Robo-advising

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The Promises and Pitfalls of Robo-Advising

ABFER

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

Panel A: Distribution of Responses to Financial Literacy Questions

<table>
<thead>
<tr>
<th>Responses</th>
<th>Correct</th>
<th>Incorrect</th>
<th>DK</th>
<th>Refuse</th>
</tr>
</thead>
<tbody>
<tr>
<td>Compound Interest</td>
<td>67.1%</td>
<td>22.2%</td>
<td>9.4%</td>
<td>1.3%</td>
</tr>
<tr>
<td>Inflation</td>
<td>75.2%</td>
<td>13.4%</td>
<td>9.9%</td>
<td>1.5%</td>
</tr>
<tr>
<td>Stock Risk</td>
<td>52.3%</td>
<td>13.2%</td>
<td>33.7%</td>
<td>0.9%</td>
</tr>
</tbody>
</table>

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

<table>
<thead>
<tr>
<th>All 3 responses correct</th>
<th>Only 2 responses correct</th>
<th>Only 1 response correct</th>
<th>No responses correct</th>
</tr>
</thead>
<tbody>
<tr>
<td>Proportion</td>
<td>34.3%</td>
<td>35.8%</td>
<td>16.3%</td>
</tr>
</tbody>
</table>

Note: DK = respondent indicated “don’t know.”
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
We define investment & wealth management tech to include fintech companies that offer an alternative to traditional wealth management firms and technology-enabled tools that are advancing the investment and wealth management profession. This includes full-service brokerage alternatives, automated and semi-automated robo-advisors, self-service investment platforms, asset class specific marketplaces, and tools for both individual investors and advisors to keep up with the changing dynamics in wealth management.

This category excludes both personal and corporate expense management and monitoring tools, tools specific to investment banks, and high-frequency trading platforms.

Click on the image below to enlarge. This market map is not meant to be exhaustive of companies in the space.

The category breakdown is as follows:

**Robo-advisor:** This category includes automated investment platforms that leverage technology to lower account minimums and reduce annual advisory fees. The investments offered are tailored to the client's risk profile typically based on a questionnaire. Robo-advisors differentiate themselves through a range of added services that can include a 24-hour automated support desk, access to a human advisor, tax optimization, and portfolio re-balancing.

**B2C:** B2C robo-advisors target individual investors.

One of the most well-funded robo-advisors is Wealthfront.

Get the full list of wealth tech startups. As an added bonus, we'll send you the disclosed funding values for each company.

Enter your email address here...

Create free account
Why Robo-Advisors?

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

Exhibit 6: US CONSUMER PRIMARY REASON FOR INTEREST IN DIGITAL ADVICE

<table>
<thead>
<tr>
<th>Reason</th>
<th>Percentage</th>
</tr>
</thead>
<tbody>
<tr>
<td>Other reason</td>
<td>1%</td>
</tr>
<tr>
<td>Not sure</td>
<td>3%</td>
</tr>
<tr>
<td>It would probably provide as good or better advice as through a personal advisor</td>
<td>18%</td>
</tr>
<tr>
<td>I would be more comfortable with a technology solution</td>
<td>19%</td>
</tr>
<tr>
<td>It would be offered by a reputable firm</td>
<td>20%</td>
</tr>
<tr>
<td>The service is in my best interest</td>
<td>20%</td>
</tr>
<tr>
<td>The advice would be objective/unemotional</td>
<td>24%</td>
</tr>
<tr>
<td>It would provide me with more choices than I have now</td>
<td>26%</td>
</tr>
<tr>
<td>Would be good for the smaller/new investor</td>
<td>27%</td>
</tr>
<tr>
<td>Believe that it would be lower cost</td>
<td>27%</td>
</tr>
<tr>
<td>No one is pushing products on me that I might not really need</td>
<td>31%</td>
</tr>
<tr>
<td>Sounds simpler</td>
<td>33%</td>
</tr>
<tr>
<td>Would be convenient</td>
<td>42%</td>
</tr>
</tbody>
</table>

