Who Benefits from Robo-Advising? Evidence from Machine Learning

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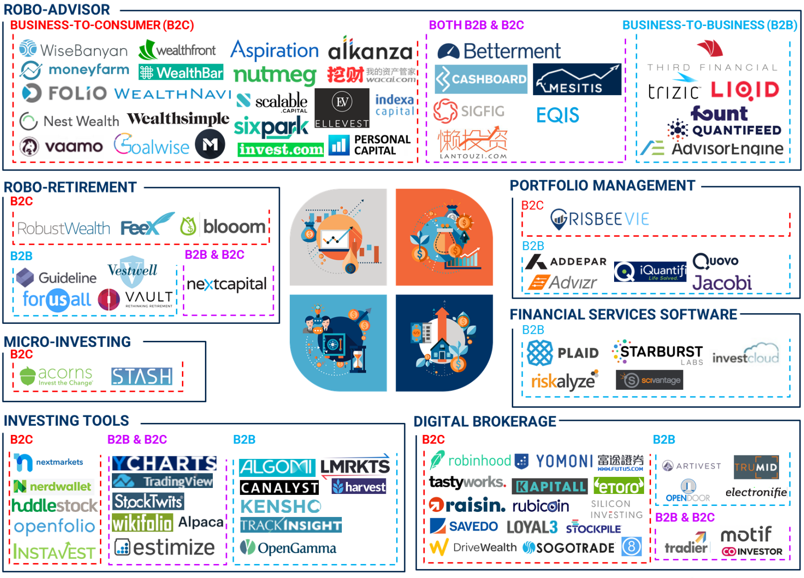
Global Financial Literacy Excellence
Center Seminar Series

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

Motivation


ROBO-ADVISOR
BUSINESS-TO-CONSUMER (B2C)
WiseBanyan
wealthfront
Aspiration
alkanza
moneyfarm
WealthBar
nutmeg
挖财 我的资产管家 wacai.com
FOLIO
WEALTHNAVI
scalable CAPITAL
ELLEVEST
indexa capital
Nest Wealth
Wealthsimple
sixpark
vaamo
Goalwise
invest.com
PERSONAL CAPITAL
BOTH B2B & B2C
Betterment
CASHBOARD
MESITIS
SIGFIG
EQIS
LANTOUZI.COM
BUSINESS-TO-BUSINESS (B2B)
THIRD FINANCIAL
trizic
LIQID
fount
QUANTIFEED
AdvisorEngine
ROBO-RETIREMENT
B2C
RobustWealth
FeeX
blooom
B2B
Guideline
Vestwell
forusall
VAULT
RETHINKING RETIREMENT
B2B & B2C
nextcapital
MICRO-INVESTING
B2C
acorns
Invest the Change
STASH
PORTFOLIO MANAGEMENT
B2C
RISBEEVIE
B2B
ADDEPAR
iQuantifi
Life Solved.
Quovo
Advizr
Jacobi
FINANCIAL SERVICES SOFTWARE
B2B
PLAID
STARBURST LABS
investcloud
riskalyze
scivantage
INVESTING TOOLS
B2C
nextmarkets
nerdwallet
hiddlestock
openfolio
INSTAVEST
B2B & B2C
YCHARTS
TradingView
StockTwits
wikifolio
Alpaca
estimize
B2B
ALGOMI
LMRKTS
CANALYST
harvest
KENSHO
TRACKINSIGHT
OpenGamma
DIGITAL BROKERAGE
B2C
robinhood
YOMONI
富途證券 WWW.FUTU5.COM
tastyworks.
KAPITALL
etoro
raisin.
rubicoin
SILICON INVESTING
SAVEDO
LOYAL3
STOCKPILE
DriveWealth
SOGOTRADE
B2B
ARTIVEST
TRUMID
OPENDOOR
electronifie
B2B & B2C
tradier
motif
INVESTOR

Research Agenda on Robo-advising

Handbook Chapter

- "*Robo-advising*," with D'Acunto (Palgrave Handbook of Tech. Finance, 2020)

Investment Decisions

- "*The Promises and Pitfalls of Robo-advising*," with D'Acunto & Prabhala (RFS, 2019)
- "*Who Benefits from Robo-advising? Evidence from Machine Learning," with Utkus*
- "*The Needs and Wants in Financial Advice: Human vs Robo-Advising*," 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

