Robo-advising

Francesco D'Acunto, Nagpurnanand Prabhala, Alberto Rossi
Robert H. Smith School of Business, University of Maryland, College Park, MD

The Promises and Pitfalls of Robo-Advising

ABFER

May 22, 2018

Household Financial Planning

- Individuals face complicated financial problems
  - Liquidity planning aka budgeting
  - Tax planning
  - Retirement planning
  - Housing and mortgages
  - Credit cards
  - Other debt
  - Insurance
  - Investments
- A very complex problem compounded by literacy issues
  - Investment literacy gap $>>$ substantial financial literacy gap

Lusardi and Mitchell 2013 NBER WP

Table 1. Financial Literacy Patterns
Source: Authors' computations from HRS 2004 Planning Module

Panel A: Distribution of Responses to Financial Literacy Questions

	Responses			
	Correct	*Incorrect*	*DK*	*Refuse*
Compound Interest	67.1%	22.2%	9.4%	1.3%
Inflation	75.2%	13.4%	9.9%	1.5%
Stock Risk	52.3%	13.2%	33.7%	0.9%

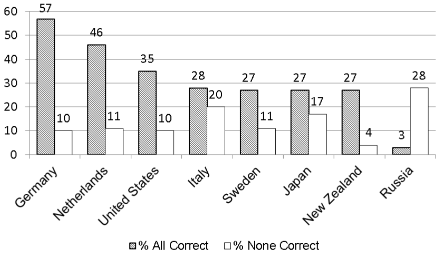
Panel B: Joint Probabilities of Being Correct to Financial Literacy Questions

	All 3 responses correct	*Only 2 responses correct*	*Only 1 response correct*	**No responses correct**
Proportion	34.3%	35.8%	16.3%	9.9%

Note: DK = respondent indicated "don't know."

Lusardi and Mitchell 2013 NBER WP

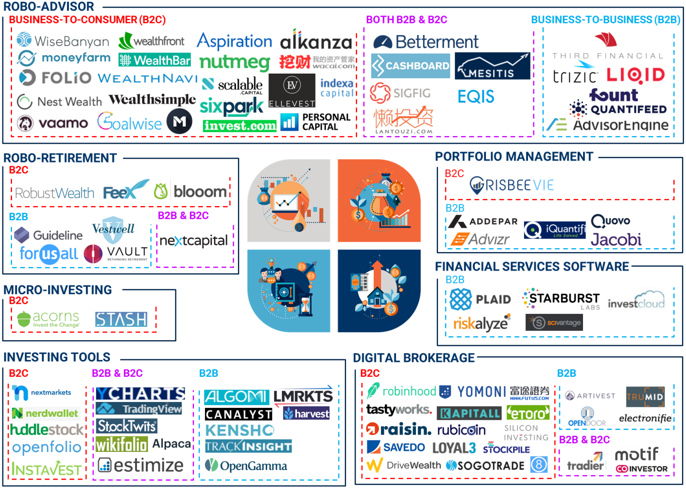
Figure 1. Financial Literacy Scores Around the World: Percent Who Correctly Answer All Three Financial Literacy Questions, or No Questions Correct
Source: Adapted from Lusardi and Mitchell (2011c)



Financial Advisor Taxonomy

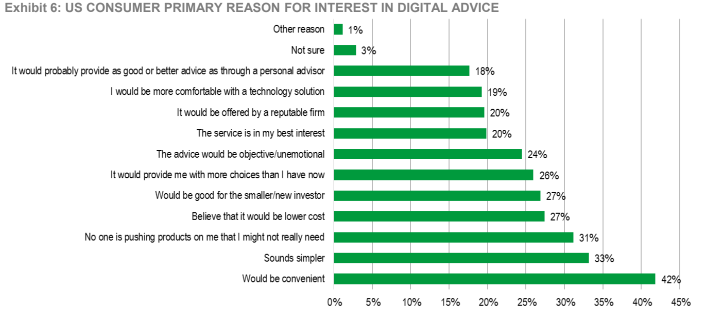
- Financial advising seems to have a lot of promise – plenty to give advice on and plenty of people need advice?
- Plenty of people dispense advice: family, newspaper columnists, institutions
- We examine robo-advising
  - B2C (robots for investors) not B2B (robots for advisors)
  - We focus on one sliver – robo-advising for stock market investment

Broader Robo-Advising Space



Why Robo-Advisors?

