCF as the sum of checking accounts, savings accounts, certificates of deposit, cash, stocks, bonds, savings bonds, mutual funds, annuities, trusts, IRAs, and employer-provided retirement plans. This definition of liquid assets most closely matches the definition in our robo advising dataset, although the two are not equivalent. For example, we include bonds and savings bonds in the SCF definition, although they are not explicitly mentioned as a liquid asset in the robo advisor’s questionnaire. Removing bonds and savings bonds from the SCF definition has little impact because it only changes the boundary between the middle and upper classes by 1%. We carefully examine how measurement error might affect our results in Section 4.3. Appendix Table A4 reports the boundaries that define the five quintiles.

A.3.2 Asset Pricing Datasets

We use data from the CRSP annually updated stock file, Ken French’s website, and the Bloomberg-Barclays aggregate U.S. and unhedged global bond indices to estimate the asset pricing factor models, as described in Appendix D.

A.3.3 Advertising Datasets

We use advertising data from Kantar, specifically Kantar's Vivvix dataset. Kantar tracks traditional media advertisements (e.g., television, print, radio) and, increasingly, digital advertisements. Kantar measures traditional advertisements by tracking which advertisements are conveyed in cable or broadcast television or radio signals. Gordon et al. (2020) discuss the relationship between a firm's traditional and digital advertisements, noting that they tend to be highly correlated.

The unit of observation in the Kantar dataset is a tuple defined by: company; time of advertising; method of advertising (e.g., television, newspaper); geographic location, if relevant for the given method; and product being advertised. We observe total dollar spending for each tuple. The only product observed for the robo advisor is their baseline service, described as "Wealthfront Online".

Kantar measures geography at the level of the Designated Market Area (DMA). Loosely, a DMA corresponds to a CBSA. We map each DMA to a set of counties using the crosswalk file from Gentzkow (2006) and Gentzkow and Shapiro (2008). Precisely, this crosswalk file maps county FIPS codes to the DMA name in a related advertising dataset, Nielsen's Ad Intel dataset. The DMA names in Nielsen are effectively the same as in Kantar after small adjustments in spelling. This mapping enables us to merge our advertising data with data on county-level imputed wealth from Chodorow-Reich, Nenov and Simsek (2021). We aggregate imputed wealth across counties by taking the average for all counties associated with a DMA, weighting by population.

We cross-reference some of the statistics from the Kantar dataset with Nielsen's Ad Intel dataset, as noted in footnote 19. The Nielsen dataset has the same format as the Kantar dataset, except that we do not observe the DMA associated with the advisor's television ad spending over our period of analysis.

A.3.4 Imputed Stock Market Wealth by County

Our data on imputed county-level stock market wealth come from Chodorow-Reich, Nenov and Simsek (2021), who apply a county-specific capitalization rate to total dividend income in a county from the IRS SOI Tax Stats county-level dataset. The baseline capitalization rate is the aggregate price-dividend ratio from the CRSP dataset. Then, Chodorow-Reich, Nenov and Simsek (2021) adjust this baseline capitalization rate for each county according to: the county's average age; and the share of wealth that is taxable. The age adjustment involves calculating the weighted average price-dividend ratio for bins defined age, using data on the positions of retail investors from Barber and Odean (2000). The weights used to calculate this average come from the joint distribution of wealth by age from the SCF dataset. Each county is assigned an age-specific capitalization rate. The adjustment for nontaxable income involves projecting total stock market wealth on taxable stock market wealth and household demographic characteristics using the SCF dataset. This projection is used to map taxable stock market wealth, obtained from the age adjustment just described, onto total stock market wealth. Finally, Chodorow-Reich, Nenov and Simsek (2021) perform this imputation on a county-by-year panel, and we simply use the imputed stock market wealth from 2015. We obtain the data from the replication file for Chodorow-Reich, Nenov and Simsek (2021).

A.3.5 Other Auxiliary Datasets

We use the Center for Disease Control's mortality tables to calibrate the survival probabilities in the portfolio choice model (Xu et al. (2020)). The CDC reports these probabilities for brackets of the age distribution, and we use the average within each bracket. We calculate the survival probability as one minus the mortality rate. For the post-retirement period (i.e., $t \geq \underline{T}$), we use the lowest survival probability across age brackets. Lastly, we calibrate the credit card interest rate of 12% using the 2015 Federal Reserve Consumer Credit Report.

A.4 Description of Variables

Our empirical analysis relies on the following variables:

- *Liquid Assets$_i$*: This variable is the sum of cash, savings accounts, certificates of deposit, mutual funds, IRAs, 401ks, and public stocks for investor i, based on the deposits dataset. We interpret "401k" to also mean other tax-advantaged, employer-sponsored plans, such as 403b or 457 plans.
- *Middle$_i$*: This variable indicates if investor i's liquid assets fall within the second or third U.S. quintile of liquid assets. Investor i's liquid assets are calculated using the deposits dataset. Quintiles of liquid assets are calculated using the SCF dataset.
- *New Participant$_i$*: This variable indicates if investor i becomes a participant with the robo advisor over the period from July 7, 2015 through February 29, 2016. Explicitly, it equals 1 for such investors and equals 0 for investors who participated before July 7, 2015.
- *Initial Deposit$_i$*: This variable is the initial deposit with the robo advisor made by investor i, based on the deposits dataset.
- *Income$_i$*: This variable is annual income for investor i, based on the deposits dataset.
- *Age$_i$*: This variable is the age of investor i, based on the deposits dataset.
- *Risk Averse$_i$*: This variable indicates if investor i chooses a lower risk tolerance score than recommended by the robo advisor, based on the deposits dataset.
- *Under Minimum$_i$*: This variable indicates if investor i's initial deposit with the robo advisor is less than \$5,000, based on the deposits dataset.
- *At Minimum$_i$*: This variable indicates if investor i's initial deposit with the robo advisor is between \$5,000 and \$5,250, based on the deposits dataset.

B Econometric Appendix

First, we provide the details for aggregation exercise referenced in Section 4.3. Next, we explain how the estimation of equation (2) can be affected by measurement error (B.2). Lastly, we provide a formal argument for how the advertising robustness in Table 3 can accommodate targeted advertising by wealth.

B.1 Details on Aggregation Exercise to Interpret the Magnitude

We provide details on the aggregation exercise referenced in Section 4.3, which is intended to help interpret the magnitude of the baseline results in Table 2. We would like to decompose the observed growth rate in the total number of robo participants into the component due to the reduction versus that due to other forces. Let g denote the observed growth rate, which we calculate directly from the data. Consider a counterfactual without the reduction, in which middle-class investors do not experience a relaxation of minimum-account constraints and, thus, $\mu = 0$. Note that the observe growth rate in the total number of robo participants can be directly calculated from the data as

$$g = \frac{\textit{New Participants}}{\textit{Existing Participants}}, \tag{B1}$$

where *New Participants* is the number of investors who become robo participants after the reduction; and, analogously, *Existing Participants* is the number who participated beforehand. It will be helpful to rewrite the numerator of equation (B1) as

$$\textit{New Participants} = \mathbb{E}\left[\textit{New Participant}_i\right] \times \textit{All Participants}, \tag{B2}$$

where $\textit{All Participants} = \textit{New Participants} + \textit{Existing Participants}$ is the sum of new and existing robo participants; and $\mathbb{E}\left[\textit{New Participant}_i\right]$ is the share of all such robo participants who are new. Substituting equations (B2) and (2) into equation (B1) allows us to express g as

$$g = \frac{\mathbb{E}\left[\textit{New Participant}_i\right]}{1 - \mathbb{E}\left[\textit{New Participant}_i\right]} = \frac{\mu\mathbb{E}\left[\textit{Middle}_i\right] + \psi\mathbb{E}\left[X_i\right] + \varrho}{1 - \left(\mu\mathbb{E}\left[\textit{Middle}_i\right] + \psi\mathbb{E}\left[X_i\right] + \varrho\right)}, \tag{B3}$$

which, by definition, is numerically equivalent to the expression in equation (B1).

Consider a counterfactual without the reduction, in which middle-class investors do not experience a relaxation of constraints and, thus, $\mu = 0$. Under this counterfactual, the overall number of robo participants grows at the rate

$$g^C = \frac{\psi\mathbb{E}\left[X_i\right] + \varrho}{1 - \left(\psi\mathbb{E}\left[X_i\right] + \varrho\right)}, \tag{B4}$$

or, equivalently,

$$g^C = \frac{\mathbb{E}\left[\textit{New Participant}_i\right] - \mu\mathbb{E}\left[\textit{Middle}_i\right]}{1 - \left(\mathbb{E}\left[\textit{New Participant}_i\right] - \mu\mathbb{E}\left[\textit{Middle}_i\right]\right)}. \tag{B5}$$

When restricting the focus to the number of middle-class participants, we have similar expressions

$$g^C\Big|_{\textit{Middle}} = \frac{\psi\mathbb{E}\left[X_i | \textit{Middle}_i = 1\right] + \varrho}{1 - \left(\psi\mathbb{E}\left[X_i | \textit{Middle}_i = 1\right] + \varrho\right)}, \tag{B6}$$

which we can rewrite as

$$g^C\Big|_{Middle} = \frac{\mathbb{E}\left[New\ Participant_i | Middle_i = 1\right] - \mu}{1 - \left(\mathbb{E}\left[New\ Participant_i | Middle_i = 1\right] - \mu\right)}.$$

Our statistic of interest is

$$\eta \equiv g - g^C, \tag{B7}$$

which equals the component of the observed growth in the total number of robo participants that is due to the reduction.

Appendix Table A10 summarizes various calculations of η and of the analogous statistic for growth in middle-class investors' robo participation. Interpreting the first row, the baseline estimates from Table 2 imply that the reduction increases the overall number of robo participants by 13%, which is driven by a 108% increase in the number of middle-class participants.[33] The additional estimates from Table 2 imply an increase in the number of middle-class participants between 127% and 148%. The economic discussion of these results is in the text in Section 4.3.

B.2 Measurement Error

As mentioned in the text, the variable $Middle_i$ may be subject to additive measurement error due to self-reporting. On the one hand, such measurement error introduces attenuation bias, which would tend to bias the estimates toward zero. Similarly, the estimates are biased toward zero if new robo participants overreport their wealth more than existing participants do. On the other hand, measurement error biases the estimates away from zero if new participants underreport their wealth relative to existing participants. Formally, if we mis-measure $Middle_i$ as $\widehat{Middle}_i = Middle_i + \varepsilon_i$, then the estimator for μ in a specification of equation (2) without controls is

$$\widehat{\mu} = \mu\left(1 - \frac{\text{Var}\left[\varepsilon_i\right] + \mathbb{E}\left[Middle_i \times \epsilon_i\right]}{\text{Var}\left[\widehat{Middle}_i\right]}\right) + \frac{\mathbb{E}\left[u_i \times \varepsilon_i\right]}{\text{Var}\left[\widehat{Middle}_i\right]}. \tag{B8}$$

The term in parentheses captures the effect of attenuation bias. The second term captures bias from differences in misreporting between new and existing participants.