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
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.
Table 1. Demographic Characteristics

A. All Accounts

<table>
<thead>
<tr>
<th>Obs</th>
<th>Mean</th>
<th>St.Dev</th>
<th>p.1</th>
<th>p.25</th>
<th>p.50</th>
<th>p.75</th>
<th>p.99</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age</td>
<td>860,943</td>
<td>47.30</td>
<td>13.63</td>
<td>20.73</td>
<td>36.72</td>
<td>45.80</td>
<td>56.80</td>
</tr>
<tr>
<td>Male</td>
<td>838,364</td>
<td>0.75</td>
<td>0.44</td>
<td>0.00</td>
<td>0.00</td>
<td>1.00</td>
<td>1.00</td>
</tr>
<tr>
<td>Account Age</td>
<td>880,254</td>
<td>7.41</td>
<td>3.68</td>
<td>0.12</td>
<td>5.16</td>
<td>8.44</td>
<td>10.12</td>
</tr>
</tbody>
</table>

B. Accounts with at Least One Trade

<table>
<thead>
<tr>
<th>Obs</th>
<th>Mean</th>
<th>St.Dev</th>
<th>p.1</th>
<th>p.25</th>
<th>p.50</th>
<th>p.75</th>
<th>p.99</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age</td>
<td>265,538</td>
<td>46.26</td>
<td>14.14</td>
<td>19.21</td>
<td>35.12</td>
<td>45.02</td>
<td>56.53</td>
</tr>
<tr>
<td>Male</td>
<td>258,656</td>
<td>0.71</td>
<td>0.46</td>
<td>0.00</td>
<td>0.00</td>
<td>1.00</td>
<td>1.00</td>
</tr>
<tr>
<td>Account Age</td>
<td>265,310</td>
<td>5.83</td>
<td>3.96</td>
<td>0.21</td>
<td>1.94</td>
<td>6.08</td>
<td>9.27</td>
</tr>
</tbody>
</table>

C. Accounts with Holdings Information

<table>
<thead>
<tr>
<th>Obs</th>
<th>Mean</th>
<th>St.Dev</th>
<th>p.1</th>
<th>p.25</th>
<th>p.50</th>
<th>p.75</th>
<th>p.99</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age</td>
<td>282,795</td>
<td>48.28</td>
<td>13.32</td>
<td>21.79</td>
<td>38.01</td>
<td>47.28</td>
<td>57.73</td>
</tr>
<tr>
<td>Male</td>
<td>274,048</td>
<td>0.72</td>
<td>0.45</td>
<td>0.00</td>
<td>0.00</td>
<td>1.00</td>
<td>1.00</td>
</tr>
<tr>
<td>Account Age</td>
<td>283,323</td>
<td>7.64</td>
<td>3.27</td>
<td>1.33</td>
<td>5.53</td>
<td>8.38</td>
<td>10.11</td>
</tr>
</tbody>
</table>

D. Accounts with Logins Information

<table>
<thead>
<tr>
<th>Obs</th>
<th>Mean</th>
<th>St.Dev</th>
<th>p.1</th>
<th>p.25</th>
<th>p.50</th>
<th>p.75</th>
<th>p.99</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age</td>
<td>138,482</td>
<td>41.52</td>
<td>13.30</td>
<td>16.98</td>
<td>31.37</td>
<td>38.84</td>
<td>50.35</td>
</tr>
<tr>
<td>Male</td>
<td>136,330</td>
<td>0.74</td>
<td>0.44</td>
<td>0.00</td>
<td>0.00</td>
<td>1.00</td>
<td>1.00</td>
</tr>
<tr>
<td>Account Age</td>
<td>138,405</td>
<td>4.06</td>
<td>3.75</td>
<td>0.12</td>
<td>0.92</td>
<td>2.29</td>
<td>7.04</td>
</tr>
</tbody>
</table>

