Who Benefits from Robo-Advising? Evidence from Machine Learning

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Fintech and Machine Learning Workshop—NUS
Motivation

Most investors are not financially savvy

Financial Advisers could help, but they
  are expensive
  generally ineffective (Linnainmaa, Melzer, and Previtero, 2016)

Robo-advising potentially helpful
  cheap and easy to use
  can reach millions of people at low costs
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. Categories are not mutually exclusive. We categorized companies based on their primary use case.
Research Agenda on Robo-advising

The Pros and Cons of Robo-advising to Investors


How Robo-advising interacts with other forms of advice

- Complementarity and substitutability between men & machines
- What do investors value in financial advice
This Paper

Vanguard’s Personal Advisor Services (PAS)

- largest hybrid robo-adviser in the world
- $120B under management
- explosive growth since inception

The paper in a nutshell:

- effect of robo-advising on portfolio allocation
- who benefits from robo-advising
Key Features of PAS

At sign-up, investors are profiled on

- financial objectives
- risk-tolerance
- investment horizons
- demographic characteristics

Investors are then proposed a comprehensive financial plan, i.e.,

- cash flow forecast
- probability of financing a secure retirement
- recommended portfolio strategy

Before approval, clients interact with a human who explains the plan

After approval, PAS trades automatically and rebalances quarterly
Main findings

Across all clients:

- **Portfolio Holdings**: ↑ bond, ↓ cash, ≈ equity
- **Investment Vehicles**: ↑ mutual funds, ↓ Individual stocks, ↓ ETFs
- **Mutual Fund Characteristics**: ↑ Indexed Mutual Funds, ↓ Fees
- ↑ International Diversification
- ↑ Risk-Adjusted Performance

Heterogeneity in robo-adviser effects:

- **High benefits**: clients with little experience, high cash holdings & trading
- **Low benefits**: clients with high share in mutual funds, high indexation
Data

- Sample of 350,000 clients that interacted with PAS
  - Trades
  - Monthly positions
  - Demographic Characteristics: Age, Gender, Tenure, etc.
  - Mutual fund characteristics and returns
  - Stock Characteristics and Returns

→ Construct investor characteristics & investment performance
## Client Characteristics at PAS Sign-up

### Panel A. Demographic Characteristics

<table>
<thead>
<tr>
<th></th>
<th>N</th>
<th>Mean</th>
<th>St. Dev</th>
<th>Median</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age</td>
<td>80,690</td>
<td>63.22</td>
<td>12.80</td>
<td>65.00</td>
</tr>
<tr>
<td>Male</td>
<td>82,526</td>
<td>0.53</td>
<td>0.50</td>
<td>1.00</td>
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<tr>
<td>Married</td>
<td>82,526</td>
<td>0.36</td>
<td>0.48</td>
<td>0.00</td>
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<tr>
<td>Tenure</td>
<td>82,498</td>
<td>14.18</td>
<td>9.30</td>
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### Panel B. Portfolio Allocation

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<td>Wealth</td>
<td>82,526</td>
<td>$588,245</td>
<td>$832,296</td>
<td>$282,449</td>
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<tr>
<td>Number of Assets</td>
<td>82,526</td>
<td>7.79</td>
<td>7.95</td>
<td>5.00</td>
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<tr>
<td>%Equity</td>
<td>81,869</td>
<td>0.54</td>
<td>0.31</td>
<td>0.59</td>
</tr>
<tr>
<td>%Bond</td>
<td>81,869</td>
<td>0.24</td>
<td>0.23</td>
<td>0.20</td>
</tr>
<tr>
<td>%Cash</td>
<td>81,869</td>
<td>0.22</td>
<td>0.34</td>
<td>0.02</td>
</tr>
<tr>
<td>%Mutual Funds</td>
<td>82,364</td>
<td>0.72</td>
<td>0.37</td>
<td>0.94</td>
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<tr>
<td>%Cash</td>
<td>82,364</td>
<td>0.20</td>
<td>0.34</td>
<td>0.01</td>
</tr>
<tr>
<td>%Stocks</td>
<td>82,364</td>
<td>0.03</td>
<td>0.10</td>
<td>0.00</td>
</tr>
<tr>
<td>%ETF</td>
<td>82,364</td>
<td>0.03</td>
<td>0.10</td>
<td>0.00</td>
</tr>
<tr>
<td>%Indexed Funds</td>
<td>82,523</td>
<td>0.47</td>
<td>0.37</td>
<td>0.46</td>
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<tr>
<td>%International Funds</td>
<td>77,083</td>
<td>0.10</td>
<td>0.14</td>
<td>0.02</td>
</tr>
<tr>
<td>%Emerging Funds</td>
<td>77,083</td>
<td>0.00</td>
<td>0.02</td>
<td>0.00</td>
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</table>
## Client Characteristics at PAS Sign-up