B.3 Interpreting the First-Difference Estimator

Section 4 wrote that one can interpret the coefficient in the first difference estimator, μ, as the share of robo participants whom the reduction has caused to participate. We now substantiate this remark. Note that the reduction causes an investor to participate if she finds it optimal to become a robo investor under the \$500 minimum but not under the \$5,000 minimum. Let C_i indicate such an investor. The share of eventual participants whom the reduction causes to participate is thus: $\Pr[C_i = 1 \mid Participant_{i,1} = 1]$. Under the assumption that the reduction does not affect existing middle-class participants or upper-class participants:

$$\Pr[C_i = 1 \mid Part_{i,1} = 1] = \Pr[New_i = 1 \mid Part_{i,1} = 1] - \Pr[New_i = 1, Middle_i = 0 \mid Part_{i,1} = 1] = \mu, \tag{B9}$$

[33] In relation to Table 2, the 108% increase in the number of middle-class participants follows from the estimated 14 pps increase in their probability of participation because the middle class was underrepresented before the reduction.

where $Part_{i,t}$ abbreviates$Participant_{i,t}$. The last equality follows from equation (2) after omitting controls X_i for brevity.

C Model Appendix

We describe the solution of the model in Section 6, derive the welfare measure studied in Section 7.2, provide details on the model extensions also studied in Section 7.2, and structurally estimate the model's preference parameters as referenced in Section 6.2.

C.1 Model Solution

We first describe the labor income process. Then, we state the problem. Finally, we describe the numerical solution algorithm.

C.1.1 Details on Labor Income Process

Investors retire at age $\underline{T}$+1. For $t \leq \underline{T}$, they receive uninsurable labor income, $Y_{i,t}$. Following the literature's convention (e.g., Carroll (1997)), labor income in years without a disaster evolves according to

$$\log(Y_{i,t}) = f_i + \xi_{i,t} + \nu_{i,t} + \Xi_t, \tag{C1}$$

where f_i is a deterministic function of age; $\xi_{i,t}$ is a transitory shock, normally distributed with mean zero and volatility of σ_ξ; and $\nu_{i,t}$ is a permanent shock that evolves according to

$$\nu_{i,t} = \nu_{i,t-1} + \upsilon_{i,t}, \tag{C2}$$

where $\upsilon_{i,t}$ is normally distributed with mean zero and volatility of σ_υ. The aggregate component, Ξ_t, covaries with financial returns according to

$$\Xi_t = \beta^Y \left(\bar{R}_t^A - \mathbb{E}[\bar{R}_t^A]\right) \tag{C3}$$

where $\bar{R}_t^A$ is the robo portfolio return at time t, averaged across investors of the same age; $\mathbb{E}[\bar{R}_t^A]$ is the expected value of this return, evaluated over the distribution of F_t; and β^Y is the loading of the robo portfolio's abnormal return in year t. Cocco, Gomes and Maenhout (2005) use the Panel Study of Income Dynamics and the method of Carroll and Samwick (1997) to estimate $\sigma_\nu = 0.103$ and $\sigma_\xi = 0.271$. They estimate a correlation coefficient between log income and the stock market's abnormal return of $\rho^Y = 0.6\%$ for their baseline income group, which maps approximately to $\beta^Y = 0.015$, but they use a correlation coefficient of zero in their baseline analysis. Accordingly, we take the average, corresponding to $\rho^Y = 0.3\%$ and $\beta^Y = 0.007$ as shown in Table 5.

Several studies find that including income skewness improves the performance of life cycle models (e.g., Guvenen, Ozkan and Song (2014); Bagliano, Fugazza and Nicodano (2018); Catherine (2022)). Following Carroll (1997) and Cocco, Gomes and Maenhout (2005), we incorporate skewness by introducing a disaster state in which investors receive zero labor income for one year. Such disasters occur with probability ϕ. In years without a disaster, labor income is given by equation (C1).

Our empirical analysis primarily concerns investment prior to retirement, and so we model the post-retirement period more simply than do benchmark models. In particular, investors do not receive labor income for $t > \underline{T}$. Thus, for $t = \underline{T}+1, ..., \overline{T}$, they solve an "eat-the-pie" problem in which they allocate their liquid assets at retirement, $W_{\underline{T}+1}$, between consumption and savings in the risk-free asset. We state the retirement problem shortly, in Appendix C.1.2.

C.1.2 Consolidated Problem

In year t, investor i allocates shares $\alpha_{i,t}^f$, $\alpha_{i,t}^S$, and $\alpha_{i,t}^A$ of her liquid assets between the risk-free asset, the self-managed portfolio, and the robo portfolio, respectively. She consumes the remaining share $1-\alpha^{f}_{i,t}-\alpha^{\mathcal{S}}_{i,t}-\alpha^{\mathcal{A}}_{i,t}$,

$$C_{i,t}=[1-\alpha^{f}_{i,t}-\alpha^{\mathcal{S}}_{i,t}-\alpha^{\mathcal{A}}_{i,t}]W_{i,t}. \tag{C4}$$

Thus, the vector $(\alpha^{f}_{i,t},\alpha^{\mathcal{S}}_{i,t},\alpha^{\mathcal{A}}_{i,t})$ defines the problem's control variables. Investors optimize over these variables subject to the constraints

$$\alpha^{f}_{i,t}\geq 0,\ \ \alpha^{\mathcal{S}}_{i,t}\geq 0,\ \ \alpha^{\mathcal{A}}_{i,t}\geq 0, \tag{C5}$$

$$1-\alpha^{f}_{i,t}-\alpha^{\mathcal{S}}_{i,t}-\alpha^{\mathcal{A}}_{i,t}\geq 0, \tag{C6}$$

$$\alpha^{\mathcal{A}}_{i,t}=0\ \text{ or }\ \alpha^{\mathcal{A}}_{i,t}\geq\frac{M}{W_{i,t}}. \tag{C7}$$

Constraint (C5) rules out borrowing and shorting, which we subsequently relax in Appendix C.4. Constraint (C6) ensures nonnegative consumption. Both of these constraints are standard. The third constraint, (C7), requires an account minimum of M to participate in wealth management.

This setup leads to a problem with two state variables, age (t) and liquid assets ($W_{i,t}$). As noted by Cocco, Gomes and Maenhout (2005), the problem is homogeneous in permanent labor income, $\nu_{i,t}$, allowing us to remove it from the set of state variables. Liquid assets evolve according to

$$W_{i,t+1}=\left[\alpha^{f}_{i,t}(1+R^{f})+\alpha^{\mathcal{S}}_{i,t}(1+R^{\mathcal{S}}_{i,t+1})+\alpha^{\mathcal{A}}_{i,t}(1+R^{\mathcal{A}}_{i,t+1})\right]W_{i,t}+Y_{i,t+1}. \tag{C8}$$

As in the text,

$$R^{\mathcal{P}}_{i,t}=\beta^{\mathcal{P}}_{i}F_t+\epsilon^{\mathcal{P}}_{i,t}, \tag{C9}$$

Collectively, therefore, investor i of age t solves the following Bellman equation,

$$\begin{aligned}V_t(W_{i,t})=&\max_{\alpha^{f}_{i,t},\alpha^{\mathcal{S}}_{i,t},\alpha^{\mathcal{A}}_{i,t}}\left\{\frac{{C_{i,t}}^{1-\gamma}}{1-\gamma}+\delta p_t\mathbb{E}_t\left[V_{t+1}(W_{i,t+1})\right]\right\}\\ &s.t.(\text{C4})\text{-}(\text{C9})\end{aligned} \tag{C10}$$

for $t_0\leq t\leq\underline{T}$. For $t>\underline{T}$, investors solve

$$V_{\underline{T}+1}(W_{i,\underline{T}+1})=\max_{\left\{\alpha^{f}_{\tau}\right\}}\sum_{\tau=\underline{T}+1}^{\tau=\overline{T}}(\delta p_{\underline{T}+1})^{\tau-\underline{T}-1}\frac{{C_{i,\tau}}^{1-\gamma}}{1-\gamma} \tag{C11}$$

$$s.t.$$

$$0\leq\alpha^{f}_{\tau}\leq 1 \tag{C12}$$

$$W_{i,\tau+1}=\alpha^{f}_{i,\tau}(1+R^{f})W_{i,\tau} \tag{C13}$$

$$C_{i,\tau}=[1-\alpha^{f}_{i,\tau}]W_{i,\tau}. \tag{C14}$$

Indirect utility has the familiar form

$$V_{\underline{T}+1}(W_{i,\underline{T}+1})=B\frac{{W_{i,\underline{T}+1}}^{1-\gamma}}{1-\gamma}, \tag{C15}$$

with

$$B = \sum_{\tau=\underline{T}+1}^{\overline{T}} \delta^{\tau-\underline{T}-1} \left[\frac{1-\chi}{1-\chi^{\overline{T}-\underline{T}}}\right] \left[\delta(1+R^f)\right]^{\frac{\tau-\underline{T}-1}{\gamma}}, \tag{C16}$$

$$\chi = \delta^{\frac{1}{\gamma}}(1+R^f)^{\frac{1-\gamma}{\gamma}} \tag{C17}$$

as, for example, shown in Costa-Dias and O'Dea (2019).

C.1.3 Numerical Algorithm

Our numerical algorithm is standard and follows the methods typically used in benchmark portfolio choice models. First, we solve equation (C10) for age $\underline{T}$ as a function of liquid assets: $V_{\underline{T}}(W_{i,\underline{T}})$. Since the solution does not have an analytic form, we discretize liquid assets. The grid ranges from the minimum value of liquid assets in the 2016 SCF to the 90$^{\text{th}}$percentile of liquid assets in increments of 0.1 on a log scale. The resulting grid has 109 points. This discretization intentionally places most of its density in the bottom four quintiles. Our empirical results imply that the strongest response to the reduction will occur in this region, and so we want to minimize approximation error in it. We obtain very similar theoretical results under alternative discretizations. The simulation used to produce Figure 10 uses a more fine grid with increments of 0.01 in liquid assets on a log scale. This more-fine grid is also used for Figure 8. We follow convention by discretizing the set of shocks and approximating their joint distribution through Gaussian quadrature (e.g., Tauchen and Hussey (1991)). For completeness, the model's shocks are: $F_t, \epsilon^{\mathcal{S}}_{i,t}, \epsilon^{\mathcal{A}}_{i,t}, \overline{\nu}_{i,t}$, with $\overline{\nu}_{i,t} \equiv \xi_{i,t} + \nu_{i,t}$. The grid has 5 points for each shock.

