Who Benefits from Robo-Advising?
Evidence from Machine Learning

Alberto G Rossi
Georgetown University

Stephen Utkus
Vanguard

Global Financial Literacy Excellence Center Seminar Series
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.

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

Categories are not mutually exclusive. We categorized companies based on their primary use case.

**ROBO-ADVISOR**
- BUSINESS-TO-CONSUMER (B2C)
  - WiseBanyan
  - moneyfarm
  - Nest Wealth
  - vaamo
  - Invest.com
  - goalwise

**ROBO-RETIREEMENT**
- B2C
  - RobustWealth
  - Feex
  - blooom

**B2B & B2C**
  - Guideline
  - Vestwell
  - forUsAll
  - nextcapital

**MICRO-INVESTING**
- B2C
  - acorns
  - STASH

**INVESTING TOOLS**
- B2C
  - nextmarkets
  - nerdwallet
  - stocktwits
  - openfolio

**B2B & B2C**
  - YCharts
  - TradingView
  - AlgoM
  - CANALYST
  - LMRKTS
  - harvest
  - TRACKINSIGHT
  - OpenGamma

**B2B**
  - Robinhood
  - tastyworks
  - rubicon
  - Alpaca
  - driveWealth

**PORTFOLIO MANAGEMENT**
- B2C
  - RisbeeVie

**B2B & B2C**
  - ADViZR
  - iQuantif
  - Quuvo
  - Jacobi

**FINANCIAL SERVICES SOFTWARE**
- B2B
  - Plaid
  - Starburst
  - investcloud

**DIGITAL BROKERAGE**
- B2C
  - Robinhood
  - tastyworks

- B2B
  - Artivest
  - Trumid

Where's this data from?

Get the full list of wealth tech startups and select investors featured on our market map. As an added bonus, we'll send you the disclosed funding values for each company.

Enter your email address here...

Yes, send me the excel file

Where's this data from?

Check us out for free

Business E-mail

jdoe@company.com

Choose a password

********


Create free account

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Research Agenda on Robo-advising

Handbook Chapter


Investment Decisions

- “Who Benefits from Robo-advising? Evidence from Machine Learning,” with Utkus

Consumption and Saving Decisions

- “Crowdsourcing Peer Information to Change Spending Behavior,” with D’Acunto & Weber (R&R at RFS)
- “There’s and App for That: Goal Setting and Saving in the FinTech Era,” with Gargano

P2P Lending Decisions

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

- 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

→ No Control from the Investor
Uniqueness of the Setting

- Post enrollment, the portfolio allocations are **mechanical**
- Difficult to argue individuals would make these changes on their own
- . . . and the results are not the effect of the robo-advisor
- If anything, concerned with timing of sign-up
  - Identification strategy for this concern

**Machine learning to back out heterogeneity of the effect across investors**

- Informative on what would be the effect on the general population.
- . . . because a function of individuals’ characteristics
- ML allows us to study non-linearities in the effects
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 investors 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
### Investor 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>
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<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>Tenure</td>
<td>82,498</td>
<td>14.18</td>
<td>9.30</td>
<td>14.17</td>
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</table>
## Investor Characteristics at PAS Sign-up

### Panel B. Portfolio Allocation

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<th>N</th>
<th>mean</th>
<th>St. Dev</th>
<th>Median</th>
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</thead>
<tbody>
<tr>
<td><strong>Wealth</strong></td>
<td>82,526</td>
<td>$588,245</td>
<td>$832,296</td>
<td>$282,449</td>
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<tr>
<td><strong>Number of Assets</strong></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>
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<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>
</tr>
<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>
</tr>
</tbody>
</table>
PAS and Portfolio Characteristics: BONDS
PAS and Portfolio Characteristics: BONDS
10th, 50th, and 90th percentiles
PAS and Portfolio Characteristics: Indexation
PAS and Portfolio Characteristics: International Exposure
PAS and Portfolio Characteristics: International 10th, 50th, and 90th percentiles
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 regressions are likely to overfit

→ use machine learning tool known as Boosted Regression Trees
→ let the data speak
Machine Learning Vs. Traditional Statistics

Machine learning likely to outperform traditional statistics if you have:

- Large set of explanatory variables
- Potentially non-linear relation btw regressand and regressors
- Many interaction effects between regressors

As bigger datasets are becoming available

→ Machine Learning is gaining momentum in finance and economics
Common Machine Learning Algorithms
(Supervised Learning)

Non-exhaustive list from more to less familiar for economists:

- Ridge Regression & LASSO
- Bagging
- Random Forests
- **Boosted Regression Trees**
  - good out-of-sample performance
  - results economically interpretable
- Neural Networks
Regression trees

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

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

- $S_1, S_2, \ldots, S_J$: $J$ disjoint states
- $x = (x_1, x_2, \ldots, x_P)$: $P$ 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
Boosting

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 vs linear models

5 Boosting Iterations

- Linear Regression
- Boosted Regression Trees
BRT vs linear models

10,000 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
Are BRT a Black Box?

NO!

