Robo Advisors and Access to Wealth Management

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3rd CEAR-RSI Household Finance Workshop

November 2022

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  - Do not trust (Gennaioli, Shleifer and Vishny (2015)).
- They want it but **lack access**.
  - Large account minimums (e.g., $100k) (Philippon (2016)).

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Robo advisors argue to promote access to wealth management.

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- Tenfold growth over 2015-20 (Top-5 AUM \$300 billion).
- Offer diversified, personalized, rebalanced portfolio.
- Automation lowers costs to accommodate smaller portfolios.
  - *"The wealth management industry stratifies customers like airlines. High net worth clients fly business class, chatting with named advisors. Cattle class gets no service at all. Technology is conspiring to change that."* (The Economist)
  - Popular and intuitive argument, but not tested empirically.

This Paper

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  - Median U.S. household has \$17,000 in liquid assets.

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  3. What are the welfare gains to investors?

Results

1. "Democratizes" the robo market by bringing in the middle class.
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2. Demand for robo advice is driven by better portfolios.
   - Exposure to multiple risk factors (value, size, etc.).
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   - Better diversification.
3. Welfare gains are moderate but heterogenous.
   - Older investors have the largest gain.

Roadmap

1. Data and background.
2. Empirics: effects on robo participation using a DiD approach.
3. Theory: a life-cycle model with robo portfolios.
   1. Can the differences in portfolios explain the effects on robo participation?
   2. Welfare gains: sources and heterogeneity.

Background

- Data from Wealthfront.
  - Second largest U.S.- based robo advisor as of 2015.
  - Not a recommendation tool.
    - D'Acunto, Prahabla and Rossi (2019), Loos, Previtero, Scheurle, Hackethal (2020), Bianchi and Briere (2021).
  - No option for a human advisor.
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- Profiling/Investment Goals + Portfolio Selection + Management.
  - Questionnaire determines portfolio weights.
  - Portfolio of 10 ETFs.
  - Periodic rebalancing.
  - Management Fee: 0% for accounts under $10k (0.25% otherwise)

Data

- Main - "Deposit Dataset":
  - Panel of clients' weekly deposits from 2014-16.
  - Demographic information: Liquid wealth, age, income, home state.
  - Liquid wealth: Cash, stocks, bonds, 401k, IRA, CDs.
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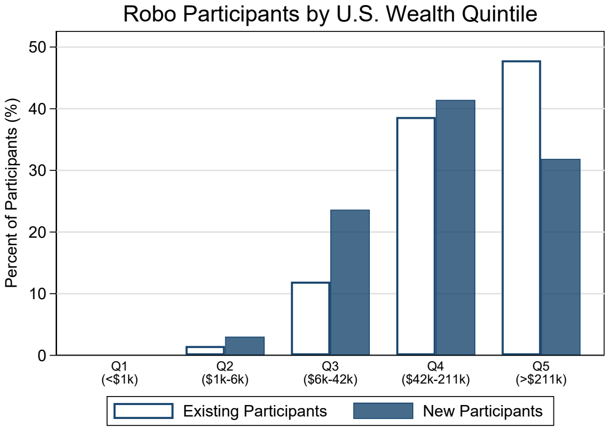
- Other datasets:
  - Wealthfront Portfolio Dataset - snapshots of self-managed portfolios.
  - 2016 Survey of Consumer Finances.
  - CRSP MFDB - fees/returns for mutual funds/ETFs.
  - CRSP Stock File.
  - 13F Thomson Reuters Institutional Holdings.
  - SEC ADV Filings.

Middle Class Becomes Better Represented

- Comparison across the U.S. wealth distribution from the SCF.
- More investors from the middle class (2nd and 3rd quintiles).



DiD Approach

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- Estimate the effects of the reduction on robo participation.
- Difference-in-differences (DiD) approach:
  - Time-series variation: Pre vs Post.
  - Cross-sectional variation: middle - treatment, upper - control.
- Key Assumption: Unobserved determinants of a *change* in robo participation do not systematically vary across the middle and upper classes.
  - No pre-trends in growth of robo participation for the middle class.
  - No other effects that coincide with the reduction (e.g. advertising)

Reduction Effects: Weekly Panel

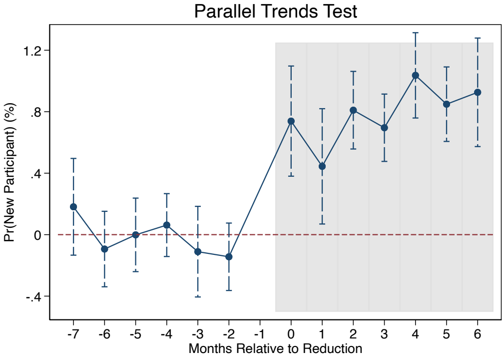
$$\textit{New Participant}_{i,t} = \mu\,(\textit{Middle}_i \times \textit{Post}_t) + \zeta_i + \varrho_t + \psi\,(\boldsymbol{X}_i \times \textit{Post}_t) + u_{i,t}.$$

- 0.6 pps increase in probability to join post-reduction **in a given week.**
- The total probability to join post-reduction $0.6 \times 32 = 19$ pps.