Following standard practice, we optimize by grid search, and so we avoid selecting local optima. Accordingly, we discretize each of the control variables, $\alpha^f_{i,t}, \alpha^{\mathcal{S}}_{i,t}$, and $\alpha^{\mathcal{A}}_{i,t}$, into a 40 point grid. We can further reduce the dimensionality of the resulting 40×3 matrix by omitting choices that violate one of the constraints (C5)-(C8). As mentioned in the text, we simplify the model's computational complexity by assuming investors cannot hold the self-managed and automated portfolios concurrently: $\min\left\{\alpha^{\mathcal{S}}_{i,t}, \alpha^{\mathcal{A}}_{i,t}\right\} = 0$. We obtain similar results without this simplification because it is rarely optimal to hold both at the same time. We also reduce computational complexity by assuming investors must maintain a minimum balance of M with the automated asset manager, whereas, in reality, investors only need to make an initial deposit of M. Otherwise, we must keep track of $\alpha^{\mathcal{A}}_{i,t}$as an additional state variable because it determines the lower bound on an investor's robo investment. Namely, under an initial deposit requirement, investors do not need to top-up their balance to M if market forces push their account balance below this threshold. We assess the validity of this simplification by solving the model under the more realistic yet intensive setup with a minimum deposit requirement, finding similar results as in Table 7. Intuitively, the high expected return on the robo portfolio makes cases of a top-up quite rare.

Next, after solving $V_{\underline{T}}(W_{i,\underline{T}})$, we iterate backward, solving $V_{\underline{T}-1}(W_{i,\underline{T}-1})$ and so forth until we arrive at the initial period, t_0. For each age t, we approximate $V_{t+1}(W_{i,t+1})$ using a linear spline interpolation in liquid assets, $W_{i,t+1}$, and we evaluate $\mathbb{E}[V_{t+1}(W_{i,t+1})]$ using Gaussian quadrature, as mentioned above. The presence of a binding account minimum in the middle of the state space complicates our problem, but the linear spline handles this challenge well, producing well-behaved policy functions. By contrast, a cubic spline generates policy functions that are less well-behaved. Moreover, a linear spline can still generate substantial curvature in the utility function for a suitably fine discretization of the state space. Lastly, we solve $V_t(W_{i,t})$ using the labor income parameters shown in Table 5, setting income equal to the median income in the 2016 SCF for the baseline cohort studied in Cocco, Gomes and Maenhout (2005).

Summarizing, this algorithm results in a sequence of value functions $\{V_\tau(W_{i,\tau})\}$ and policy rules $\left\{\alpha_\tau^f(W_{i,\tau}), \alpha_\tau^S(W_{i,\tau}), \alpha_\tau^{\mathcal{A}}(W_{i,\tau})\right\}$ that we use in the positive and welfare analyses of Section 7.

C.2 Discussion of Policy Functions and Life Cycle Intuition

Figure 8 summarizes the model's policy functions for the following outcomes: decision to participate with the robo advisor (Robo Participation); share of investible wealth allocated to the robo portfolio (Robo Share); share of investible wealth allocated to either the self-managed portfolio or the robo portfolio (Risky Share); and share of liquid assets that is saved (Savings Rate), recalling that we use "liquid assets" and "cash-on-hand" synonymously. By "investible wealth", we mean the difference between liquid assets and optimal consumption. We report the optimal choice of each outcome for pairs of age and liquid assets, which are, effectively, the model's two state variables. We consider policy functions before the reduction, in which the account minimum equals $5,000.

First, consider robo participation in panel (d). We plot the minimum threshold of liquid assets at which the investor decides to participate with the robo advisor as a function of investor age. This threshold remains relatively stable at around $27,000 until the investor reaches peak earning years. Notably, the fact that the threshold exceeds the account minimum by a factor of 5 accords with the empirical observation that the reduction has a large effect on investors from the third quintile of the U.S. wealth distribution, which is bounded by $6,000 and $42,000. After age 40, the threshold starts to decline, meaning that older investors are willing to invest a larger share of their liquid assets with the robo advisor. This reflects how investors' consumption-to-wealth ratio falls as they approach retirement, or, equivalently, their savings rate increases, which is a well-known life cycle pattern generated by benchmark models summarized by Gomes (2020). Our model also generates this pattern, shown in panel (a) of Figure 8.

In benchmark models, investors reduce their risky share as they age to offset a decline in bond-like labor income. According to canonical life cycle intuition, this channel should increase the robo participation threshold as investors age, thus working in the opposite direction as the savings rate channel described in the previous paragraph. However, robo portfolios differ from the risky asset featured in most life cycle models, the latter of which is modelled as a stock index fund. In particular, robo portfolios feature a glide path towards less total risk as investors age. For example, recall how robo portfolios for older or less-wealth investors have a stronger tilt towards bonds and away from stocks (Figure 1). This glide path feature incentivizes older investors to invest a larger share of their wealth in the robo portfolio. In fact, panel (c) of Figure 8 implies that, beginning around age 40, the optimal robo share increases as investors age, holding liquid assets fixed. This increase in robo share drives an increase in risky share, as we now describe.

Panel (b) of Figure 8 plots the optimal risky share as a function of age and wealth. Consistent with benchmark models, the optimal risky share declines in age until the investor reaches peak earning years, which is best seen by the lightening of color as one moves up the vertical axis holding liquid assets fixed at around $25,000. In addition, the optimal risky share weakly increases in wealth. Since our baseline setup does not feature fixed costs of stock market participation, the optimal risky share is always positive, even for very low levels of wealth. Note, however, that most investors in the middle class select a risky share well below 100%. Benchmark models, by contrast, predict a 100% risky share for almost all investors. This difference arises because investors in benchmark models invest in the total stock market, and, thus, have a relatively low level of idiosyncratic risk. By contrast, less-wealthy investors in our setting must invest in the self-managed portfolio, which, per Table 4, has a relatively low Sharpe ratio. This underdiversification reduces their demand for risky assets. However, once liquid assets reaches around $27,000, investors begin to invest in the robo portfolio, and the risky share jumps to 100%.

Lastly, we point out three features of the savings rate policy function in panel (a) that accord with benchmark life cycle models. First, as already described, the savings rate begins to increase in age after the investor reaches her peak earning years, holding liquid assets fixed. Second, the savings rate decreases in age leading up to peak earning years, again holding liquid assets fixed. This pattern reflects how the investor wishes to accumulate a buffer against idiosyncratic labor income shocks. Such a motive arises because isoelastic preferences feature prudence, as controlled by γ. Third, the savings rate increases in liquid assets, which is another standard feature of benchmark models.

Summarizing, the model's policy functions resemble those of benchmark models, with several exceptions that are due to our unique setting. In particular, the combination of an account minimum and inefficiency in self-managed portfolios generates a jump in the risky share once the investor's liquid assets reach some threshold. Benchmark models feature no such jump. Moreover, a personalized risk profile by both age and wealth increases older investors' and less-wealthy investors' demand for risky assets beyond what a benchmark model would predict.

C.3 Welfare Measure

Repeating from the text, we measure investor i's welfare gain by the percent increase in annual consumption under the previous minimum that raises her expected lifetime utility by the same amount as the reduction, denoted by q_i . Let $\{\underline{C}_{\{i,\tau\}}\}_{\tau \geq t}$ denote the optimal consumption stream for investor i under the previous minimum of \$5,000 and let $\{\overline{C}_{\{i,\tau\}}\}_{\tau \geq t}$ denote the optimal consumption stream under the reduced minimum of \$500. Then q_i is defined by solving

$$\mathbb{E}_t \left[\sum_{\tau=t}^{\tau=\overline{T}} \delta^{\tau-t} \left(\prod_{j=t}^{j=\tau-1} p_j \right) \frac{\left((1+q_i)\underline{C}_{i,\tau}\right)^{1-\gamma}}{1-\gamma} \right] = \mathbb{E}_t \left[\sum_{\tau=t}^{\tau=\overline{T}} \delta^{\tau-t} \left(\prod_{j=t}^{j=\tau-1} p_j \right) \frac{\left(\overline{C}_{i,\tau}\right)^{1-\gamma}}{1-\gamma} \right] \equiv \overline{V}_i, \tag{C18}$$

where, as in the text, $\overline{V}_i$ denotes investor i's value function under the \$500 minimum. Likewise, let

$$\underline{V}_i \equiv \mathbb{E}_t \left[\sum_{\tau=t}^{\tau=\overline{T}} \delta^{\tau-t} \left(\prod_{j=t}^{j=\tau-1} p_j \right) \frac{\left(\underline{C}_{i,\tau}\right)^{1-\gamma}}{1-\gamma} \right] \tag{C19}$$

denote i's value function under the \$5,000 minimum. Rearranging terms gives

$$q_i = \left(\frac{\overline{V}_i}{\underline{V}_i} \right)^{\frac{1}{1-\gamma}} - 1, \tag{C20}$$

as shown in equation (10). Note that equation (C20) is increasing in the difference between $\overline{V}_i$ and $\underline{V}_i$because a standard isoelastic utility function is bounded above by zero.

C.4 Extensions and Robustness

We describe the model extensions in Table A18.

C.4.1 Participation Costs

The first extension introduces a per-period cost of holding the self-managed portfolio. As already noted, quantitative models generate counterfactually high stock market participation rates without such a cost. In this extension, investors incur a per-period cost of κ = \$200 when holding the self-managed portfolio, which we obtain from the structural estimation described in Appendix C.5. Explicitly, flow utility becomes: $\frac{(C_{i,t}-\kappa \mathbf{1}\cdot[\alpha^S_{i,t}>0])^{1-\gamma}}{1-\gamma}$.

This cost equals around 20% of the inflation-adjusted cost in Vissing-Jørgensen (2002), which reflects how we already incorporate features that discourage stock market participation, like inefficient self-managed portfolios. Under this extension, we calculate a welfare gain of 1.23% due to the reduction, as shown in panel (a) of Table A18. In relation to Table 7, our baseline effect of 0.77% equals around two-thirds of the effect with stock market participation costs. Thus, in a more realistic setting with limited stock market participation, the reduction adds value by bringing investors into the stock market, but this channel does not drive the welfare gain. Intuitively, the welfare loss from stock market non-participation is small if the alternative is investing inefficiently on one's own (e.g., Calvet et al. (2007)). Consistent with this interpretation, we find almost the same effect under a higher cost of $\kappa = \$700$, also shown in Table A18.