<table>
<thead>
<tr>
<th>Panel C. Transactions and Fees</th>
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<th>mean</th>
<th>St. Dev</th>
<th>p50</th>
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<tbody>
<tr>
<td>Management Fees</td>
<td>76,986</td>
<td>0.14</td>
<td>0.12</td>
<td>0.11</td>
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<tr>
<td>Turnover Ratio</td>
<td>72,930</td>
<td>0.32</td>
<td>0.26</td>
<td>0.25</td>
</tr>
<tr>
<td>N. of Transactions</td>
<td>82,526</td>
<td>3.31</td>
<td>6.55</td>
<td>1.00</td>
</tr>
<tr>
<td>Volume ($)</td>
<td>$82,526</td>
<td>$85,246</td>
<td>$226,358</td>
<td>$226</td>
</tr>
</tbody>
</table>
PAS and Portfolio Characteristics: CASH
PAS and Portfolio Characteristics: BONDS
PAS and Portfolio Characteristics: Mutual Fund
PAS and Portfolio Characteristics: Stocks
PAS and Portfolio Characteristics: Indexation
PAS and Portfolio Characteristics: International Exposure
PAS and Portfolio Characteristics: Mgt Fees
PAS and Portfolio Characteristics

Some of the plots can be misleading: Equity Shares
PAS and Portfolio Characteristics

Equity share changes for low and high Equity holders at sign-up

(a) Low Equity Share

(b) High Equity Share
Who benefits from Robo-advising?

Focus on two measures:

- change in *portfolio allocations*
- change in *investment performance*

**Problem:**

- Not clear what investor characteristics matter *ex-ante*
- Not clear if the functional relations btw:
  - regressors
  - regressands
  - are linear and/or monotonic
- kitchen sink linear regression are likely to overfit

→ use machine learning tool known as Boosted Regression Trees
→ let the data speak
Regression trees

A regression tree, \( T_J \), with \( J \) regions (states) and parameters \( \Theta_J = \{ S_j, c_j \}_{j=1}^J \) can be written as

\[
T(x, \Theta_J) = \sum_{j=1}^{J} c_j I(x \in S_j).
\]

- \( S_1, S_2, ..., S_J \): \( J \) disjoint states
- \( x = (x_1, x_2, ..., x_P) \): \( P \) predictor ("state") variables
- The dependent variable is constant, \( c_j \), within each state, \( S_j \)
Regression Trees: Intuition

Key features:

- Partitioning using lines parallel to the coordinate axes
- Recursive binary partitioning
- Very hierarchical
- Use less and less data → overfit
A Boosted Tree Model is a sum of Regression Trees:

\[ f_B(x) = \sum_{b=1}^{B} T(x; \Theta_{J,b}). \]

The B-th boosting iteration fits a tree on:

\[
\hat{\Theta}_{J,B} = \arg \min_{\Theta_{J,B}} \sum_{t=0}^{T-1} [e_{t+1,B-1} - T(x_t; \Theta_{J,B})]^2
\]

where

\[ e_{t+1,B-1} = y_{t+1} - f_{B-1}(x_t) \]

are the residuals of the model with “B-1” iterations.

To minimize the current residuals, the B-th tree finds:

- The optimal splitting regions, \( S_{j,B} \)
- The optimal constants, \( c_{j,B} \)
BRT vs linear models

1 Boosting Iteration

- BRT
- Linear Regression
- Boosted Regression Trees

Motivation
Data
Basic Facts
Boosted Regression Trees (BRT)
Portfolio Changes
Performance Changes
OOS Analysis
Conclusions
Appendix
BRT vs linear models

5 Boosting Iterations
BRT vs linear models

10,0000 Boosting Iterations
Why don’t BRT overfit?