- "*How Costly Are Cultural Biases? Evidence from FinTech,*" with D'Acunto, Ghosh, Jain

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

$\longrightarrow$ 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: $\uparrow$ bond, $\downarrow$ cash, $\approx$ equity
- Investment Vehicles: $\uparrow$ mutual funds, $\downarrow$ Individual stocks, $\downarrow$ ETFs
- Mutual Fund Characterstics: $\uparrow$ Indexed Mutual Funds, $\downarrow$ Fees
- $\uparrow$ International Diversification
- $\uparrow$ 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

$\rightarrow$ Construct investor characteristics & investment performance

Investor Characteristics at PAS Sign-up

Panel A. Demographic Characteristics

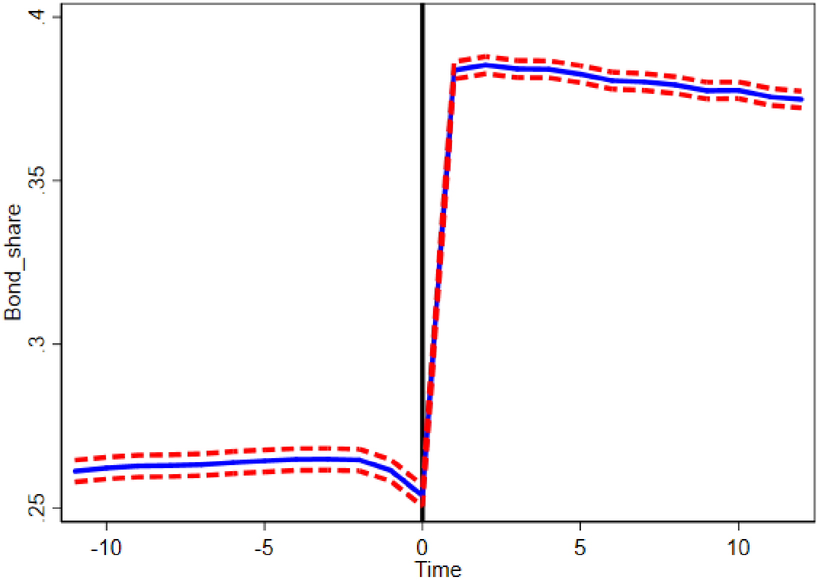
	N	Mean	St. Dev	Median
Age	80,690	63.22	12.80	65.00
Male	82,526	0.53	0.50	1.00
Tenure	82,498	14.18	9.30	14.17

Investor Characteristics at PAS Sign-up

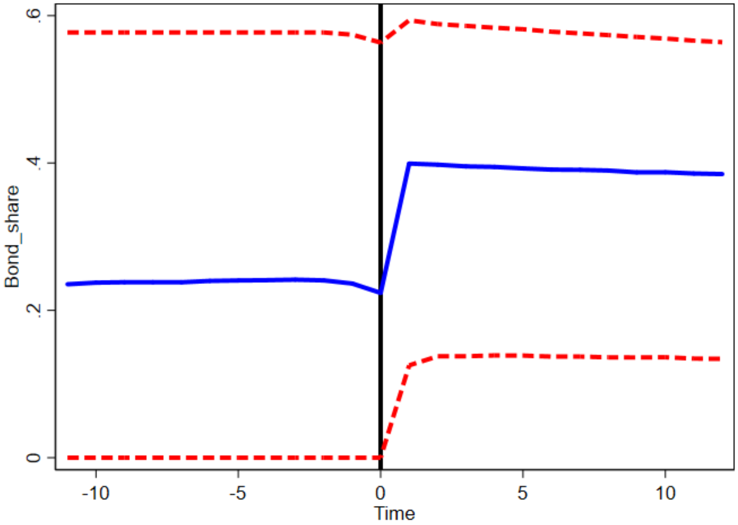
Panel B. Portfolio Allocation

	N	mean	St. Dev	Median
Wealth	82,526	$588,245	$832,296	$282,449
Number of Assets	82,526	7.79	7.95	5.00
%Equity	81,869	0.54	0.31	0.59
%Bond	81,869	0.24	0.23	0.20
%Cash	81,869	0.22	0.34	0.02
%Mutual Funds	82,364	0.72	0.37	0.94
%Cash	82,364	0.20	0.34	0.01
%Stocks	82,364	0.03	0.10	0.00
%ETF	82,364	0.03	0.10	0.00
%Indexed Funds	82,523	0.47	0.37	0.46
%International Funds	77,083	0.10	0.14	0.02
%Emerging Funds	77,083	0.00	0.02	0.00