C.4.2 Borrowing

Next, we allow investors to borrow up to $b = 30\%$ of liquid wealth. Explicitly, constraint (C5) becomes: $\alpha^f_{i,t} \geq -b$. One can interpret the borrowing limit, b, as reflecting how, for example, lender-friendly bankruptcy laws allow recourse up to 30% of liquid wealth. The interest rate at which investors borrow equals 12%, the average interest rate on credit card debt in 2015. The resulting welfare gain in panel (a) of Table A18 equals 0.8%, almost equivalent to the baseline gain. This similarity partly reflects a precautionary savings motive, which discourages middle-class investors from borrowing. Moreover, borrowing to invest in the robo portfolio would be suboptimal given the high interest rate on credit card debt.

C.4.3 Calibration of Portfolio Parameters

We recalculate welfare implications under a different calibration of portfolio parameters. We do so by using the relationship between the portfolio characteristics of Swedish investors and their demographics as estimated in Table 5 of Calvet, Campbell and Sodini (2007). In particular, we use their estimated coefficients to describe a self-managed portfolio's market beta and its idiosyncratic volatility as functions of the model's state variables. Panel (b) of Table A18 shows that the welfare gains under these alternative calibrations are comparable to the baseline.

C.4.4 Calibration of Preference Parameters

We reproduce the main results under the following parameterizations: structurally estimated preference parameter values, based on the estimation described shortly in Appendix C.5; and a high discount factor of $\delta = 0.85$. Panel (c) of Table A18 shows that the distribution of welfare gains is robust to these parameterizations. The level of this gain rises under the structurally estimated parameter values, which is driven by a higher coefficient of relative risk aversion ($\gamma = 5.1$).

The last row of panel (c) recalculates the welfare gain when the correlation between log labor income and the robo portfolio's abnormal return equals 80%, corresponding to $\beta^Y = 3.3$.This extension results in only a very small welfare loss, which may seem counterintuitive. Indeed, the strong positive correlation raises the total risk of investing with the robo advisor, which would tend to reduce the welfare gain. However, by the same logic, this correlation reduces an investor's unconstrained-optimal risky share, which makes investing under a lower minimum especially valuable. On net, the two forces approximately cancel out, leading to almost the same results as in our baseline calculation.

C.5 Structural Parameter Estimation

We assess the validity of the preference parameter values in Table 5 by estimating these parameters through a generalized method of moments estimator (GMM). The 3×1 parameter vector is (γ, δ, κ). The 9×1 moment vector consists of: a 4×1 vector containing the share of robo participants from the second through the fifth U.S. wealth quintiles under the previous account minimum; an analogous 4×1 vector containing the shares under the reduced minimum; and the coefficient μ from an uncontrolled specification of equation (2), our baseline regression equation.[34] Let θ_m denote moment m, and let

$$\Theta = [\theta_1, ..., \theta_9]'$$

denote the full moment vector.

We solve for the value of (γ, δ, κ) that minimizes the weighted squared distance between the theoretical moment vector, $\tilde{\Theta}(\gamma, \delta, \kappa)$, and the empirical moment vector, $\hat{\Theta}$, using a similar solution technique as in Appendix C.1. Denote the solution by

$$(\hat{\gamma}, \hat{\delta}, \hat{\kappa}) = \arg \min_{(\gamma,\delta,\kappa)} (\tilde{\Theta}(\gamma, \delta, \kappa) - \hat{\Theta})' \Psi (\tilde{\Theta}(\gamma, \delta, \kappa) - \hat{\Theta}), \tag{C21}$$

where Ψ is a 9×9 weight matrix. Our baseline weight matrix is the GMM optimal matrix (Newey (2007)), in which moments are weighted by the inverse standard error of the empirical moment. Accordingly, we estimate $\hat{\gamma} = 5.1$, $\hat{\delta} = 0.92$, and $\hat{\kappa} = 169$ as shown in column (1) of Appendix Table A19.

[34] We do not include moments related to the share of robo participants from the first U.S. wealth quintile, since this share has no empirical variance and, thus, would have infinite weight in the GMM optimal weight matrix.

D Asset Pricing Appendix

This appendix describes the method for estimating the idiosyncratic volatilities and factor loadings on self-managed and robo portfolios in Section 6.2.1. We follow Calvet et al. (2007) in our methodology. For each security k in the portfolio dataset described in Section 3.2 and a given asset pricing model F, we estimate the following equation

$$R_{k,m} = \beta_k^F F_m + \epsilon_{k,m}^F, \tag{D1}$$

where F_m denotes a column vector of pricing factors in month m; β_k^F denotes the respective row vector of loadings; $R_{k,m}$ denotes the monthly return on security k in excess of the risk-free return, measured by the one-month Treasury yield, and net of expense ratios and other fees; and $\epsilon_{k,m}^F$ is an idiosyncratic, zero-mean shock to security k with standard deviation $\sigma_{\epsilon,k}^F$. We estimate equation (D1) using the longest available time series of monthly returns for each security k and factor vector F within the window from July 1990 through February 2016. Following Calvet et al. (2007), we restrict the set of securities to stocks and funds traded on an exchange. We obtain data on the returns for each security k from the Center for Research in Security Prices (CRSP). Once we have the estimated the loadings $\hat{\beta}_k^F$ from equation (D1) for model F, it is straightforward to compute the idiosyncratic volatility and factor loadings for investor i's self-managed and robo portfolios, as in equation (9).

We estimate equation (D1) for the following asset pricing models,

$$F_m^{CAPM} = \left[R_m^M\right]', \tag{D2}$$

$$F_m^{FF} = \left[R_m^M, \quad R_m^{HML}, \quad R_m^{SMB}\right]', \tag{D3}$$

$$F_m^{FF+} = \left[R_m^M, \quad R_m^{HML}, \quad R_m^{SMB}, \quad R_m^{USB}, \quad R_m^{GLB}\right]', \tag{D4}$$

where R_m^M is the monthly market return, net of the risk-free rate; R_m^{HML} is the spread in monthly return between high book-to-market stocks and low book-to-market stocks (HML); and R_m^{SMB} denotes the spread in monthly return between stocks with a small market capitalization and a big market capitalization (SMB). We measure R_m^M, R_m^{HML}, and R_m^{SMB} using data from Ken French's website, specifically the "Fama/French 3 Factors for Developed Markets" series. The two bond factors are the return on U.S. and global bonds, denoted R_m^{USB} and R_m^{GLB}. We measure R_m^{USB} and R_m^{GLB} using the monthly percent changes in the Bloomberg-Barclays Aggregate U.S. Bond Index Unhedged (R_m^{USB}) and in the Bloomberg-Barclays Global Aggregate Bond Index Unhedged (R_m^{GLB}). Data on these indices come from the robo advisor.[35]

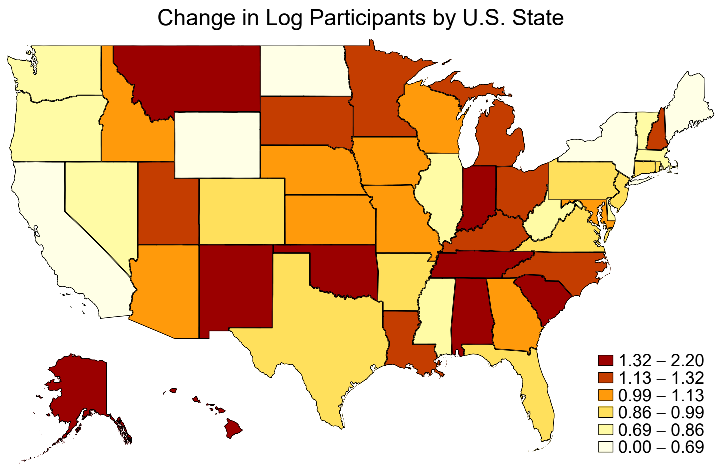
We calibrate the factor covariance matrix and risk prices as follows. The covariance matrix is that of: (i) the return on the CRSP Value-Weighted Index minus the one-month Treasury yield; (ii) the HML return for the U.S. market from Ken French's website; (iii) the SMB return for the U.S. market from Ken French's website; (iv) the return on the Bloomberg-Barclays Aggregate U.S. Bond Index Unhedged; and (v) the return on the Bloomberg-Barclays Global Aggregate Bond Index Unhedged. The covariance matrix is calculated using the subperiod from January 1990 through February 2016 because we only observe the bond factors over that subperiod. We calculate risk prices using the sample means of the series (i)-(v),

[35]The bond indices used to estimate equation (D4) differ slightly from the actual Bloomberg-Barclays indices because of an artefact in the delivery of these indices in January 2017. We later cross-referenced the actual indices with the indices that we work with. The monthly percent change in our indices is on average 0.002 lower than with the actual indices, and the standard deviation of this difference is 0.002. We interpret this noise as a manifestation of the Roll (1977) critique that applies to factor models more generally. Econometrically, this is another argument in favor of using a model to estimate expected returns, since such noise biases the estimated mean of the factor but not necessarily the estimated loading of a security on that factor.

taken over January 1960 through December 2017 for (i)-(iii) and over January 1990 through February 2016 for (iv)-(v). The corresponding covariances and risk prices are shown in Appendix Table A14.