- **Small Trees**: Each tree fitted has only two states, \( J = 2 \)

- **Shrinkage**: Parameter, \( \lambda = 0.001 \), determines how much each tree contributes to the overall fit:

  \[
  f_B(x_t) = f_{B-1}(x_t) + \lambda \sum_{j=1}^{J} c_{j,B} I\{x_t \in S_{j,B}\}.
  \]

- **Subsampling**: using half the data to fit each tree

- **Objective function**:

  \[
  \text{MSE} = \frac{1}{T} \sum_{t=1}^{T} (y_{t+1} - f(x_t))^2 \quad \text{or} \quad \text{MAE} = \frac{1}{T} \sum_{t=1}^{T} |y_{t+1} - f(x_t)|
  \]

- **Key Parameter to Choose**: Number of Boosting Iterations

  - Baseline results: 10,000 iterations, but conduct sensitivity analysis
Are BRT a Black Box?

NO!

Much more **intuitive** and **interpretable** than other AI techniques

Possible to obtain

- **Relative Influence Estimates:**
  Relative importance of each predictor variable in a model

- **Partial Dependence Plots:**
  Recovers functional relation btw regressand and each regressor
Use BRT to Explain Portfolio Changes

Approach:

- Model the pre and post-PAS Equity Share using BRT
- 10,000 boosting iterations

Covariates:

- **4 Demographics**: Age; Married; Male; Tenure
- **7 Portfolio**: %Equity; %Cash; %Mutual Funds; %Stocks; %ETFs; %Indexed Funds; %Emerging Funds
- **4 Trading**: Management Fees; Number of assets; Volume; N. of Transactions
Use BRT to Explain Portfolio Changes

Equity Share (81.9%); Age (15.6%); Percentage in Cash (2.1%)
Use BRT to Explain Portfolio Changes

Bi-variate Plots: Equity Share and Age
Comparison with linear model
(Significant Regressors)

<table>
<thead>
<tr>
<th>Linear Model</th>
<th>BRT</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age</td>
<td>✓</td>
</tr>
<tr>
<td>Male</td>
<td>✓</td>
</tr>
<tr>
<td>Married</td>
<td>✓</td>
</tr>
<tr>
<td>Tenure</td>
<td>✓</td>
</tr>
<tr>
<td>Number of Assets</td>
<td>✓</td>
</tr>
<tr>
<td>%Equity</td>
<td>✓</td>
</tr>
<tr>
<td>%Cash</td>
<td>✓</td>
</tr>
<tr>
<td>%Mutual Funds</td>
<td>✓</td>
</tr>
<tr>
<td>%Stocks</td>
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</tr>
<tr>
<td>%ETFs</td>
<td>✓</td>
</tr>
<tr>
<td>%Indexed Funds</td>
<td>✓</td>
</tr>
<tr>
<td>%Emerging Funds</td>
<td>✓</td>
</tr>
<tr>
<td>Management Fees</td>
<td>✓</td>
</tr>
<tr>
<td>Volume</td>
<td>✓</td>
</tr>
<tr>
<td>N. Transactions</td>
<td>✓</td>
</tr>
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</table>
## PAS & Performance Changes

Compute realized Abnormal Sharpe ratios pre- and post-PAS sign-up

<table>
<thead>
<tr>
<th></th>
<th>All Accounts</th>
<th>Matched Accounts</th>
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<tbody>
<tr>
<td></td>
<td>After</td>
<td>Before</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>3-Months</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.103***</td>
<td>-0.013***</td>
</tr>
<tr>
<td></td>
<td>(28.97)</td>
<td>(-3.23)</td>
</tr>
<tr>
<td><strong>N</strong></td>
<td>65,061</td>
<td>48,008</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>9-Months</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.094***</td>
<td>0.021***</td>
</tr>
<tr>
<td></td>
<td>(36.82)</td>
<td>(7.47)</td>
</tr>
<tr>
<td><strong>N</strong></td>
<td>47,839</td>
<td>35,024</td>
</tr>
</tbody>
</table>
PAS and Performance Changes