$Y =$	$\textit{New Participant}_{i,t}$	
$\textit{Middle}_i \times \textit{Post}_t$	0.823***	0.608***
	(0.067)	(0.067)
Week FE	Yes	Yes
Controls $\times$ $\textit{Post}_t$	No	Yes
State FE $\times$ $\textit{Post}_t$	No	Yes
R-squared	0.008	0.008
Number of Observations	620,928	620,928

Reduction Effects: Event Study

$$\textit{New Participant}_{i,t} = \sum_{m \neq \textit{June } \mathbf{2015}} (\mu_m \times \textit{Middle}_i \times \mathbf{1}_{t \in m}) + \zeta_i + \varrho_t + \sum_{m \neq \textit{June } \mathbf{2015}} (\psi_m \times \boldsymbol{X}_i \times \mathbf{1}_{t \in m}) + u_{i,t}.$$



Advertising

- Use Wealthfront blog posts and Google News articles.

$Y_{i,t}$ =	*New Participant*$_{i,t}$					
$Middle_i \times Post_t$	0.784***	0.513**	0.487*	0.806***	0.842**	0.817**
	(0.166)	(0.188)	(0.188)	(0.231)	(0.291)	(0.294)
$Middle_i \times Post_t \times Adv_t$	-0.004	0.004	0.004	-0.033	-0.106	-0.106
	(0.013)	(0.013)	(0.013)	(0.083)	(0.102)	(0.102)
$Middle_i \times Adv_t$	-0.006	-0.008	-0.008	-0.026	-0.024	-0.023
	(0.006)	(0.006)	(0.006)	(0.018)	(0.022)	(0.022)
Measure of Advertising (*Adv*)	Google News			Advisor Blog Posts		
Household FE	Yes	Yes	Yes	Yes	Yes	Yes
Week FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls $\times Post_t$	No	Yes	Yes	No	Yes	Yes
Controls $\times Adv_t$	No	Yes	Yes	No	Yes	Yes
Controls $\times Adv_t \times Post_t$	No	Yes	Yes	No	Yes	Yes
State FE $\times Post_t$	No	No	Yes	No	No	Yes
State FE $\times Adv_t$	No	No	Yes	No	No	Yes
State FE $\times Adv_t \times Post_t$	No	No	Yes	No	No	Yes
R-squared	0.011	0.012	0.012	0.011	0.012	0.012
Number of Observations	504,504	504,504	504,504	504,504	504,504	504,504

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- The novel ingredient - 2 risky assets:
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  - Robo portfolio $\mathcal{A}$ with return $R^{\mathcal{A}}_{i,t}$ and account minimum of M.

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- Factor structure for risky returns on portfolio $\mathcal{P} \in \{\mathcal{S}, \mathcal{A}\}$

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

  - $F_t \sim N(\pi^F, \Sigma^F)$ is a vector of priced risk factors.
  - $\beta^{\mathcal{P}}_i$ is the loading on F_t.
  - $\epsilon^{\mathcal{P}}_{i,t} \sim N(0, \sigma^{\mathcal{P}}_{\epsilon,i})$ is an idiosyncratic shock.
  - Loadings and shocks vary across households and portfolios.

Calibration

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4. Embed the parameters in the model.
   - Project parameters on household age and wealth.
   - Add fitted values to the model.

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   - Add fitted values to the model.
5. Other parameters are taken from the literature (see Table 5).

Portfolio Differences:Baseline

- Higher Sharpe ratio.
- Higher expected return.
- Lower idiosyncratic volatility.

	Self-Managed	Matched Robo	Difference
Sharpe Ratio	0.452	0.750	0.298
			(0.000)
Expected Return	0.080	0.102	0.023
			(0.000)
Total Volatility	0.209	0.137	-0.071
			(0.000)
Idiosyncratic Volatility	0.146	0.034	-0.111
			(0.000)

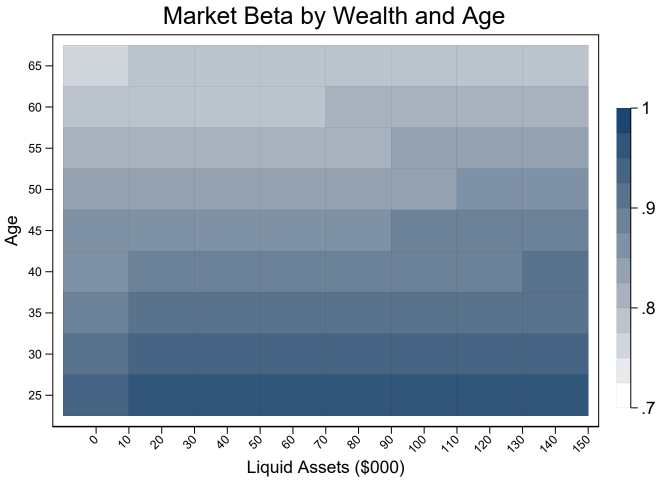
Portfolio Differences: Factors

- Lower exposure to small stocks.
- Higher exposure to value stocks.
- Higher exposure to U.S. bonds.