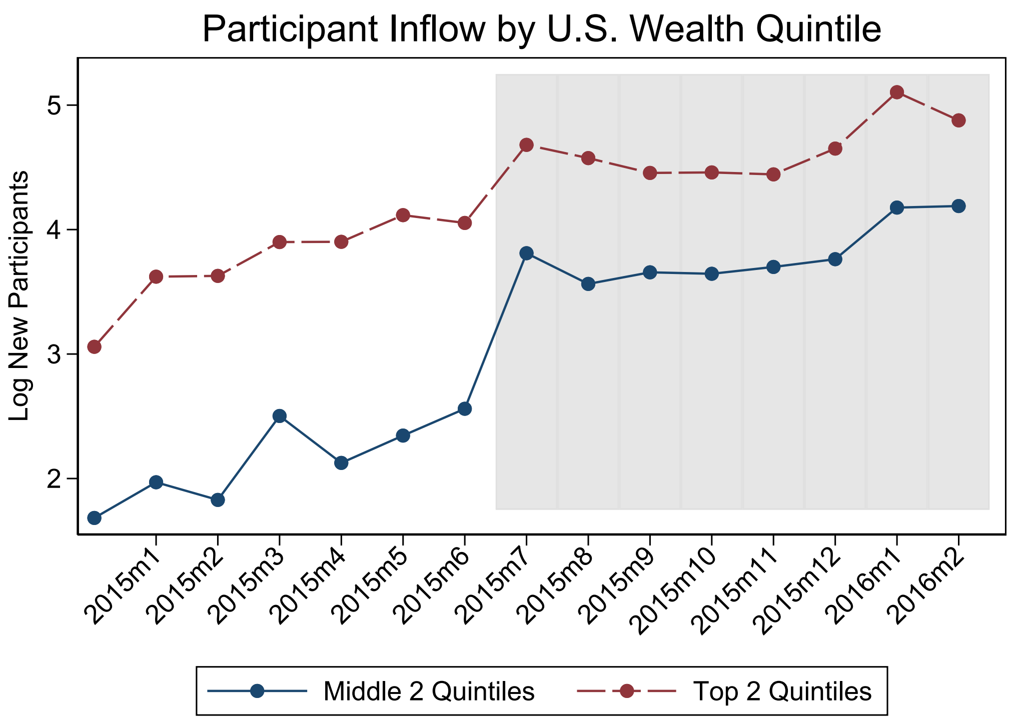
Additional Figures and Tables

Figure A1: Growth in Robo Participation by U.S. State



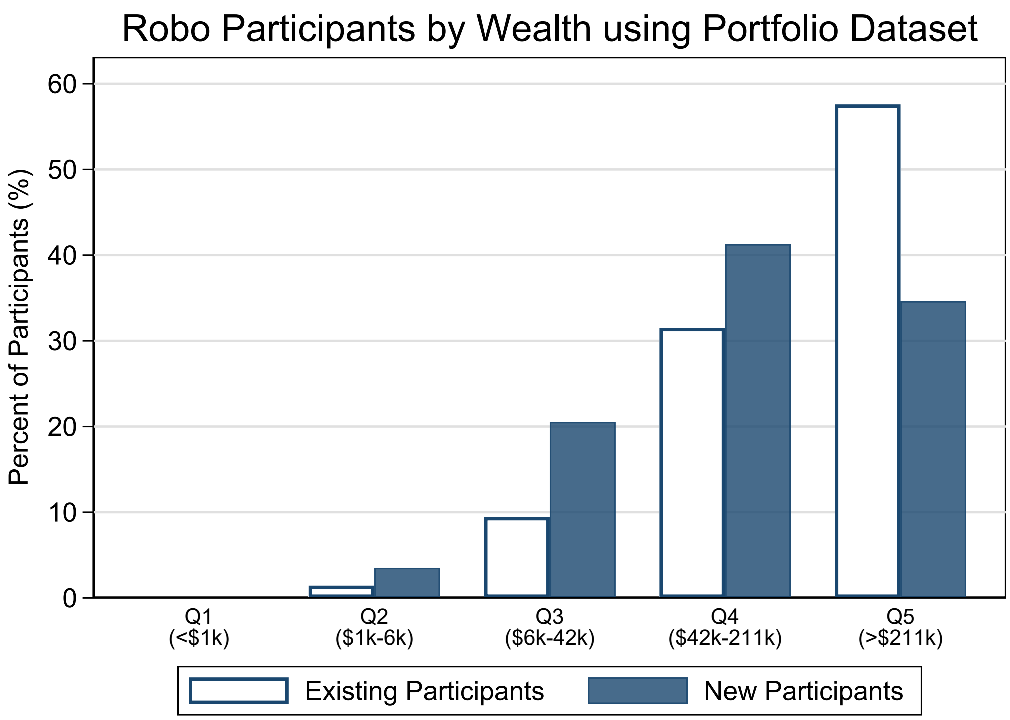
Note: This figure plots the change in the log of the number of robo participants from each U.S. state. The change is from the pre-reduction period (December 1, 2014 to July 7, 2015) to the post-reduction period (July 7, 2015 to February 29, 2016).

Figure A2: Parallel Trends in Robo Participation. Raw Data.



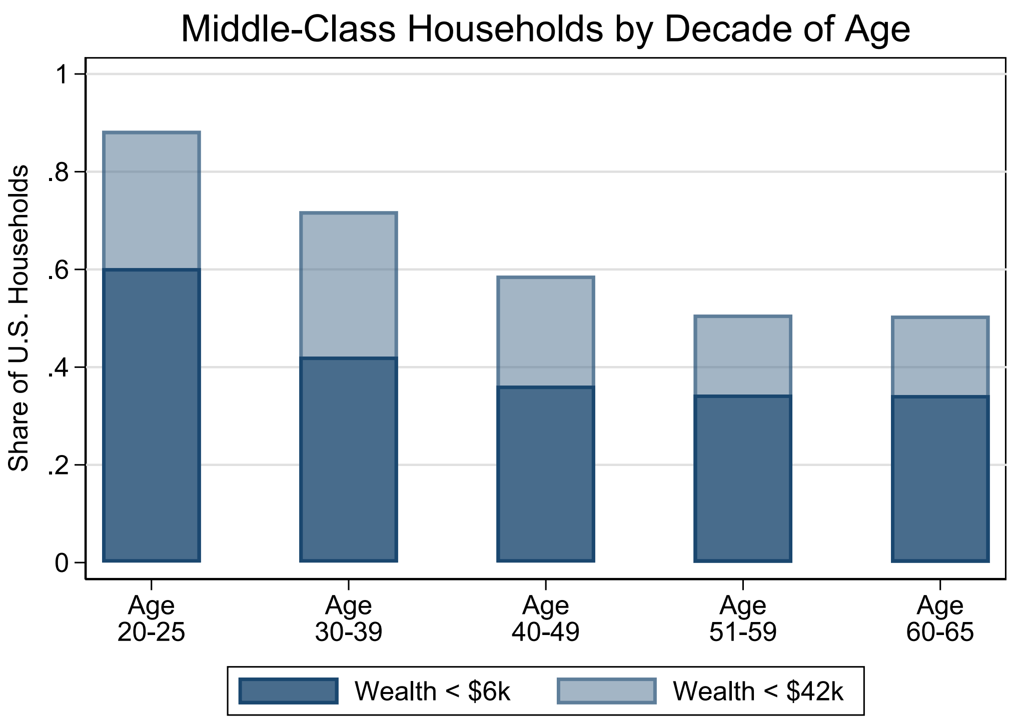
Note: This figure plots the log number of new robo participants from the second and third U.S. wealth quintiles and the fourth and fifth U.S. wealth quintiles, by month. The remaining notes are the same as in Figure 3.

Figure A3: Robustness of the Change in Representativeness to Portfolio Dataset



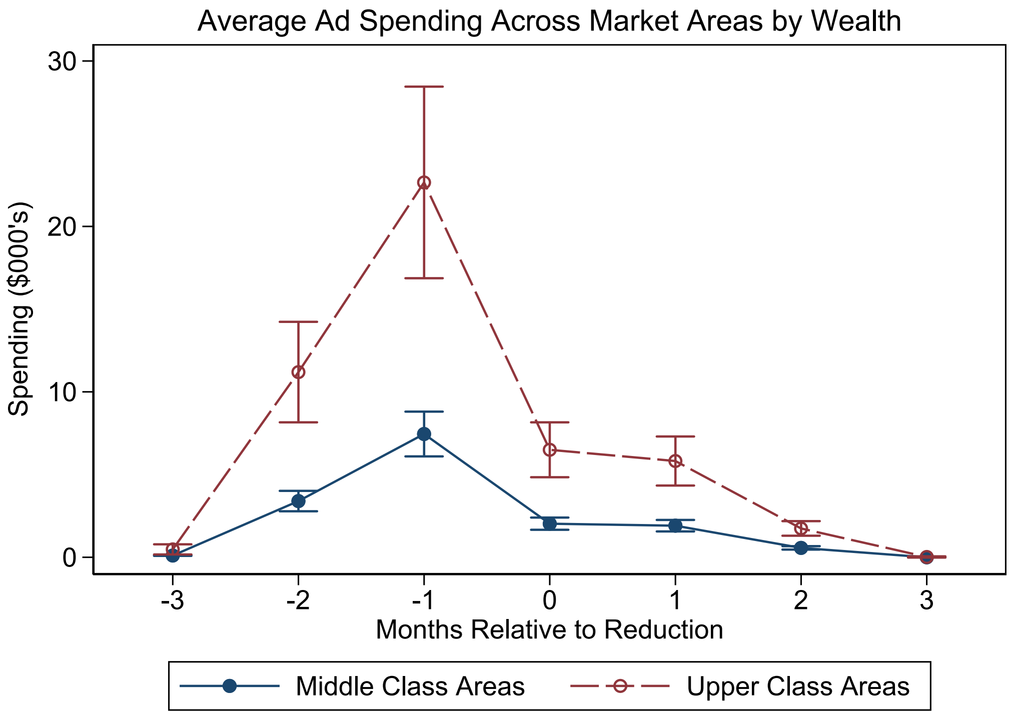
Note: This figure replicates Figure 3 using the subset of robo participants who are also in the portfolio dataset. The remaining notes are the same as in Figure 3.

Figure A4: Share of U.S. Households in the Middle Class by Age



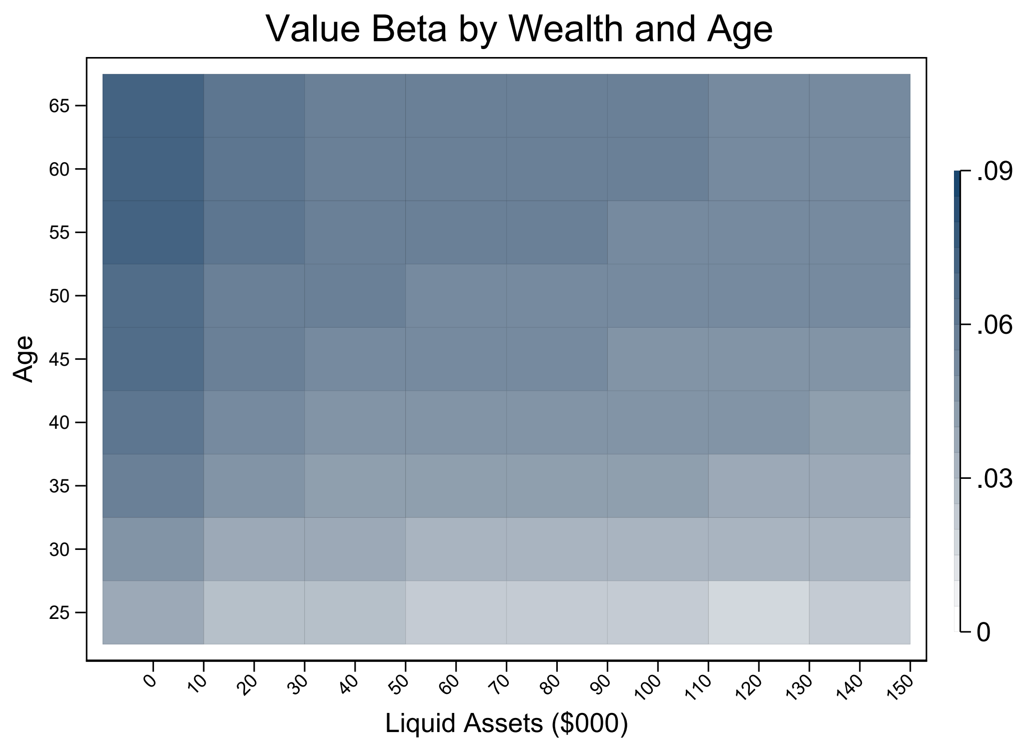
Note: This figure plots the share of U.S. households in the first or second quintile of the overall U.S. distribution of liquid assets (under $6k) and also the share in the first, second, or third quintiles (under $42k). The shares are calculated for each decade of investor age. Data are from the SCF dataset.