E. Accounts that Use the Portfolio Optimizer

<table>
<thead>
<tr>
<th>Obs</th>
<th>Mean</th>
<th>St.Dev</th>
<th>p.1</th>
<th>p.25</th>
<th>p.50</th>
<th>p.75</th>
<th>p.99</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age</td>
<td>12,714</td>
<td>48.00</td>
<td>14.49</td>
<td>17.02</td>
<td>36.54</td>
<td>47.10</td>
<td>59.03</td>
</tr>
<tr>
<td>Male</td>
<td>12,386</td>
<td>0.71</td>
<td>0.45</td>
<td>0.00</td>
<td>0.00</td>
<td>1.00</td>
<td>1.00</td>
</tr>
<tr>
<td>Account Age</td>
<td>12,706</td>
<td>6.01</td>
<td>4.09</td>
<td>0.28</td>
<td>1.88</td>
<td>6.06</td>
<td>9.61</td>
</tr>
</tbody>
</table>

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 1st, 25th, 50th, 75th and 99th percentiles of the distribution.
Table 2. Portfolio Characteristics and Investment Behavior: Non-Users Vs Users of the Portfolio Optimizer

### A. Demographic Characteristics

<table>
<thead>
<tr>
<th></th>
<th>Non-Users</th>
<th>Users</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Obs</td>
<td>Mean</td>
</tr>
<tr>
<td>Age</td>
<td>254,273</td>
<td>46.19</td>
</tr>
<tr>
<td>Male</td>
<td>247,674</td>
<td>0.71</td>
</tr>
<tr>
<td>Account Age</td>
<td>254,053</td>
<td>5.83</td>
</tr>
</tbody>
</table>

### B. Attention and Trading Behavior

<table>
<thead>
<tr>
<th></th>
<th>Non-Users</th>
<th>Users</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Obs</td>
<td>Mean</td>
</tr>
<tr>
<td>Total Logins</td>
<td>98,771</td>
<td>432.85</td>
</tr>
<tr>
<td>Total Trades</td>
<td>254,281</td>
<td>122.38</td>
</tr>
<tr>
<td>Total Volume ($'000)</td>
<td>254,281</td>
<td>5,992</td>
</tr>
<tr>
<td>Total Fees ($'000)</td>
<td>254,281</td>
<td>10.07</td>
</tr>
</tbody>
</table>

### C. Trading performance

<table>
<thead>
<tr>
<th></th>
<th>Non-Users</th>
<th>Users</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Obs</td>
<td>Mean</td>
</tr>
<tr>
<td>Returns Buys (1m)</td>
<td>205,484</td>
<td>-1.22</td>
</tr>
<tr>
<td>Returns Sells (1m)</td>
<td>237,395</td>
<td>-0.67</td>
</tr>
<tr>
<td>Returns Buys (3m)</td>
<td>201,413</td>
<td>-3.60</td>
</tr>
<tr>
<td>Returns Sells (3m)</td>
<td>232,449</td>
<td>-2.54</td>
</tr>
</tbody>
</table>

### D. Holdings as of January 1st 2016

<table>
<thead>
<tr>
<th></th>
<th>Non-Users</th>
<th>Users</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Obs</td>
<td>Mean</td>
</tr>
<tr>
<td>Total AUM</td>
<td>165,983</td>
<td>434,149</td>
</tr>
<tr>
<td>Number of Assets</td>
<td>165,983</td>
<td>9.52</td>
</tr>
<tr>
<td>AUM Stocks</td>
<td>160,402</td>
<td>411,997</td>
</tr>
<tr>
<td>Number of Stocks</td>
<td>160,402</td>
<td>9.30</td>
</tr>
<tr>
<td>AUM Bonds</td>
<td>19,175</td>
<td>141,315</td>
</tr>
<tr>
<td>Number of Bonds</td>
<td>19,175</td>
<td>1.61</td>
</tr>
<tr>
<td>AUM Funds</td>
<td>30,390</td>
<td>78,726</td>
</tr>
<tr>
<td>Number of Funds</td>
<td>30,390</td>
<td>1.58</td>
</tr>
<tr>
<td>AUM ETFs</td>
<td>8,522</td>
<td>54,158</td>
</tr>
<tr>
<td>Number of ETFs</td>
<td>8,522</td>
<td>1.19</td>
</tr>
</tbody>
</table>