- 73% of millennials prefer advice from “tech” firms



Source: Investor Pulse 2015. Depicts responses of US respondents to the question, “Why would you be interested in this type of service?”

Individual Investors and Financial Advice For Wealth Management

- Individual investors benefit from stock market participation
- But they are consistently under-diversified. Median number of stocks:
  - 3 in the 1996, US (Barber and Odean's data)
  - 4 in 2013, US (Gargano and Rossi, 2016)
  - 3 in 2016, India (this paper)
- Under-diversification reduces the full benefits of stock market participation.

Can Advice Mitigate Under-Diversification?

- There may be no demand for diversification
  - Investors broadly diversified, don't care about stock portfolio diversification
  - Investors have lottery type preferences
  - Transaction costs of diversification too high
  - Investors not literate enough to understand diversification
- There is diversification demand but (human) financial advisors do not help
  - Financial advisors are expensive and don't cater to retail investors
  - Advisors are conflicted by incentives to sell brokerage products
  - Advisors have cognitive limitations and themselves have behavioral biases and mistakes
  - Advisors use one-size fits all approach (Linnainmaa, Melzer, and Previtero, 2016)
  - Advisors face suspicion from investors

Can Robo-advising work?

- Large brokerage house in India introduced portfolio optimization tool in July 2015
- Basic features of tool
  - Obtain existing portfolio holdings
  - Markowitz mean-variance analysis
  - Suggests “optimal” weights with or without new capital
  - Allows investors to experiment with alternatives
  - Single click execution with whatever investor chooses
- Tool is reasonable but we don’t test if it is optimal or first best. Our tests do not rely on such a tool.

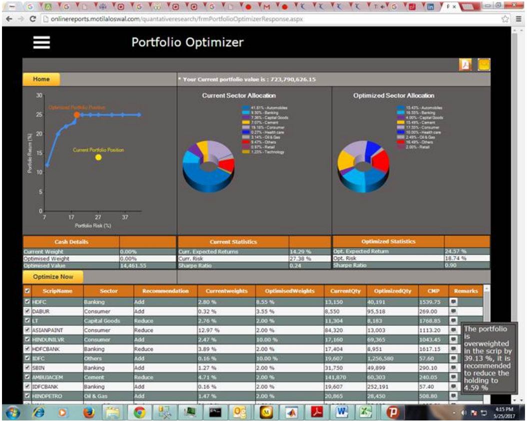
More on robo-advising tool: *Portfolio Optimizer*

- Markowitz mean-variance portfolio optimization targeting the Sharpe ratio
- Uses 3 years of daily data to compute the variance-covariance matrix
- Existing stocks + up to 15 stocks chosen by the broker
- Imposes short-sales constraints, uses techniques such as shrinkage
- All suggested trades can be executed in batch mode

Portfolio optimizer data contain:

- Time-stamp of usage by the investor
- Portfolio weights of the investor at the time of usage

Screenshot of Optimizer



Comments on Tool

- Our tool is a Thalerian “nudge” in between full libertarianism and full paternalism
- Two features of tool that are critical to uptake
  - Investor control mitigates algorithm aversion (Logg, 2015; Dietvorst et al. 2015)
  - Simplified execution bundled with tool
- Other features of tool
  - Literacy intervention in the field, real (own) money, learning by doing
  - Can this have side-effects? Perhaps, as we will see.
  - Tool introduced after years of “human” advising

Baseline Research Questions

1. Selection into Robo-advising
   - Uptake and use of robo-advising tool when offered?
2. Effects: some results and basic health checks
   - Uptake and effects on # stocks held
   - Portfolio volatility and returns
   - Ex-post trading
   - Underdiversification is probably not an immutable optimal choice
3. We do tests that exploit inbuilt randomization in experiment
   - Clients called by advisers to promote the portfolio optimizer
   - Clients whose calls go through versus "missed calls"
   - Introduces randomization *within* called clients, heterogeneity within this subset
   - Claiming much more requires more – we leave for future work

Behavioral Finance Research Questions

- Individuals have complex preferences and sub-rational information processing capabilities.
- A partial list from behavioral economics (Shefrin 2009, Behavioralizing Finance)
    - Loss aversion
    - Trend chasing
    - Availability bias
    - Anchoring
    - Optimism
    - Myopic
    - Extrapolation bias
    - Confirmation bias
    - Self-attribution
    - Regret aversion