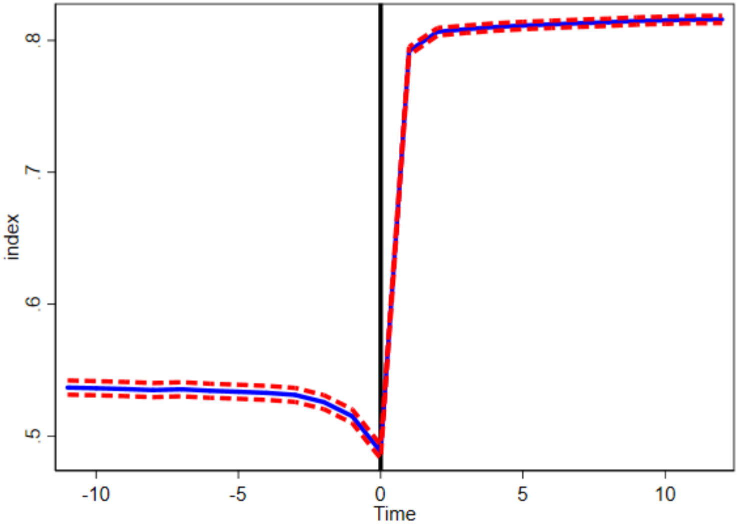
PAS and Portfolio Characteristics: BONDS



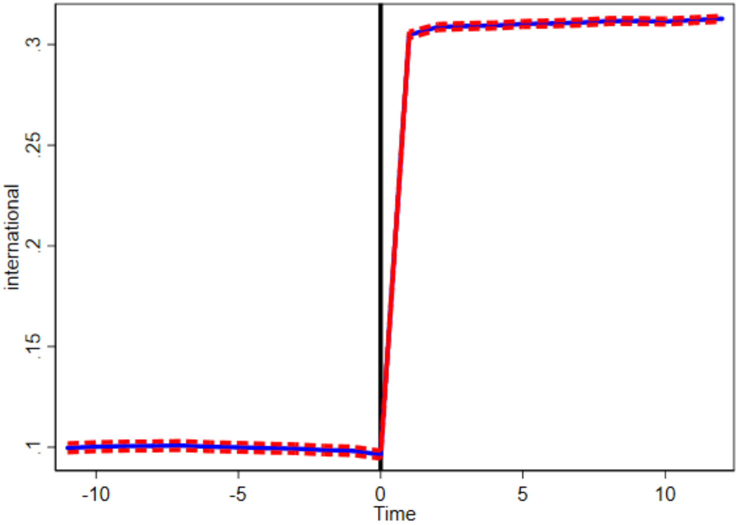
PAS and Portfolio Characteristics: BONDS 10th, 50th, and 90th percentiles



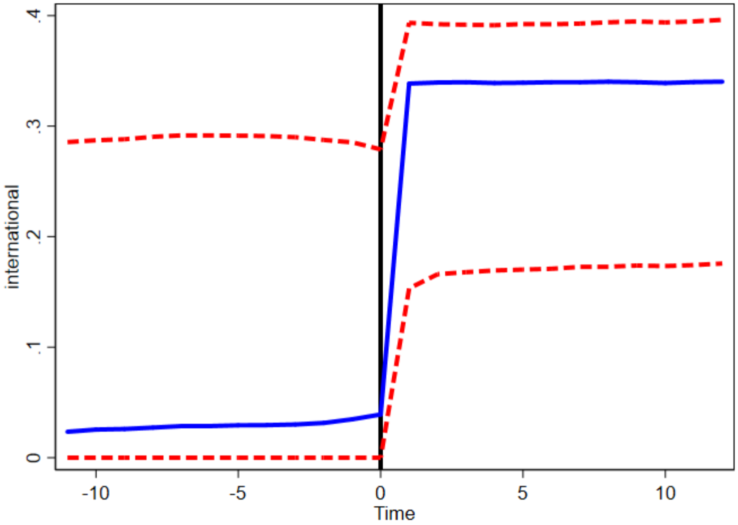
PAS and Portfolio Characteristics: Indexation