Matched accounts. Horizon: 9-Months
Use AI to Explain Performance Changes

Approach:

- Model the pre and post-PAS Abnormal Sharpe Ratio using BRT
- 10,000 boosting iterations

Covariates:

- **4 Demographics:** Age; Married; Male; Tenure
- **7 Portfolio:** %Equity; %Cash; %Mutual Funds; %Stocks; %ETFs; %Indexed Funds; %Emerging Funds
- **4 Trading:** Management Fees; Number of assets; Volume; N. of Transactions
Use AI to Explain **Performance Changes** (Relative Influence Measures)
Use AI to Explain Performance Changes (Partial Dependence Plots)

Some make a lot of economic sense
Use AI to Explain Performance Changes (Partial Dependence Plots)

Some make a lot of economic sense
Use AI to Explain **Performance Changes**

(Partial Dependence Plots)

Some are more challenging
Out-of-Sample Performance

Crucial to evaluate the out-of-sample performance of BRT to

- Establish we are not over-fitting the training data ...
- ... and capturing the true structural relation btw the variables

Do the analysis on both:

- Changes in portfolio allocation (Easy)
- Changes in investment performance (More Challenging)
Out-of-Sample Performance

Cross-Validation Exercise:

- Use a BRT model and a linear model with the same covariates
- Estimate the model on all observations except for 1000 observations randomly removed
- Test the model on the remaining 1000 observations
- Compute in- and out-of-sample $R^2$
- Compute the analysis 1000 times and average the results across simulation rounds
Results for Portfolio Changes

- BRT In-Sample
- BRT Out-Of-Sample
- Linear Model In-Sample
- Linear Model Out-Of-Sample

R-squared vs. boosting iterations graph.
Results for Performance Changes

- BRT In-Sample
- BRT Out-Of-Sample
- Linear Model In-Sample
- Linear Model Out-Of-Sample

R-squared vs. boosting iterations.
With Higher Order Terms

- BRT In-Sample
- BRT Out-Of-Sample
- Linear Model In-Sample
- Linear Model Out-Of-Sample

R-squared vs. boosting iterations graph.
Results for Performance Changes

- Linear Model
- BRT

Out-of-Sample R-Squared

Density
We can explain a lot of the variation in portfolio changes

Only small part of the variation for investment performance

Mean-Squared-Error is not an ideal measure of performance

BRT outperform linear model both in- and out-of-sample

BRT out-of-sample performs better than linear model in-sample
Conclusions

Use AI to study which investors benefit the most from PAS

- Difficult to know what factors matter *ex-ante*
- Not clear if the relations are linear and/or monotonic *ex-ante*
- BRT uncovers significant non-linearities
- BRT performs well in- and out-of-sample
Use AI to Explain Portfolio Changes—No Equity Share

- %Mutual Funds (33%)
- Fees (31%)
- %Ind. Stocks (11%)
Use AI to Explain Portfolio Changes—No Equity Share

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Age (10%)

Indexation (8%)

%ETF (6%)

\[ R^2 = 26\% \]
## Portfolio Holdings of PAS and non-PAS clients

### Top Mutual Fund Tickers in January 2017

<table>
<thead>
<tr>
<th>Rank</th>
<th>Ticker</th>
<th>Pct of Assets</th>
<th>Ticker</th>
<th>Pct of Assets</th>
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</thead>
<tbody>
<tr>
<td>1</td>
<td>VTSAX</td>
<td>16%</td>
<td>VTSAX</td>
<td>28%</td>
</tr>
<tr>
<td>2</td>
<td>VFIAX</td>
<td>7%</td>
<td>VTIAAX</td>
<td>18%</td>
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<tr>
<td>3</td>
<td>VBTLX</td>
<td>7%</td>
<td>VBTLX</td>
<td>16%</td>
</tr>
<tr>
<td>4</td>
<td>VTIAAX</td>
<td>5%</td>
<td>VTABX</td>
<td>11%</td>
</tr>
<tr>
<td>5</td>
<td>VWIUX</td>
<td>4%</td>
<td>VFIDX</td>
<td>6%</td>
</tr>
<tr>
<td></td>
<td>Total</td>
<td>39%</td>
<td>Total</td>
<td>79%</td>
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