Behavioral Finance Research Questions

- Perhaps robo-advising has effects on behavioral “biases”
- Possible if biases have roots in investor literacy
- Maybe not, if biases have other roots or are immutable
  - This is basically an empirical issue
  - We examine disposition effect, trend chasing after robo-advising
- We find some detectable effects in what is perhaps the more novel part of the paper

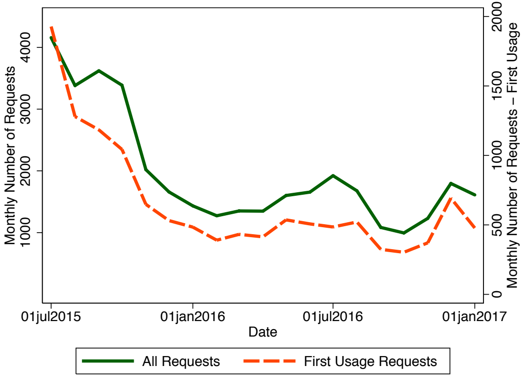
Rich Data

1. *Demographics dataset*
   - Gender, age, city of residence, number of years with the firm
2. *Transactions dataset*
   - Time-stamp for each transaction
   - Quantity, price, ticker name, ISIN number, type of trade (buy or sell)
3. *Holdings dataset*
   - Monthly frequency
   - ISIN number, ticker name, quantity held and price
4. *Logins dataset*
   - Date and time at which the account was accessed
5. *Interactions with advisor dataset*
   - Date, time and length of conversations between investor and advisor
   - Info on who initiated the call

Who Adopts Robo-advising

- Demographic characteristics (time invariant)
    - Age, Gender, Experience: no significant differences
- Holdings and Trading Behavior (time-varying)
    - Adopters, on average:
        - have more assets under management (AUM)
        - pay more attention to their portfolios
        - trade more, pay more fees
        - but, perform better overall

Picture



This figure plots the overall number of requests to use the portfolio optimizer by all the brokerage house clients (solid line, left y-axis), as well as the requests to use the portfolio optimizer for the first time (dashed lines, right y-axis), for each week between July 1st 2015 – when the tool was first introduced to the clients of the brokerage house – and January 2017.

Demographics

Table 1. Demographic Characteristics

A. All Accounts

	Obs	Mean	St.Dev	p.1	p.25	p.50	p.75	p.99
Age	860,943	47.30	13.63	20.73	36.72	45.80	56.80	82.17
Male	838,364	0.75	0.44	0.00	0.00	1.00	1.00	1.00
Account Age	880,254	7.41	3.68	0.12	5.16	8.44	10.12	13.21

B. Accounts with at Least One Trade

	Obs	Mean	St.Dev	p.1	p.25	p.50	p.75	p.99
Age	265,538	46.26	14.14	19.21	35.12	45.02	56.53	80.60
Male	258,656	0.71	0.46	0.00	0.00	1.00	1.00	1.00
Account Age	265,310	5.83	3.96	0.21	1.94	6.08	9.27	13.08

C. Accounts with Holdings Information

	Obs	Mean	St.Dev	p.1	p.25	p.50	p.75	p.99
Age	282,795	48.28	13.32	21.79	38.01	47.28	57.73	81.15
Male	274,048	0.72	0.45	0.00	0.00	1.00	1.00	1.00
Account Age	283,323	7.64	3.27	1.33	5.53	8.38	10.11	13.10

D. Accounts with Logins Information

	Obs	Mean	St.Dev	p.1	p.25	p.50	p.75	p.99
Age	138,482	41.52	13.30	16.98	31.37	38.84	50.35	76.59
Male	136,330	0.74	0.44	0.00	0.00	1.00	1.00	1.00
Account Age	138,405	4.06	3.75	0.12	0.92	2.29	7.04	12.86

E. Accounts that Use the Portfolio Optimizer

	Obs	Mean	St.Dev	p.1	p.25	p.50	p.75	p.99
Age	12,714	48.00	14.49	17.02	36.54	47.10	59.03	81.14
Male	12,386	0.71	0.45	0.00	0.00	1.00	1.00	1.00
Account Age	12,706	6.01	4.09	0.28	1.88	6.06	9.61	13.08

This table presents summary statistics of the demographic characteristics in our datasets. For each variable in each panel, we report the total number of observations (*Obs*), the sample mean (*Mean*), the sample standard deviation (*St.Dev*) and the 1*st*, 25*th*, 50*th*, 75*th* and 99*th* percentiles of the