Much more **intuitive** and **interpretable** than other ML 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%)

[Graphs showing partial dependence of Equity Share, Age, and Percentage in Cash]
Use BRT to Explain Portfolio Changes

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

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

\[ \text{Sharpe}_{i,t} = \alpha_i + \beta_t + \sum_{j=-5}^{35} \gamma_j \text{ROBO}_{i,j,t} + \epsilon_{i,t} \]
PAS & Performance Changes (Identification Strategy)

**Problem**
Results reported so far do not control for endogenous decision to sign-up

People who do poorly may be the one who sign-up
→ Performance improvement may be overstated

**Solution**
Construct counter-factual returns for those who sign-up for those periods when they were not signed-up

→ Confirm the baseline results in this setting
PAS and Performance Changes

Within-individual Changes in Abnormal Sharpe Ratio
Use BRT 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
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Use BRT to Explain **Performance Changes** (Partial Dependence Plots)
Use AI to Explain Performance Changes (Partial Dependence Plots)
Attention and Robo-advising

\[ \text{Attention}_{i,t} = \alpha_i + \beta_t + \sum_{j=-5}^{35} \gamma_j \text{ROBO}_{i,j,t} + \delta \, X_{i,t} + \epsilon_{i,t}, \]

(a) Total (Days with Logins per month)
Attention and Robo-advising

\[ Attention_{i,t} = \alpha_i + \beta_t + \sum_{j=-5}^{35} \gamma_j \ ROBO_{i,j,t} + \delta X_{i,t} + \epsilon_{i,t}, \]

(a) Attention Through Desktop Computer  
(b) Attention Through Mobile App

Attention is measured as “Days with Logins” per month
Attention and Robo-advising

\[ \text{Attention}_{i,t} = \alpha_i + \beta_t + \sum_{j=-5}^{35} \gamma_j \ ROBO_{i,j,t} + \delta \ X_{i,t} + \epsilon_{i,t}, \]

(a) Attention Through Desktop Computer  
(b) Attention Through Mobile App

Attention is measured as “Minutes” per month
Interaction with Human Advisors

\[ Interaction_{i,t} = \alpha_i + \beta_t + \sum_{j=0}^{35} \gamma_j \ ROBO_{i,j,t} + \delta \ X_{i,t} + \epsilon_{i,t}, \]

(a) Any Interactions
Interaction with Human Advisors

(a) Level 3

(b) Level 2

(c) Level 1
Attrition

(a) Female; Male
(b) Long-tenure; Short-tenure
(c) Slow to Enroll; Quick to Enroll
(d) Level 3; Level 2; Level 1
Additional Results

In the paper, additional results on

- Determinants of robo-advice sign-up
- Determinants of robo-advice attrition
- Emphasis on the role of hybrid forms of robo-advice
Conclusions

- Robo-advice can improve portfolio allocations of already diversified investors
- Robo-advice has the potential to disrupt the entire financial advisory industry
- Simple forms of robo-advice can be successful
- Forms of hybrid robo-advising reduce attrition, likely because they reduce algorithmic-aversion
- Significant benefits unrelated to financial performance
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

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

### Top Mutual Fund Tickers in January 2017

<table>
<thead>
<tr>
<th>Rank</th>
<th>NON-PAS</th>
<th>Pct of Assets</th>
<th>PAS</th>
<th>Pct of Assets</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>VTSAW</td>
<td>16%</td>
<td>VTSAW</td>
<td>28%</td>
</tr>
<tr>
<td>2</td>
<td>VFIAX</td>
<td>7%</td>
<td>VTIAX</td>
<td>18%</td>
</tr>
<tr>
<td>3</td>
<td>VBTLX</td>
<td>7%</td>
<td>VBTLX</td>
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<tr>
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<td>VTIAW</td>
<td>5%</td>
<td>VTABX</td>
<td>11%</td>
</tr>
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<td>5</td>
<td>VWIUW</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>
</tr>
</tbody>
</table>
PAS & Performance Changes
(Identification Strategy)

Problem
Results reported so far do not control for endogenous decision to sign-up

People who do poorly may be the one who sign-up
→ Performance improvement may be overstated

Solution
Construct counter-factual returns for those who sign-up for those periods when they were not signed-up
PAS & Performance Changes
(Identification Strategy)

Example to fix ideas
## PAS & Performance Changes (Identification Strategy)

Identification Results Using Matched Investor Returns as Benchmarks

<table>
<thead>
<tr>
<th></th>
<th>Top Decile</th>
<th>Top 2 Deciles</th>
<th>Top 3 Deciles</th>
<th>All Investors</th>
</tr>
</thead>
<tbody>
<tr>
<td>Difference</td>
<td>-0.069***</td>
<td>-0.071***</td>
<td>-0.074***</td>
<td>-0.072***</td>
</tr>
<tr>
<td></td>
<td>(-29.98)</td>
<td>(-30.74)</td>
<td>(-31.60)</td>
<td>(-30.96)</td>
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<tr>
<td>N</td>
<td>297,134</td>
<td>297,134</td>
<td>297,134</td>
<td>297,134</td>
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</tbody>
</table>
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)

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

BRTs out-of-sample performs better than linear model in-sample
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)

→ Show that BRT easily outperform linear model
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
Results for Portfolio Changes

- **linear Model**
- **BRT**
Results for Performance Changes

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

R-squared

0.00
0.01
0.02
0.03
0.04
0.05
0.06

0
5000
10000
15000
20000
With Higher Order Terms
Results for Performance Changes

![Graph showing out-of-sample R-Squared for linear model and BRT.](image)
Comments

- 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.