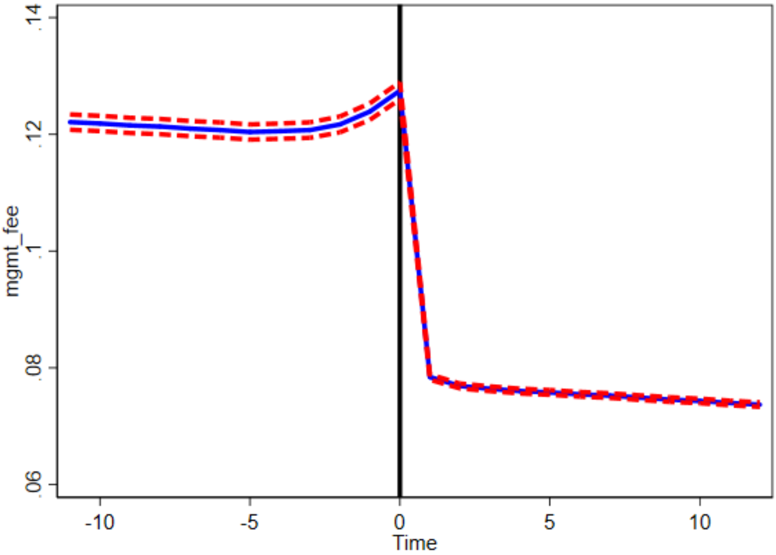
PAS and Portfolio Characteristics: International Exposure



PAS and Portfolio Characteristics: International
10th, 50th, and 90th percentiles

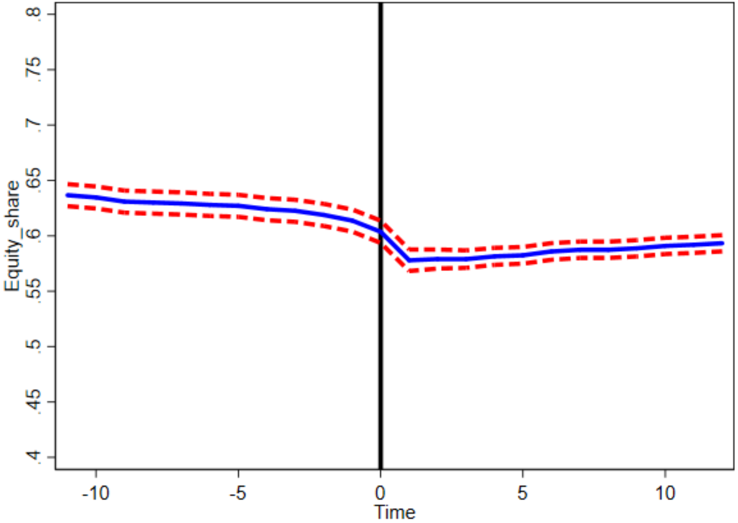


PAS and Portfolio Characteristics: Mgt Fees



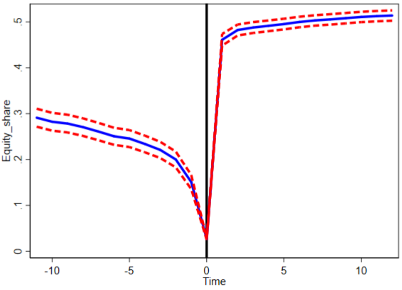
PAS and Portfolio Characteristics

Some of the plots can be misleading: Equity Shares

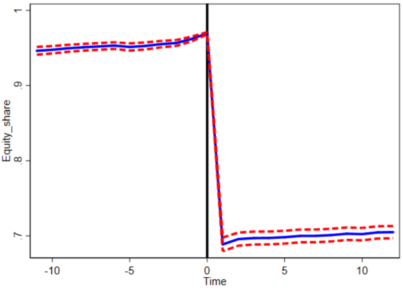


PAS and Portfolio Characteristics

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

$\rightarrow$ 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

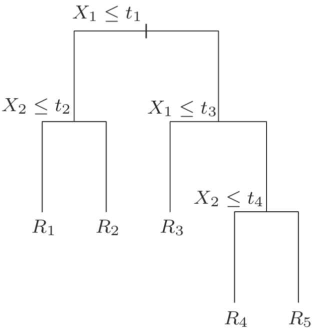
Regression trees

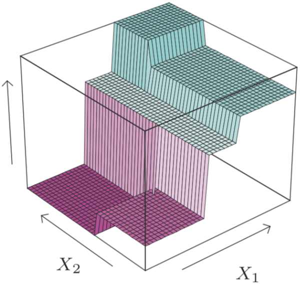
A regression tree, $\mathcal{T}_J$, with J regions (states) and parameters $\Theta_J = \{S_j, c_j\}_{j=1}^{J}$ can be written as