Demographics

Table 2. Portfolio Characteristics and Investment Behavior: Non-Users Vs Users of the Portfolio Optimizer

A. Demographic Characteristics

	Non-Users				Users			
	Obs	**Mean**	**St.Dev**	**Median**	**Obs**	**Mean**	**St.Dev**	**Median**
Age	254,273	46.19	14.13	44.92	11,265	47.81	14.48	46.87
Male	247,674	0.71	0.46	1	10,982	0.71	0.45	1
Account Age	254,053	5.83	3.95	6.09	11,257	5.81	4.09	5.54

B. Attention and Trading Behavior

	Non-Users				Users			
	Obs	**Mean**	**St.Dev**	**Median**	**Obs**	**Mean**	**St.Dev**	**Median**
Total Logins	98,771	432.85	844.19	84	7,310	657.87	1,020.29	220
Total Trades	254,281	122.38	339.03	15.00	11,265	186.47	398.57	45
Total Volume (₹ 000)	254,281	5,992	19,181	323	11,265	10,599	25,979	1,196
Total Fees (₹ 000)	254,281	10.07	27.43	1.09	11,265	17.69	37.03	3.58

C. Trading performance

	Non-Users				Users			
	Obs	**Mean**	**St.Dev**	**Median**	**Obs**	**Mean**	**St.Dev**	**Median**
Returns Buys (1m)	205,484	-1.22	5.52	-1.11	10,468	-0.86	4.10	-0.86
Returns Sells (1m)	237,395	-0.67	6.38	-0.96	10,797	-0.42	4.81	-0.71
Returns Buys (3m)	201,413	-3.60	10.33	-3.29	10,378	-2.55	7.61	-2.42
Returns Sells (3m)	232,449	-2.54	11.66	-2.77	10,666	-1.79	8.70	-2.22

D. Holdings as of January 1st 2016

	Non-Users				Users			
	Obs	**Mean**	**St.Dev**	**Median**	**Obs**	**Mean**	**St.Dev**	**Median**
Total AUM	165,983	434,149	1,210,555	72,476	9,327	1,107,550	2,054,217	313,195
Number of Assets	165,983	9.52	12.48	5	9,327	17.27	16.79	12
AUM Stocks	160,402	411,997	1,157,347	68,317	9,208	1,032,630	1,946,557	284,572
Number of Stocks	160,402	9.30	12.27	5	9,208	16.43	16.35	11
AUM Bonds	19,175	141,315	510,280	2,722	2,099	194,415	639,247	5,813
Number of Bonds	19,175	1.61	1.32	1	2,099	1.84	1.64	1
AUM Funds	30,390	78,726	212026	11,890	2,413	125,968	270,957	31,710
Number of Funds	30,390	1.58	1.33	1	2,413	1.97	1.62	1
AUM ETF	8,522	54,158	104,577	18,502	921	63,073	10,9765	22,801
Number of ETFs	8,522	1.19	0.46	1	921	1.30	0.57	1

This table reports summary statistics of the demographic characteristics (Panel A), attention and

Single-difference Results

- Compare portfolio-level outcomes before and after usage of the optimizer
  - Accounts for time-invariant investor characteristics that determine adoption

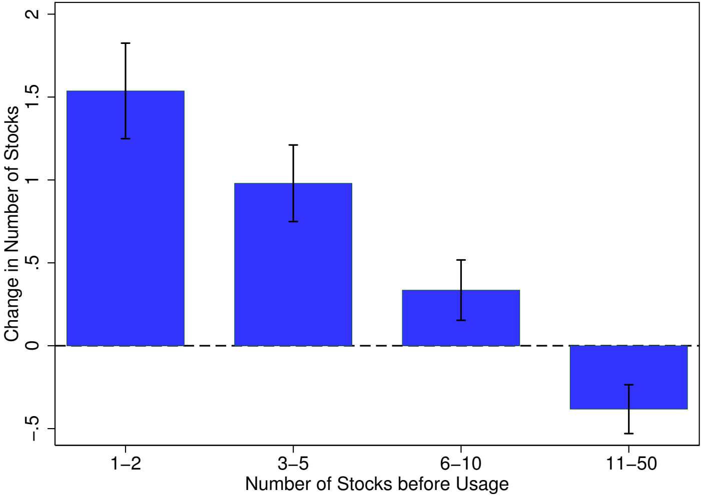
- *Promises*:

  robo-adviser increases diversification, performance of underdiversified investors