Figure A5: Average Ad Spending Across Market Areas by Wealth



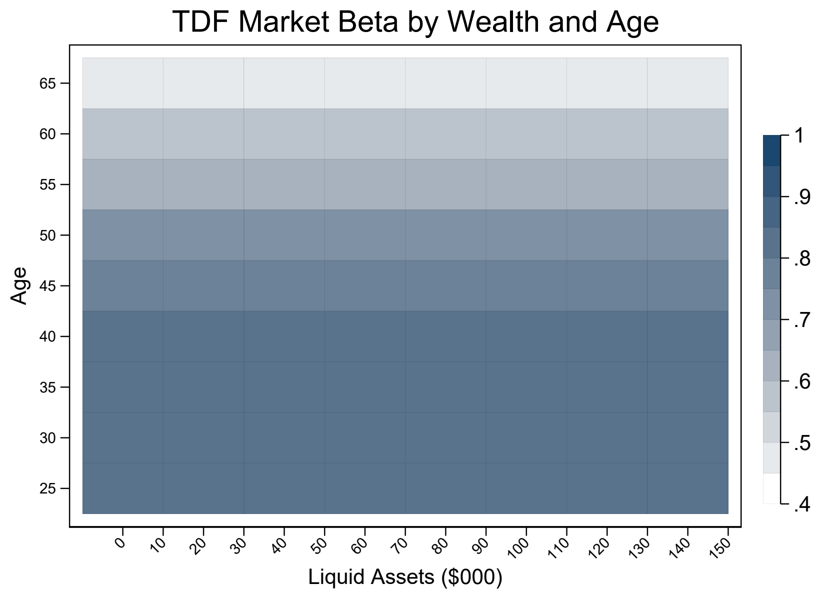
Note: This figure presents the times-series of average monthly ad spending by the advisor across middle-class and upper-class Designated Market Areas (DMAs). Time 0 is the month when the reduction in account minimum was implemented. A DMA is classified as middle-class if its average imputed stock market wealth falls within quintiles 2 and 3 of the wealth distribution across all DMAs. DMAs in the top two quintiles are classified as upper-class. The ad spending data are sourced from Vivvix by Kantar. Details on data construction are outlined in Appendix A. Brackets represent 95% confidence intervals.

Figure A6: Robo Value Exposure by Age and Wealth

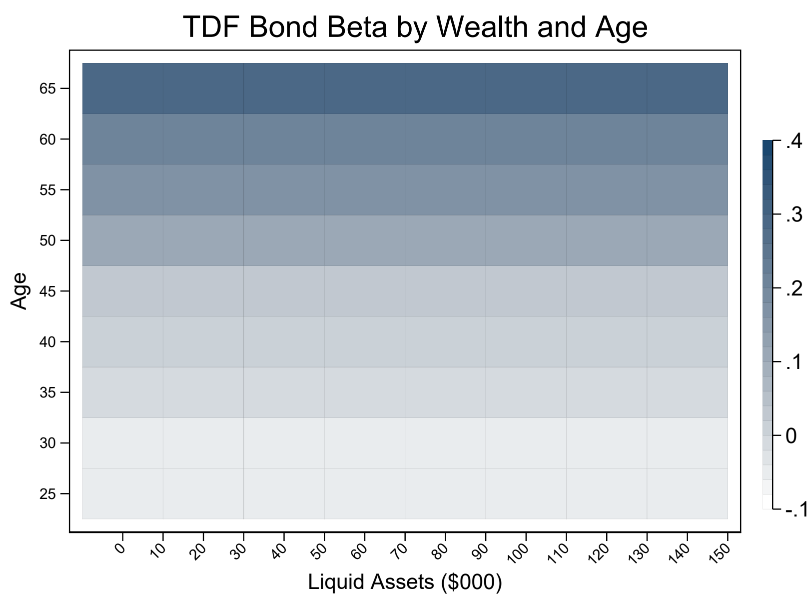


Note: This figure is analogous to Figure 1, and it shows the loading on the High-minus-Low factor (Value Beta). The remaining notes are the same as in Figure 1.

Figure A7: TDF Stock and Bond Exposure by Age and Wealth



Panel (a)



Panel (b)

Note: This figure is analogous to Figure 1, and it shows the loading on the market factor (*Market Beta*) and U.S. bond factor (*Bond Beta*) by investor age and wealth for the Fidelity Freedom TDF with target year that an investor of a given age would choose in 2015 to retire at age 65. The remaining notes are the same as in Figure 1.

Table A1: Summary of the U.S. Robo Advising Market around the Reduction

Robo advisor	AUM ($bil)	Fees by Account Size	Account Minimum	Presence of Human Advisor
Wealthfront	2.43	0% (under $10k) 0.25% (over $10k)	$500	No
Betterment	2.33	0.35% or $36 (under $10k) 0.25% ($10k to $100k) 0.15 % (over $100k)	$0	Yes (2017)
Personal Capital	1.44	0.89% (under $1mil) 0.49% to 0.89% (over $1mil)	$100k	Yes (2009)
Charles Schwab, Intelligent Portfolios	3	0% (see note)	$5k	Yes (2017)
Vanguard, Personal Advisor Services	21.2	0.3%	$50k	Yes (2015)

Note: This table presents information about the five largest robo advisors in the U.S. market around the time of Wealthfront's reduction in account minimum in July 2015. AUM denotes assets under management around July 2015, which we obtain from the Q2, 2015 Form 13-F for Wealthfront, Betterment, and Personal Capital and from company press releases for Schwab and Vanguard. Fees denotes annual management fees in July 2015, which we obtain from company press releases and contemporaneous industry publications. Fees do not include expense ratios on ETFs in the robo portfolio. Betterment charged 0.35% on accounts under $10,000 which auto-invest at least $100 per month, or $3 monthly (i.e., $36 annually) if they do not auto-invest. Schwab's robo advising service does not charge a management fee, and it instead monetizes by holding 8-10% of clients' portfolios in cash. Account Minimum denotes the account minimum required to open an account in July 2015, which we obtain from company press releases and contemporaneous industry publications. Presence of Human Advisor denotes whether the advisor offers the option to speak with a human advisor, which we obtain from company websites, industry publications, and phone calls with company representatives. The year when the option to speak with a human became available is listed in parentheses. Wealthfront, Betterment, Personal Capital, Schwab, and Vanguard respectively held $23, $22, $13, $45.9, and $179.7 billion in June 2020. Collectively, these five advisors held $283.6 billion in AUM in June 2020, compared to $30.4 billion in July 2015.

Table A2: Summary of Robo Portfolios

Risk Tolerance (0.5 to 10) (1)	CAPM Beta (2)	Stocks (%) (3)	Bonds (%) (4)	Other (%) (5)	Percent of Investors (%) (6)	Average Age (7)
0.50	0.32	33.00	60.00	7.00	0.67	39
2.00	0.45	47.00	48.00	5.00	0.39	46
2.50	0.49	50.00	44.00	6.00	0.20	48
3.00	0.52	53.00	41.00	6.00	0.89	48
3.50	0.57	59.00	35.00	6.00	0.86	46
4.00	0.58	59.00	35.00	6.00	1.56	39
4.50	0.61	62.00	33.00	5.00	1.14	42
5.00	0.64	66.00	29.00	5.00	1.68	42
5.50	0.67	69.00	26.00	5.00	1.21	48
6.00	0.70	72.00	23.00	5.00	2.27	40
6.50	0.72	74.00	21.00	5.00	2.32	42
7.00	0.75	77.00	18.00	5.00	6.41	36
7.50	0.77	80.00	15.00	5.00	8.06	39
8.00	0.79	82.00	13.00	5.00	14.39	33
8.50	0.82	86.00	9.00	5.00	16.50	34
9.00	0.85	89.00	6.00	5.00	16.30	33
9.50	0.88	90.00	5.00	5.00	5.43	35
10.00	0.91	90.00	5.00	5.00	19.72	31

Note: This table summarizes robo portfolios assigned to investors in our sample. Portfolios are indexed by risk tolerance score, which ranges from 0.5 to 10 in increments of 0.5, and tax status. Each portfolio has a unique vector of weights across 10 possible ETFs, which are chosen to represent exposure to different asset classes. Stocks, Bonds, and Other respectively denote the sum of weights for ETFs that track stock market indices (VIG, VTI, VEA, VWO), bond market indices (LQD, EMB, MUB, SCHP), and other asset classes, namely real estate (VNQ) and commodities (XLE). Beta is based on the CAPM, as described in Appendix D. Column (6) shows the percent of robo participants with the indicated portfolio. Column (7) shows the average age of participants with the indicated portfolio. The table only shows taxable portfolios to emphasize how the allocation varies across risk scores, rather than tax status.

Table A3: Primary and Secondary ETFs in Robo Portfolios

Asset Class	Primary ETF	Secondary ETF	Correlation Coefficient
U.S. Stocks	VTI	SCHB	0.999
High-Dividend Stocks	VIG	SCHD	0.948
Developed Market Stocks	VEA	SCHF	0.998
Emerging Market Stocks	VWO	IEMG	0.993
U.S. Corporate Bonds	LQD	.	.
Emerging Market Bonds	PCY	EMB	0.894
Municipal Bonds	MUB	TFI	0.929
Treasuries	SCHP	VTIP	0.843
Commodities	XLE	VDE	0.998
Real Estate	VNQ	SCHH	0.994

Note: This table reports the primary and secondary ETFs for each asset class defined by the robo advisor. The robo advisor will use the secondary ETF for accounts under $5,000 if the primary ETF is too expensive. Most of our results are based on the primary ETF and the approximation that the robo advisor can hold fractional shares. Table A11 assesses robustness of portfolio-level statistics to this approximation. The rightmost column reports the coefficient of correlation in total return between the primary and secondary ETFs. The correlation is calculated over the longest available time series for each ETF through December 2022. The robo advisor does not have a secondary ETF to LQD for U.S. Corporate Bonds.