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

- $S_1, S_2, ..., S_J$: 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 $\rightarrow$ overfit

Boosting

A Boosted Tree Model is a sum of Regression Trees:

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

The B-th boosting iteration fits a tree on:

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

where

$$e_{t+1,B-1} = y_{t+1} - f_{B-1}(x_t)$$

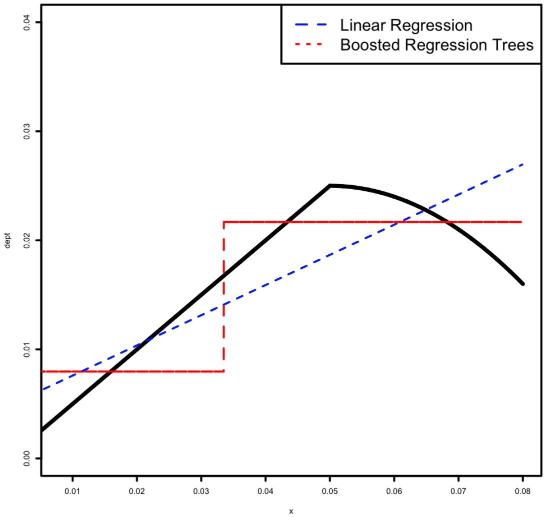
are the residuals of the model with “B-1” iterations.