This table reports summary statistics of the demographic characteristics (Panel A), attention and trading behavior (Panel B), trading performance (Panel C) and portfolio holdings (Panel D) of the brokerage account holders in our datasets. In each panel, the results for those that do not use the portfolio optimizer are reported in columns 2 through 5, while the results for those that use the portfolio optimizer at least once are reported in columns 6 through 9. 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 sample median (Median). The results in panels A through C are computed over the full sample, while the results in Panel D are computed as of January 1st 2016.
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

![Chart showing the change in number of stocks held by the number of stocks before usage. The chart indicates that there is a significant increase in the number of stocks held when the number of stocks before usage is 1-2.]
Robo-advising and Number of Stocks Held: Extensive margin

The graph shows the relationship between the number of stocks before usage and the percentage of clients decreasing or increasing their stocks holdings. The data points indicate a trend where clients with a higher number of stocks before usage are more likely to decrease their holdings, while those with fewer stocks are more likely to increase them. This suggests that robo-advising may be more effective for clients with a moderate number of stocks before usage in terms of stock management decisions.
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.

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

#### Panel A. Adoption of the Optimizer and Diversification

<table>
<thead>
<tr>
<th>Change after Adoption</th>
<th>Number of Stocks</th>
<th>Portfolio Market Adjusted Risk</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0.156**</td>
<td>-0.006***</td>
</tr>
<tr>
<td>($p$-value)</td>
<td>(0.04)</td>
<td>(0.02)</td>
</tr>
<tr>
<td>Obs</td>
<td>4,672</td>
<td>3,115</td>
</tr>
</tbody>
</table>

#### Panel B. Adoption of the Optimizer and Investment Performance

<table>
<thead>
<tr>
<th>Change after Adoption</th>
<th>Performance of Trades</th>
<th>Portfolio Market Adjusted Returns</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0.003</td>
<td>0.005**</td>
</tr>
<tr>
<td>($p$-value)</td>
<td>(0.47)</td>
<td>(0.03)</td>
</tr>
<tr>
<td>Obs</td>
<td>1,192</td>
<td>3,428</td>
</tr>
</tbody>
</table>

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

<table>
<thead>
<tr>
<th>Change after Adoption</th>
<th>Trading Fees</th>
<th>Days with Logins</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>155.4***</td>
<td>0.853***</td>
</tr>
<tr>
<td>($p$-value)</td>
<td>(0.00)</td>
<td>(0.00)</td>
</tr>
<tr>
<td>Obs</td>
<td>6,594</td>
<td>4,000</td>
</tr>
</tbody>
</table>
Robo-advising and Portfolio Volatility

Bar chart showing the change in market-adjusted risk for different ranges of the number of stocks before usage. The ranges are 1-2, 3-5, 6-10, and 11-50 stocks. The bars for 1-2 and 3-5 show a decrease in risk, while the bars for 6-10 and 11-50 show a smaller decrease. The chart suggests that the number of stocks before usage affects portfolio volatility.
Robo-advising and Portfolio Performance

Change in Market Adjusted Performance

Number of Stocks before Usage

1−2
3−5
6−10
11−50

Baseline Results
Behavioral Biases
Identification Strategy
Conclusions
Robo-advising and Fees Paid

![Bar chart showing the change in fees paid based on the number of stocks before usage. The chart shows that fees paid decrease as the number of stocks increases from 1-2 to 11-50.](chart.png)
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

\[
PGR = \frac{\text{Realized Gains}}{\text{Realized Gains} + \text{Paper Gains}}
\]

\[
PLR = \frac{\text{Realized Losses}}{\text{Realized Losses} + \text{Paper Losses}}
\]

Disposition effect:

\[PGR > PLR\]
Change in the Disposition Effect

Difference PGR minus PLR

Before Usage

After Usage

0.022
Trend Chasing

Fraction Days with Positive Returns Before Purchase =

= \frac{\text{Days Positive Returns Before Purchase}}{5 \text{ Days}}
Trend Chasing