- *Pitfalls*:

  robo-advising worsens performance of diversified investors – excessive trading

Robo-advising and Number of Stocks Held: Intensive Margin



Robo-advising and Number of Stocks Held: Extensive margin

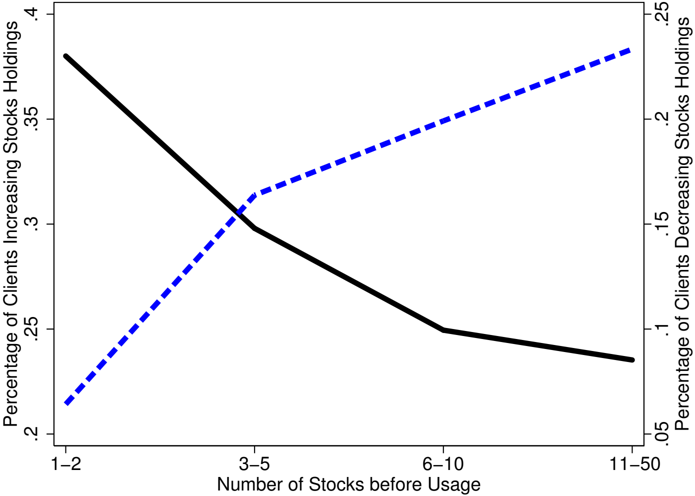


Table for baseline results

Table 3. Diversification, Attention and Trading Behavior Before and After Adopting the Portfolio Optimizer – Baseline Results

Panel A. Adoption of the Optimizer and Diversification

	Number of Stocks	Portfolio Market Adjusted Risk
Change after Adoption	0.156**	-0.006***
(p-value)	(0.04)	(0.02)
Obs	4,672	3,115

Panel B. Adoption of the Optimizer and Investment Performance

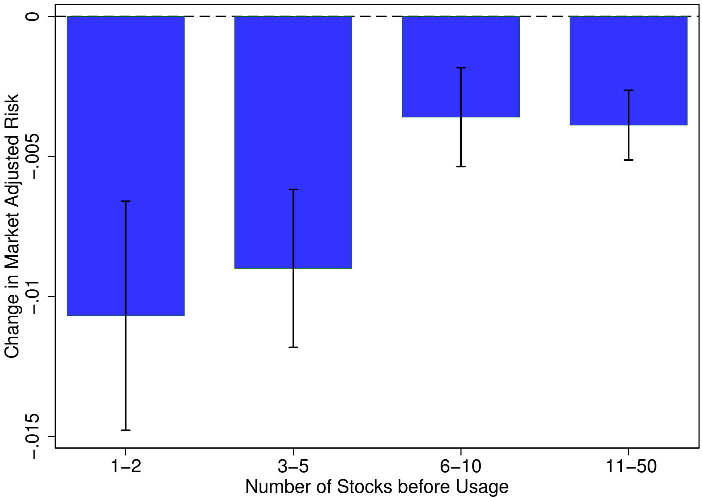
	Performance of Trades	Portfolio Market Adjusted Returns
Change after Adoption	0.003	0.005**
(p-value)	(0.47)	(0.02)
Obs	1,192	3,428

Panel C. Adoption of the Optimizer, Trading Activity and Attention

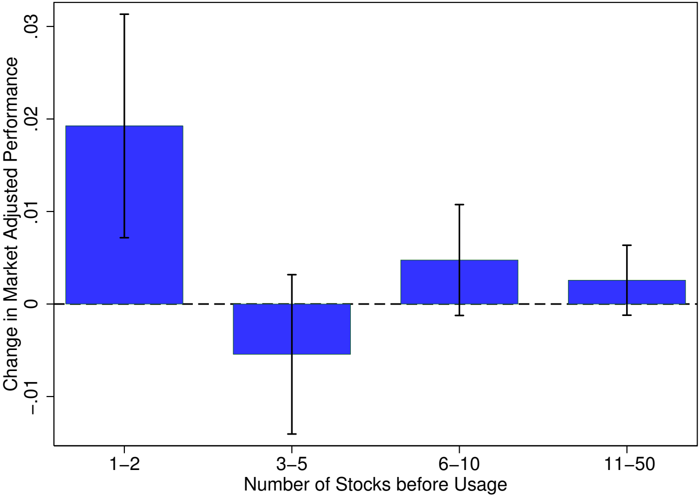
	Trading Fees	Days with Logins
Change after Adoption	155.4***	0.853***
(p-value)	(0.00)	(0.00)
Obs	6,594	4,000