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

- The optimal splitting regions, $S_{j,B}$
- The optimal constants, $c_{j,B}$

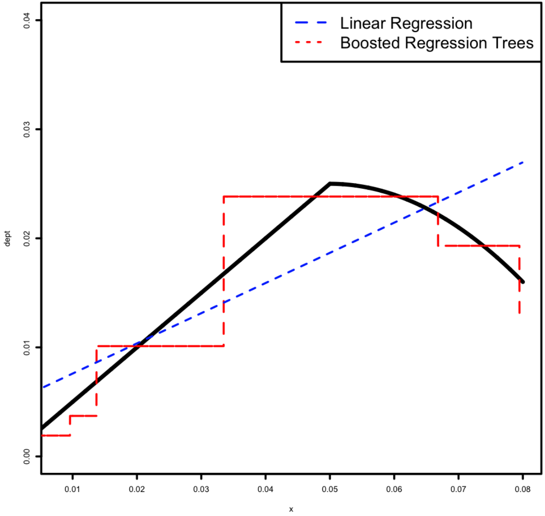
BRT vs linear models

1 Boosting Iteration



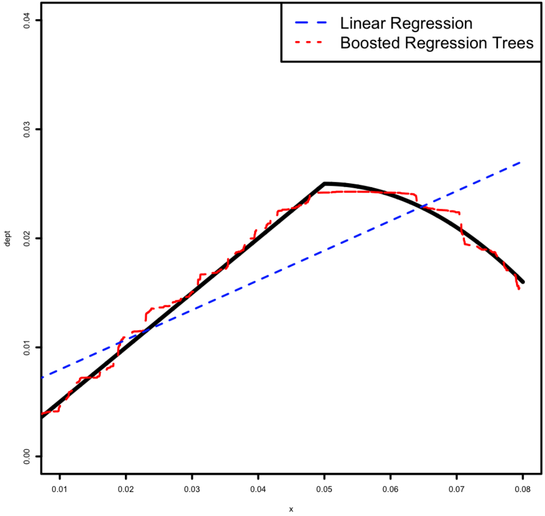
BRT vs linear models

5 Boosting Iterations



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

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

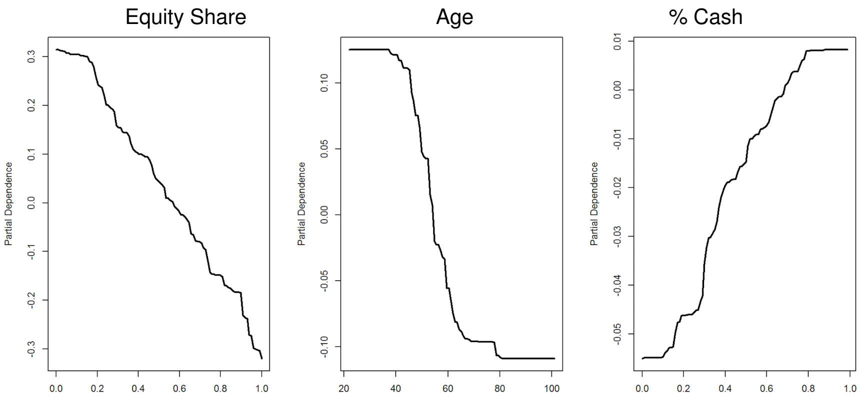
Use BRT to Explain Portfolio Changes

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

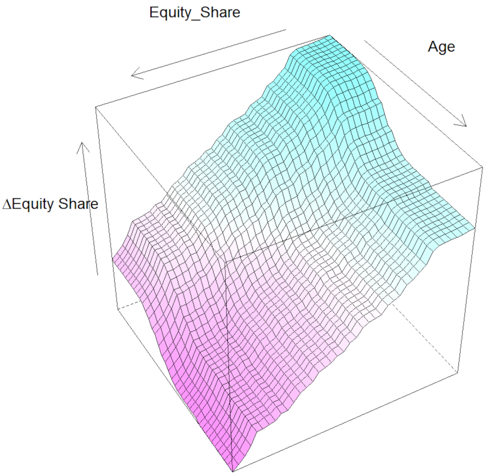
Use BRT to Explain Portfolio Changes

Equity Share (81.9%); Age (15.6%); Percentage in Cash (2.1%)



Use BRT to Explain Portfolio Changes

Bi-variate Plots: Equity Share and Age

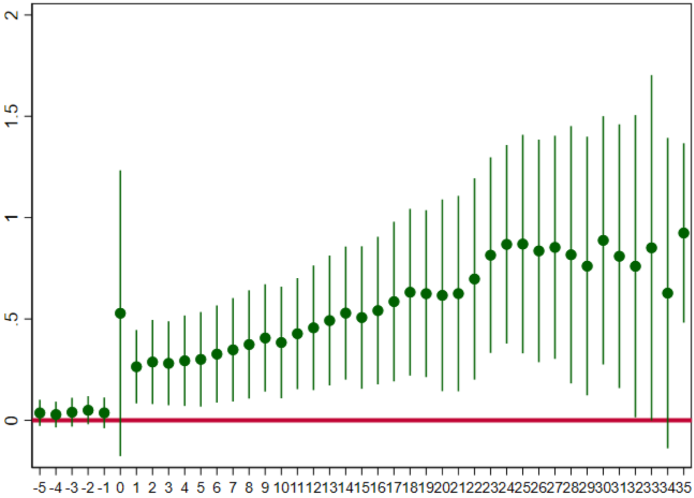


Comparison with linear model (Significant Regressors)

	Linear Model	BRT
Age	✓	✓
Male	✓	
Married	✓	
Tenure		
Number of Assets	✓	
%Equity	✓	✓
%Cash	✓	✓
%Mutual Funds		
%Stocks		
%ETFs		
%Indexed Funds		
%Emerging Funds		
Management Fees	✓	
Volume		
N. Transactions		

PAS & Performance Changes

$$Sharpe_{i,t} = \alpha_i + \beta_t + \sum_{j=-5}^{35} \gamma_j \, ROBO_{i,j,t} + \epsilon_{i,t}$$



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
$\rightarrow$ Performance improvement may be overstated