Table A4: Summary of U.S. Wealth Quintiles

Wealth Quintile:	First	Second	Third	Fourth	Fifth
Participation in the Stock Market (%)	0.3%	6.4%	31.4%	57.9%	87.0%
Participation with Professional Assistance (%)	0.2%	4.1%	20.7%	41.8%	69.3%
Range of Liquid Assets ($000)	[0,0.6]	[0.6,6.3]	[6.3,42]	[42,211]	>211

Note: This table summarizes the share of U.S. households who participate in the stock market and in asset management by wealth quintile in 2016, based on the SCF dataset. The first row summarizes participation in the stock market, defined as owning stocks, mutual funds, a trust, or an IRA. The second row summarizes participation in the stock market with professional assistance, defined as both participating in the stock market and consulting with a broker, financial planner, banker, accountant or lawyer regarding investment. The bottom row summarizes the range of liquid assets that define each U.S. wealth quintile, in thousands of dollars. Wealth consists of liquid assets, defined as the sum of checking accounts, savings accounts, certificates of deposit, cash, stocks, bonds, savings bonds, mutual funds, annuities, trusts, IRAs, and employer-provided retirement plans.

Table A5: Summary of Investors in Portfolio Dataset

	All ($N = 1,913$)			Robo Participants ($N = 860$)			Robo Non-Participants ($N = 1,053$)		
	Mean	Standard Deviation	Median	Mean	Standard Deviation	Median	Mean	Standard Deviation	Median
Liquid Assets$_i$ ('000)	484.24	770.1	200	447.29	739.97	184.5	514.4	792.94	200
Income$_i$ ('000)	166.91	131.07	130	170.44	131.67	140	164.02	130.57	125
Age$_i$	38.24	11.91	35	35.55	10.17	33	40.44	12.74	37
Self-Managed Sharpe$_i$	0.46	0.16	0.47	0.44	0.17	0.45	0.47	0.16	0.49
Middle$_i$	0.19	0.39		0.19	0.39		0.19	0.39	
Participant$_i$	0.45	0.5							

Note: This table summarizes investors in the portfolio dataset. The sample consists of investors who consult the robo advisor for a free portfolio review, of which 45% become participants and the remainder do not. The left, center, and right panels summarize all investors in the dataset, the subsample of robo participants, and the subsample of non-participants, respectively. The variable *Self-Managed Sharpe*$_i$ equals the Sharpe ratio of the investor's self-managed portfolio, as in Table 4. The remaining notes are the same as in Tables 1 and 4.

Table A6: Effect on Participation after Dropping Investors with Multiple Accounts.

	First Difference	Dynamic DiD
$Y_i =$	*New Participant*$_i$	*New Participant*$_{i,t}$
	(1)	(2)
$Middle_i$	12.320***	
	(1.413)	
$Middle_i \times Post_t$		0.646***
		(0.095)
Controls	Yes	
State FE	Yes	
Investor FE		Yes
Week FE		Yes
Controls $\times$ $Post_t$		Yes
State FE $\times$ $Post_t$		Yes
R-squared	0.069	0.007
Number of Observations	7,034	463,232

Note: Standard errors are in parentheses. Point estimates are multiplied by 100. This table re-estimates the main specifications from Table 2 after restricting the sample to account holders with only a single account with the robo advisor, which applies to 88% of account holders. This exercise assesses whether the estimated effects in Table 2 are driven by gambling motives induced by a lower account minimum. Account holders are identified by the user ID assigned by the robo advisor. The remaining notes are the same as in Table 2.

Table A7: Effects on Participation Within Middle Class

$Y_i =$	*New Participant$_i$*		
	(1)	(2)	(3)
Lower Middle$_i$	27.068***	16.313***	15.065***
	(3.058)	(3.046)	(3.004)
Upper Middle$_i$	21.328***	14.928***	13.588***
	(1.214)	(1.387)	(1.370)
Controls	No	Yes	Yes
State FE	No	No	Yes
R-squared	0.033	0.067	0.097
Number of Observations	9,349	9,349	9,349

Note: Standard errors are in parentheses. This table reestimates the effects from Table 2 separating between investors from the second U.S. wealth quintile (*Lower Middle$_i$*) and the third quintile (*Upper Middle$_i$*). We use a specification of the form:

$$New\ Participant_i = \mu_1 Lower\ Middle_i + \mu_2 Upper\ Middle_i + \psi X_i + \varrho + u_i.$$

The remaining notes are the same as in Table 2.

Table A8: Robustness of Democratization to State-Clustered Standard Errors

$Y_i =$	*New Participant$_i$*	
	(1)	(2)
Middle$_i$	15.051***	13.718***
	(0.901)	(1.070)
Controls	Yes	Yes
State FE	No	Yes
R-squared	0.067	0.097
Number of Observations	9,349	9,349

Note: Standard errors are in parentheses. This table reestimates the specifications in columns (1)-(2) of Table 2 after clustering standard errors by state of residence.

Table A9: Testing the Constraints Channel. The Effect on Bunching at the Previous Minimum.

$Y_{i,t} =$	$\mathbb{1}[First\ Deposit_{i,t} = \$5k]$				
	(1)	(2)	(3)	(5)	(6)
$Middle_i \times Post_t$	-30.236***	-30.538***	-23.724***		
	(3.175)	(3.189)	(3.475)		
$Middle_i$	27.129***	24.673***	19.656***		
	(3.028)	(3.131)	(3.273)		
$Lower\ Middle_i \times Post_t$				-43.073***	-36.419***
				(8.400)	(7.837)
$Lower\ Middle_i$				33.922***	29.390***
				(8.135)	(7.586)
$Upper\ Middle_i \times Post_t$				-29.276***	-22.468***
				(3.355)	(3.714)
$Upper\ Middle_i$				23.814***	18.759***
				(3.294)	(3.506)
Week FE	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	Yes	Yes	Yes
State FE	No	Yes	Yes	Yes	Yes
Controls $\times$ $Post_t$	No	No	Yes	No	Yes
State FE $\times$ $Post_t$	No	No	Yes	No	Yes
R-squared	0.113	0.119	0.120	0.281	0.288
Number of Observations	7,162	7,162	7,162	7,162	7,162

Note: Standard errors are in parentheses. Point estimates are multiplied by 100. This table estimates a variant of equation (4) that assesses the robustness of interpreting investors from the second or third U.S. wealth quintiles as constrained by the previous account minimum. Subscripts i and t index investor and week. The baseline regression equation is of the form,

$$\mathbb{1}[First\ Deposit_{i,t} = \$5k] = \mu\,(Middle_i \times Post_t) + \varrho_t + \psi_t X_i + u_{i,t},$$

where $\mathbb{1}[First\ Deposit_{i,t} = \$5k]$ indicates the initial deposit made by investor i in week t equals the previous account minimum or is no more than 5% higher. This variable measures bunching of initial deposits around the previous minimum. The sample consists of investor-weeks in which the investor makes its initial deposit, and, thus, we cannot include investor fixed effects. Columns (4)-(5) estimate separate effects for investors from the second U.S. wealth quintile ($Lower\ Middle_i$) and the third quintile ($Upper\ Middle_i$). The remaining notes are the same as in Table 2.

Table A10: Interpreting the Magnitude of the Effect on Robo Participation

	Growth in Number of Robo Participants					
	All Participants			Middle-Class Participants		
	Data (g)	No Reduction (g^C)	Effect (η)	Data (g)	No Reduction (g^C)	Effect (η)
	(1)	(2)	(3)	(4)	(5)	(6)
Baseline Estimates:						
Table 2, Column (3)	119.4%	106.0%	13.4%	239.4%	131.6%	107.8%
Additional Estimates:						
Table 2, Column (6)	119.4%	117.6%	1.8%	301.0%	153.5%	147.5%
Table 2, Column (7)	119.4%	105.6%	13.8%	256.2%	129.7%	126.5%

Note: This table summarizes the observed and counterfactual growth rates in the number of robo participants around the reduction, which assesses the magnitude of the results in Table 2. Column (1) summarizes the observed growth rate in the total number of robo participants, denoted g, and column (2) summarizes the counterfactual growth rate in the absence of the reduction, denoted g^C and defined in equation (B4). Column (3) summarizes the effect of the reduction, defined as the difference between g and g^C, that is, $\eta = g - g^C$. Columns (4)-(5) summarize the analogous observed and counterfactual growth rates in the number of middle-class robo participants, and column (6) summarizes the analogous value of η. Each row calculates these statistics using the estimated coefficient μ and definition of $Middle_i$ from the indicated specification in Table 2, using the methodology described in Appendix Section B.1. The observed growth rate in the number of middle-class participants differs across specifications in column (4) because the definition of $Middle_i$ varies across specifications. The remaining notes are the same as in Table 2.

Table A11: Summary of Self-Managed and Robo Portfolios without Fractional Shares

	Middle Class ($N = 354$)			Upper Class ($N = 1,559$)		
	Self-Managed	Matched Robo	Difference	Self-Managed	Matched Robo	Difference
	(1)	(2)	(3)	(4)	(5)	(6)
Sharpe Ratio	0.452	0.748	0.296***	0.459	0.755	0.296***
Expected Return	0.080	0.101	0.022***	0.078	0.101	0.023***
Total Volatility	0.209	0.136	-0.072***	0.196	0.134	-0.062***
Idiosyncratic Volatility	0.146	0.0343	-0.113***	0.138	0.033	-0.105***
Robo-Sharpe Expected Return	0.154			0.147		
Return Loss	-0.074			-0.069		

Note: This table is analogous to Table 4 without approximating robo portfolio weights as though the advisor can hold fractional shares. The robo portfolio weights used in this table solve an optimization problem similar to that of the robo advisor (Wealthfront (2023)). Explicitly, we minimize the excess cash in the portfolio, subject to the constraints that: robo portfolios hold a discrete number of shares of any ETF; and the tracking error relative to the target weight for each asset class lies below some threshold. The solution requires selecting the ETF with the lowest price among the primary and secondary ETFs for each asset class shown in Table A3. We compute this ranking using each ETF's average price over the post-reduction period. We preserve computational feasibility by restricting the solution to equal either the integer floor or the integer ceiling of the fractional number of shares implied by the ETF's target weight. This restriction also implies a bound on the admissible tracking error. We solve this problem for all portfolios smaller than $5,000 because the fractional shares approximation is less accurate for small portfolios. The resulting average excess cash share equals 0.1% for the portfolios shown in the table, and it equals 0.2% for the subset of portfolios held by middle-class investors. Given the revised weights, we recalculate the portfolio statistics as in Table 4, assuming that the factor loadings for the primary and secondary ETFs in each asset class are the same, and similarly for the idiosyncratic volatilities. This assumption accords with the high correlation coefficients shown in Table A3. The remaining notes are the same as in Table 4.

Table A12: Summary of Self-Managed and Robo Portfolios excluding Possible Gambling Accounts

	Middle Class ($N = 351$)			Upper Class ($N = 1,497$)		
	Self-Managed	Matched Robo	Difference	Self-Managed	Matched Robo	Difference
	(1)	(2)	(3)	(4)	(5)	(6)
Sharpe Ratio	0.451	0.751	0.299***	0.458	0.754	0.296***
Expected Return	0.080	0.102	0.0230***	0.078	0.101	0.0230***
Total Volatility	0.209	0.137	-0.072***	0.196	0.134	-0.061***
Idiosyncratic Volatility	0.147	0.034	-0.112***	0.136	0.0330	-0.103***
Robo-Sharpe Expected Return	0.155			0.146		
Return Loss	-0.075			-0.068		

Note: This table is analogous to Table 4 after excluding self-managed accounts smaller than 10% of the investor's liquid wealth, which are possibly intended to serve as gambling accounts. The remaining notes are the same as in Table 4.