This table reports results on investor behavior before and after adopting the portfolio optimizer. Panel A reports the changes in the number of stocks held (first column) and the market adjusted risk of the investor portfolio (second column). Panel B reports the changes in the risk-adjusted performance of the trades (first column) and the market adjusted performance of the investor portfolio (second column). Panel C reports the changes in the trading fees paid to the brokerage house (first column) and the number of days with logins (second column). All panels compare the behavior over the month after the usage and the behavior over the month before the usage. Each panel reports first-difference coefficients, the associated p-values and the number of observations.

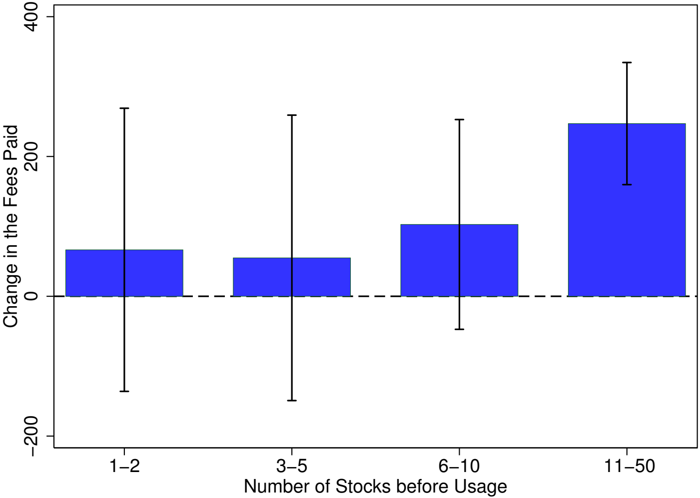
Robo-advising and Portfolio Volatility



Robo-advising and Portfolio Performance



Robo-advising and Fees Paid



Single-difference Results

- Compare portfolio-level outcomes before and after usage of the optimizer
    - Accounts for time-invariant investor characteristics that determine adoption

- *Promises*:

  robo-adviser increases diversification, performance of underdiversified investors

- *Pitfalls*:

  robo-advising worsens performance of diversified investors – excessive trading

Disposition Effect

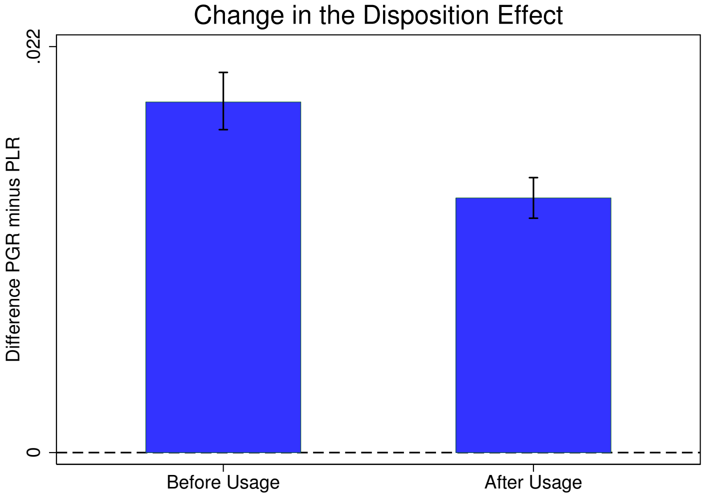
$$PGR = \frac{Realized\ Gains}{Realized\ Gains + Paper\ Gains}$$

$$PLR = \frac{Realized\ Losses}{Realized\ Losses + Paper\ Losses}$$

Disposition effect:

$$\text{PGR} > \text{PLR}$$

Disposition Effect

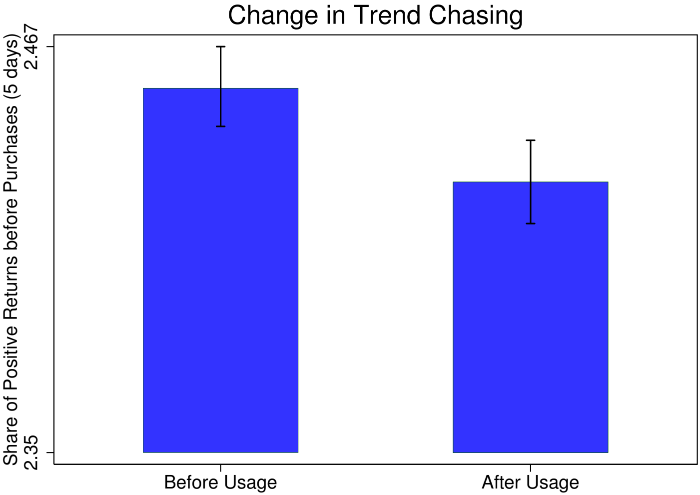


Trend Chasing

$$\textit{Fraction Days with Positive Returns Before Purchase} =$$

$$= \frac{\textit{Days Positive Returns Before Purchase}}{5 \textit{ Days}}$$

Trend Chasing



Rank Effect

$$\textit{Best} = \frac{\textit{Best Sold}}{\textit{Best Sold} + \textit{Best not Sold}}$$

$$\textit{Worst} = \frac{\textit{Worst Sold}}{\textit{Worst Sold} + \textit{Worst not Sold}}$$

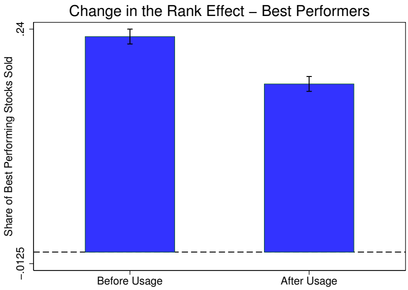
$$\textit{Middle} = \frac{\textit{Middle Sold}}{\textit{Middle Sold} + \textit{Middle not Sold}}.$$

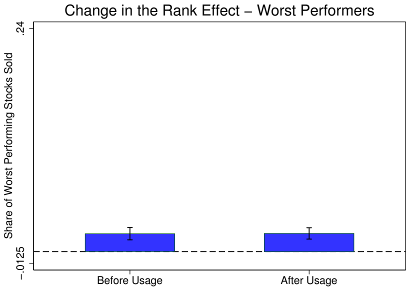
Rank effect:

Best-Middle > 0

Worst-Middle > 0

Rank Effect


Change in the Rank Effect – Best Performers
Share of Best Performing Stocks Sold
.24
-.0125
Before Usage
After Usage


Change in the Rank Effect – Worst Performers
Share of Worst Performing Stocks Sold
.24
-.0125
Before Usage
After Usage

Behavioral Biases

Table 4. Behavioral Biases Before and After Adopting the Portfolio Optimizer – Baseline Results

	Panel A. Disposition Effect	**Panel B. Trend Chasing Behavior**
Change after Adoption	−0.00588***	−0.0273***
(p-value)	(0.00)	(0.00)
Obs	7,506	6,938
	Panel C. Rank Effect – Best	**Panel D. Rank Effect – Worst**
Change after Adoption	−0.0573***	0.00742
(p-value)	(0.00)	(0.123)
Obs	4,264	4,264

This table tests whether the change in behavioral biases by investors that use the portfolio optimizer is different from zero before and after usage. Panel A reports the results for the disposition effect. *Change after Adoption* is the difference between the proportion of gains realized (PGR) and the proportion of losses realized (PLR) for each investor before and after using the optimizer. Panel B reports the results for trend chasing. *Change after Adoption* is the difference between the average number of days in which a stock purchased by the investor had positive daily returns among the 5 business days before the purchase, before and after adoption. Panel C and Panel D report the results for the rank effect. *Change after Adoption* is the average difference between the number of best/worst performing stocks sold and the number of mid-performing stocks sold before and after the use of the optimizer. Each panel reports first-difference coefficients, the associated p-values and the number of observations.

Missed calls

- Single-difference results account for selection into adoption
- Typical concern: time-varying, investor-specific trading motives
  - We examine variation *within* those called to use robo-adviser by brokerage firm

Difference-in-differences Strategy

1. Exploit the fact that advisers promote the portfolio optimizer in specific days
   - Each promotion day, advisers call a subset of clients to promote the optimizer
   - Some clients pick up the call and use the optimizer → reached, *treated group*
   - *Other clients happen to not answer the phone → missed, control group*