Change in Trend Chasing

Share of Positive Returns before Purchases (5 days)

Before Usage

After Usage

2.35

2.467

33 / 44
Rank Effect

\[ \text{Best} = \frac{\text{Best Sold}}{\text{Best Sold} + \text{Best not Sold}} \]

\[ \text{Worst} = \frac{\text{Worst Sold}}{\text{Worst Sold} + \text{Worst not Sold}} \]

\[ \text{Middle} = \frac{\text{Middle Sold}}{\text{Middle Sold} + \text{Middle not Sold}} \]

Rank effect:

Best-Middle > 0

Worst-Middle > 0
Rank Effect

Change in the Rank Effect – Best Performers

Change in the Rank Effect – Worst Performers

Share of Best Performing Stocks Sold

Share of Worst Performing Stocks Sold

Behavioral Biases

Identification Strategy

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

<table>
<thead>
<tr>
<th></th>
<th>Panel A. Disposition Effect</th>
<th>Panel B. Trend Chasing Behavior</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Change after Adoption</strong></td>
<td>-0.00588****</td>
<td>-0.0273***</td>
</tr>
<tr>
<td><strong>(p-value)</strong></td>
<td>(0.00)</td>
<td>(0.00)</td>
</tr>
<tr>
<td><strong>Obs</strong></td>
<td>7,506</td>
<td>6,938</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>Panel C. Rank Effect – Best</th>
<th>Panel D. Rank Effect – Worst</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Change after Adoption</strong></td>
<td>-0.0573***</td>
<td>0.00742</td>
</tr>
<tr>
<td><strong>(p-value)</strong></td>
<td>(0.00)</td>
<td>(0.123)</td>
</tr>
<tr>
<td><strong>Obs</strong></td>
<td>4,264</td>
<td>4,264</td>
</tr>
</tbody>
</table>

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

   \[ (\text{Outcome}_{\text{reached}, \text{post}} - \text{Outcome}_{\text{reached}, \text{pre}}) - (\text{Outcome}_{\text{missed}, \text{post}} - \text{Outcome}_{\text{missed}, \text{pre}}) \]

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

![Chart showing change in number of stocks with different categories of stocks before usage.]{fig}

- **Number of Stocks before Usage**: 1-2, 3-5, 6-10, 11-50
- **Change in Number of Stocks**: -2, 0, 2, 4, 6

*Note: The chart illustrates the difference in the number of stocks before and after usage, categorized by the number of stocks before usage.*
**Diff-in-diffs: Behavioral Biases**

<table>
<thead>
<tr>
<th>Panel A. Disposition Effect</th>
<th>Panel B. Trend Chasing Behavior</th>
</tr>
</thead>
<tbody>
<tr>
<td>Treated</td>
<td>−0.0687***</td>
</tr>
<tr>
<td>(p)-value</td>
<td>(0.00)</td>
</tr>
<tr>
<td>Obs</td>
<td>2,766</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Panel C. Rank Effect – Best</th>
<th>Panel D. Rank Effect – Worst</th>
</tr>
</thead>
<tbody>
<tr>
<td>Treated</td>
<td>−0.00758***</td>
</tr>
<tr>
<td>(p)-value</td>
<td>(0.00)</td>
</tr>
<tr>
<td>Obs</td>
<td>2,766</td>
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</thead>
<tbody>
<tr>
<td>Treated</td>
<td>−0.0576***</td>
<td>−0.006</td>
</tr>
<tr>
<td>(p)-value</td>
<td>(0.00)</td>
<td>(0.27)</td>
</tr>
<tr>
<td>Obs</td>
<td>2,621</td>
<td>2,621</td>
</tr>
</tbody>
</table>
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

This figure reports 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 $i$:

$$\text{AbnormalLengthPhoneCalls}_i = \text{CumulativeLengthCalls}_{i,0 \rightarrow h} - \text{CumulativeLengthCalls}_{i,-h \rightarrow 0}$$