Table A13: Summary of Self-Managed and Robo Portfolio Loadings

	Middle Class ($N = 354$)			Upper Class ($N = 1,559$)		
	Self-Managed	Matched Robo	Difference	Self-Managed	Matched Robo	Difference
	(1)	(2)	(3)	(4)	(5)	(6)
Factor Loadings (β_i)						
Market	0.930	0.893	-0.036***	0.899	0.876	-0.023***
SMB	0.044	0.003	-0.040***	0.030	-0.001	-0.032***
HML	-0.086	0.061	0.147***	-0.074	0.061	0.135***
GLB	0.629	-0.020	-0.649***	0.574	-0.023	-0.597***
USB	-0.447	0.508	0.955***	-0.391	0.512	0.903***

Note: This table summarizes the factor loadings for self-managed and matched robo portfolios, based on the Fama-French Three Factor Model augmented with two bond factors. Subscript i indexes portfolio. Each row summarizes the loading on a different factor: Market is the return on the CRSP Value-Weighted Index, net of the risk-free rate; HML is the spread in monthly return between high book-to-market stocks and low book-to-market stocks; SMB is the spread in monthly return between stocks with a small market capitalization and a big market capitalization; USB is the return on the Bloomberg-Barclays Aggregate U.S. Bond Index Unhedged; and GLB is the return on the Bloomberg-Barclays Global Aggregate Bond Index Unhedged. The remaining notes are the same as in Table 4.

Table A14: Covariances and Risk Prices of Factors

Panel (a): Covariance Matrix

	Market	SMB	HML	GLB	USB
Market	0.022	0.005	-0.004	0.001	0.000
SMB	0.005	0.011	-0.002	-0.001	-0.001
HML	-0.004	-0.002	0.009	0.001	0.001
GLB	0.001	-0.001	0.001	0.003	0.001
USB	0.000	-0.001	0.001	0.001	0.001

Panel (b): Risk Prices

	Market	SMB	HML	GLB	USB
	0.076	0.021	0.042	0.060	0.062

Note: This table summarizes the covariance matrix and mean of the baseline asset pricing factor vector, defined in Appendix Table A13. The statistics are calculated as follows. The covariance matrix is that of: (i) the return on the CRSP Value-Weighted Index minus the one-month Treasury yield; (ii) the HML return for the U.S. market from Ken French's website; (iii) the SMB return for the U.S. market from Ken French's website; (iv) the return on the Bloomberg-Barclays Aggregate U.S. Bond Index Unhedged; and (v) the return on the Bloomberg-Barclays Global Aggregate Bond Index Unhedged. The covariance matrix is calculated using the subperiod from January 1990 through February 2016 because we only observe the bond factors over that subperiod. We calculate risk prices using the sample means of the series (i)-(v), taken over January 1960 through December 2017 for (i)-(iii) and over January 1990 through February 2016 for (iv)-(v). Over the 2010-2017 period, the volatility of the market factor equals 12.3% and the mean equals 12.6%. The remaining notes are the same as in Appendix Table A13.

Table A15: Summary of Self-Managed and Robo Portfolios by Factor Model

	Middle Class ($N = 354$)			Upper Class ($N = 1,559$)		
	Self-Managed	Matched Robo	Difference	Self-Managed	Matched Robo	Difference
	(1)	(2)	(3)	(4)	(5)	(6)
(a) Sharpe Ratio						
Fama-French	0.366	0.516	0.150***	0.370	0.517	0.146***
CAPM	0.334	0.442	0.108***	0.339	0.439	0.100***
(b) Expected Return						
Fama-French	0.064	0.071	0.007***	0.062	0.069	0.007***
CAPM	0.058	0.063	0.006***	0.056	0.062	0.006***
(c) Total Volatility						
Fama-French	0.213	0.137	-0.077***	0.197	0.134	-0.063***
CAPM	0.212	0.143	-0.068***	0.198	0.142	-0.057***
(d) Idiosyncratic Volatility						
Fama-French	0.151	0.036	-0.115***	0.142	0.035	-0.106***
CAPM	0.173	0.079	-0.094***	0.160	0.079	-0.081***
(e) Return Loss from Difference in Sharpe Ratio						
Fama-French	-0.046			-0.039		
CAPM	-0.035			-0.030		

Note: This table assesses the robustness of Table 4 by summarizing self-managed and counterfactual robo portfolios under different asset pricing factor models: the CAPM; and the Fama-French Three Factor Model (Fama-French). The remaining notes are the same as in Table 4.

Table A16: Additional Heterogeneity in Welfare Gain

	Increase in Lifetime Consumption
(a) Extensive vs. Intensive Margin	
New Participants	0.77%
Existing Participants	0.05%
Weighted Average	0.62%
(b) New Participants by Initial Deposit	
Initial Deposit: $500 to $2,000	0.86%
Initial Deposit: $2,000 to $3,500	0.70%
Initial Deposit: $3,500 to $4,500	0.55%
(c) New Participants by Wealth Quintile	
Quintile 2	1.21%
Quintile 3	0.52%

Note: This table calculates the welfare gains from the reduction for various subpopulations of robo participants. Panel (a) reports the gain separately for investors who become participants after the reduction (New) and who participated under the previous minimum (Existing). Note that Table 7 only reports the welfare gain for new participants. The bottom row of panel (a) shows the weighted average welfare gain across new and existing participants. Panel (b) reports the gain for new participants according to whether their initial deposit lies in one of the indicated ranges. Panel (c) reports the gain for new participants according to whether they are in the second or third U.S. wealth quintile. All panels restrict to middle-class participants. The remaining notes are the same as in Table 7.

Table A17: Summary of Robo Participants by Wealth Quintile.

	Existing Participants			New Participants			
	Mean	Standard Deviation	Median	Mean	Standard Deviation	Median	Difference in Mean
(a) Third Wealth Quintile:							
Initial Deposit$_i$ ('000)	7.74	5.51	5	5.35	13.33	2	-2.387***
Liquid Assets$_i$ ('000)	25.43	10.41	25	21.83	10.5	20	-3.6***
Income$_i$ ('000)	91.23	60.69	80	69.21	43.26	61.27	-22.015***
Age$_i$	30.27	6.39	29	30.06	6.96	29	-0.215
			$N = 568$			$N = 1,415$	
(b) Second Wealth Quintile:							
Initial Deposit$_i$ ('000)	6.05	2.31	5.02	2.1	3.33	1	-3.945***
Liquid Assets$_i$ ('000)	5.15	.37	5	4.53	.95	5	-0.623***
Income$_i$ ('000)	106.31	72.65	90	52.34	33.29	50	-53.967***
Age$_i$	30.82	5.77	30	29.91	7.83	28	-0.910
			$N = 69$			$N = 198$	

Note: This table summarizes a subset of variables from Table 1 for various subsamples defined by the investor's wealth. The remaining notes are the same as in Table 1.

Table A18: Welfare Implications under Model Extensions

	Increase in Lifetime Consumption			
	Middle Class			
	Pooled	Age 25-35	Age 36-55	Age 56-65
	(1)	(2)	(3)	(4)
(a) Extensions				
Self-Managed Participation Cost				
GMM Cost ($\kappa = \$200$)	1.23%	0.89%	0.91%	2.87%
Higher Cost ($\kappa = \$700$)	1.24%	0.89%	0.91%	2.90%
Borrowing	0.80%	0.60%	0.60%	1.67%
(b) Calibration of Portfolio Parameters				
Calvet, Campbell and Sodini (2007)	0.88%	0.64%	0.66%	1.97%
(c) Calibration of Other Parameters				
Larger Reduction (\$5,000 to \$200)				
GMM Estimates ($\gamma = 5.1$, $\delta = 0.92$)	1.19%	0.84%	0.97%	2.38%
High Impatience ($\delta = 0.85$)	0.74%	0.56%	0.59%	1.53%
Procyclical Labor Income ($\rho^Y = 80\%$)	0.72%	0.51%	0.58%	1.61%
(d) Other Counterfactuals				
Comparison portfolio is Fidelity TDF	0.16%	0.05%	0.10%	0.57%

Note: This table recalculates the welfare gains from the reduction under various extensions and reparameterizations of the baseline model in Table 7. Panel (a) summarizes the average welfare gain under models with the following extensions: a per-period cost of κ when holding the self-managed portfolio (Self-Managed Participation Costs); and the ability to borrow up to 30% of one's liquid assets at the average rate on credit card debt in 2015 of 12% (Borrowing). The participation cost κ equals either \$200, based on the GMM estimates in Appendix Table A19, or a higher value of \$700. Panel (b) assesses robustness to the calibration of the self-managed portfolio parameters β_i^S and $\sigma_{\epsilon,i}$, where we modify the projection of portfolio characteristics onto the model's state variables described in Section 6.2.1. We use the projection summarized in Table 5 of Calvet, Campbell and Sodini (2007) to calibrate a self-managed portfolio's loading on the market factor and its idiosyncratic volatility as a function of the model's state variables. Panel (c) assesses robustness to the calibration of other parameters. Note that a correlation coefficient between log labor income and financial returns of $\rho^Y = 80\%$ corresponds to a loading of β^Y of 3.3. Panel (d) computes the gain under a counterfactual where the self-managed match is replaced by the Fidelity Freedom Fund TDF in which an investor of a given age t in 2015 and retirement age 65 would invest, not the Vanguard TDF as used in Table 7. The remaining notes are the same as in Table 7.

Table A19: GMM Estimates of Preference Parameters

Parameter	Estimate
Coefficient of Relative Risk Aversion (γ)	5.1
	[4.420, 5.830]
Discount Factor (δ)	0.92
	[0.880, 0.962]
Stock Market Participation Cost (κ)	168.75
	[31.338, 306.162]

Note: This table estimates the model's preference parameters using the generalized method of moments estimator described in Appendix C. The 9×1 moment vector consists of: a 4×1 vector containing the share of robo participants from the second through the fifth U.S. wealth quintiles under the previous account minimum; an analogous 4×1 vector containing the shares under the reduced minimum; and the coefficient μ from an uncontrolled specification of the regression in column (1) of Table 2. Each empirical moment is weighted by its inverse standard error (Newey (2007)). For this reason, the share of participants from the first U.S. wealth quintile is excluded from the moment vector, as this share has no empirical variance. Standard errors are bootstrapped. Brackets correspond to 95% confidence intervals under an asymptotically normal distribution.

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