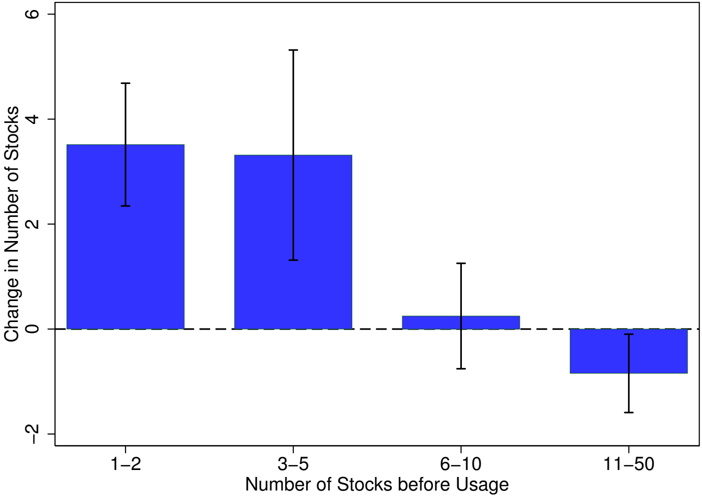
$$(\overline{Outcome}_{reached_t,\ post} - \overline{Outcome}_{reached_t,\ pre}) - (\overline{Outcome}_{missed_t,\ post}) - \overline{Outcome}_{missed_t,\ pre})$$

2. Identifying assumption:
   - trading behavior of reached clients would be similar relative to missed clients had the "reached" clients not used the optimizer

Other things

- The clients human advisers call to promote the robo-adviser are selected – yes
  - But both reached and missed clients are selected under the SAME unobservable dimensions
  - More similar groups than what the econometrician could construct based on observables
- Clients might diversify because human advisers tell them, not the robo-adviser
  - BUT human advisers contact their clients often, also before the portfolio optimizer

Diff-in-diffs: Number of Stocks



Diff-in-diffs: Behavioral Biases

	Panel A. Disposition Effect	**Panel B. Trend Chasing Behavior**
Treated	-0.00758^{***}	-0.0687^{***}
(p-value)	(0.00)	(0.00)
Obs	2,766	2,752

	Panel C. Rank Effect – Best	**Panel D. Rank Effect – Worst**
Treated	-0.0576^{***}	-0.006
(p-value)	(0.00)	(0.27)
Obs	2,621	2,621

Promises and Pitfalls of Robo-Advising

Robo-advising has different effects on different types of investors

For *under-diversified* investors, access to robo-advice:

- Increases diversification, reduces portfolio volatility
- Increases investor attention to their portfolio
- Improves portfolio performance

For *already diversified* investors, access to robo-advice:

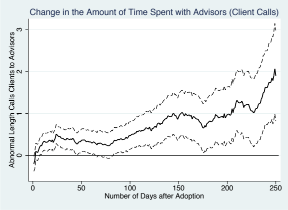
- No change, or reduction in the number of stocks held
- Increases number of trades and fees paid, but not performance

Bigger finding: lower incidence of behavioral biases

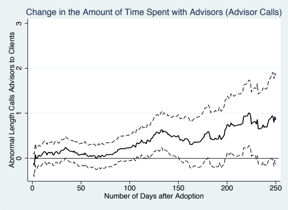
- Behavioral finance conjectures
  - Connection between financial literacy and behavioral biases
  - Financial literacy interventions may be effective in reducing biases
  - Channel not clear – preferences are altered versus already-latent preferences are made salient
  - Permanence of these effects unclear
- Conjectures for advising industry
  - Robo advising may be fundamentally different from human advising. Why?
  - Advising should account for behavioral biases. How?
- Will robo-advising (and AI) eliminate human advisor jobs?
  - Early evidence suggests that this is *not* the case. But this is another paper

Demand for human advising when robo-advising is introduced

Panel A. Change in Length of Client initiated Calls



Panel B. Change in Length of Advisor initiated Calls



This figure report the difference in the cumulative length of phone calls (in hours) between clients and advisors. Panel A refers to calls initiated by clients and directed to their advisor, and hence reflects the change in the propensity of clients to actively reach out to their advisors after the adoption of the portfolio optimizer, compared to before the adoption. Panel B refers to calls initiated by advisors and directed to their clients, and hence reflects the change in the propensity of advisors to reach out actively to their clients after the adoption of the portfolio optimizer, compared to before the adoption. In both Panels, for each horizon h and investor i:

$$AbnormalLengthPhoneCalls_i = CumulativeLengthCalls_{i,0\to h} - CumulativeLengthCalls_{i,-h\to 0}$$