	Self-Managed	Matched Robo	Difference
Factor Loadings (β_i)			
Market	0.930	0.893	-0.036
			(0.002)
SMB	0.044	0.003	-0.040
			(0.004)
HML	-0.086	0.061	0.147
			(0.000)
GLB	0.629	-0.020	-0.649
			(0.000)
USB	-0.447	0.508	0.955
			(0.000)

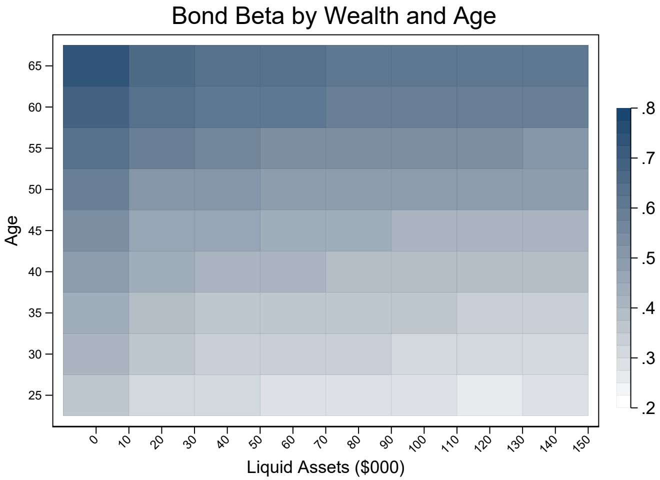
Double Glide Path:Equity Exposure

- More equity exposure with wealth.
- Less equity exposure with age.



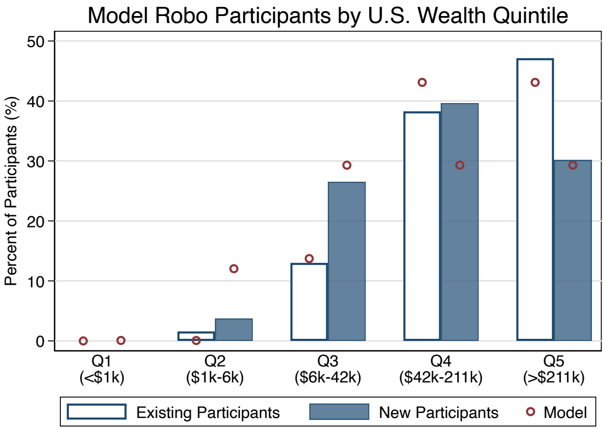
Double Glide Path: U.S. Bond Exposure

- Less bond exposure with wealth.
- More bond exposure with age.



Model Fit:Baseline

- Reduce the account minimum from $5,000 to $500 in the model.
- Reproduce the shift in wealth distribution.



Welfare Gains: Methodology

- Follow the life-cycle literature (Cocco, Gomes and Maenhout (2005)).
    - Calculate the expected lifetime increase in utility from the reduction.
    - Now assume that the minimum remains $5K.
    - Calculate an increase in annual consumption to generate the same increase.
    - Welfare gains = This increase in consumption.

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- Calculate gains under many counterfactuals.

Welfare Gains: Results

- Comparable to 1.5 pps increase in equity premium.

	Increase in Lifetime Consumption			
	Pooled	Age 25-35	Age 36-55	Age 56-65
Welfare Gain From the Reduction:	0.77%	0.58%	0.59%	1.68%
(i) Asset Allocation Counterfactuals				
Same Idiosyncratic Volatility as Self-Managed Portfolio	0.23%	0.11%	0.10%	0.81%
Same Market Loading as Self-Managed Portfolio	0.72%	0.55%	0.52%	1.62%
Same Value and Size Loadings as Self-Managed Portfolio	0.46%	0.32%	0.27%	1.32%
Same Bond Loadings as Self-Managed Portfolio	0.20%	0.15%	0.10%	0.58%
(ii) Glide Path Counterfactuals				
No Adjustment for Age	0.37%	0.33%	0.23%	0.88%
No Adjustment for Wealth	0.34%	0.34%	0.20%	0.73%
No Adjustment for Age or Wealth	0.24%	0.26%	0.15%	0.45%

Conclusion

- Do-less wealthy participate in robo advice when it becomes accessible?
  - Yes, middle-class is 15 pps more likely to participate.
  - No effect on the lower class.
  - Ambiguous effects on wealth inequality.
- What drives investor demand and how large are the gains?
  - Optimal response to the differences in portfolios.
  - Moderate average gain = 1.5 pps increase in equity premium.
  - Older investors have the highest gains.

Thank You!