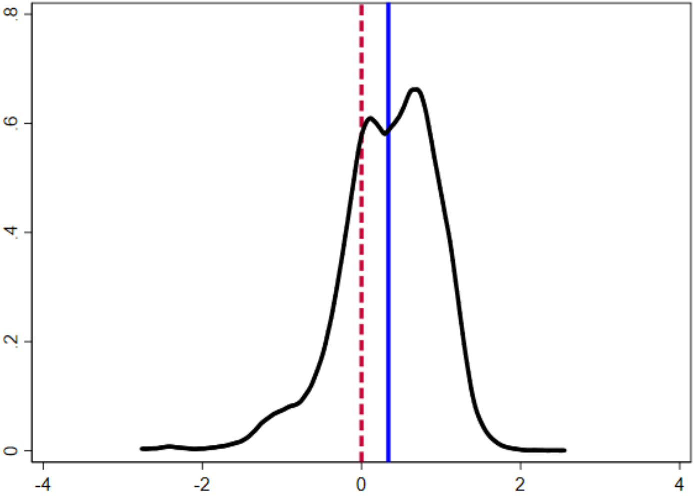
Solution

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

$\rightarrow$ Confirm the baseline results in this setting

PAS and Performance Changes

Within-individual Changes in Abnormal Sharpe Ratio

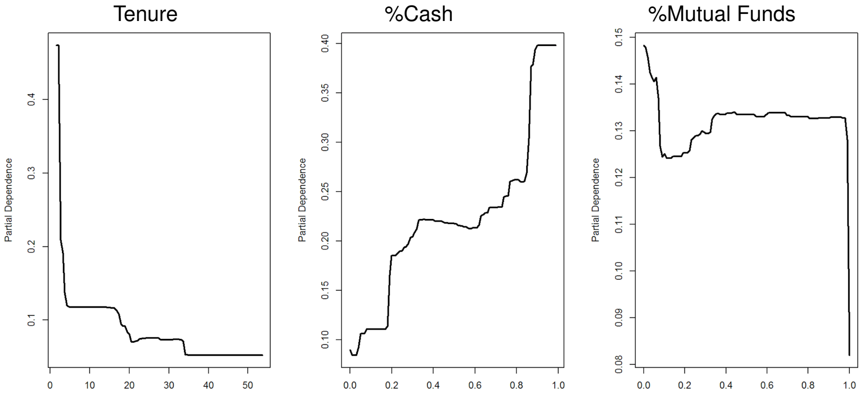


Use BRT to Explain Performance Changes

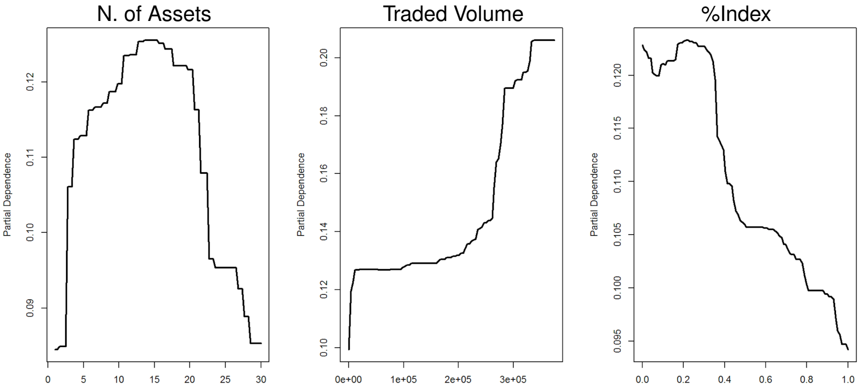
Approach:

- Model the pre and post-PAS Abnormal Sharpe Ratio using BRT
- 10,000 boosting iterations
- Covariates:
  - **4 Demographics:** Age; Married; Male; Tenure
  - **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 Performance Changes (Partial Dependence Plots)

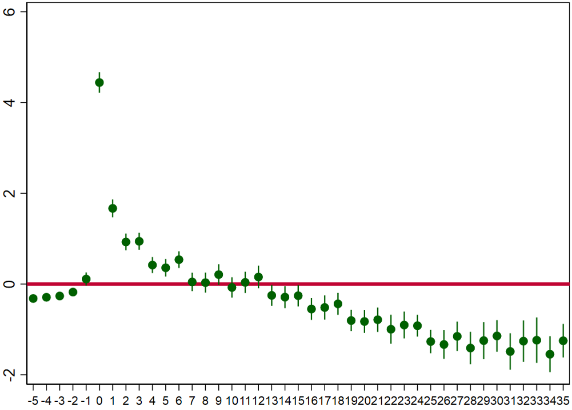


Use AI to Explain Performance Changes (Partial Dependence Plots)



Attention and Robo-advising

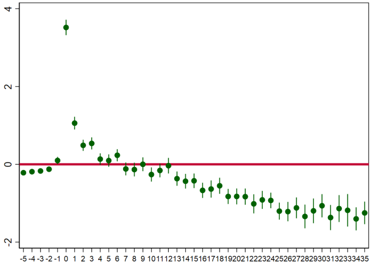
$$Attention_{i,t} = \alpha_i + \beta_t + \sum_{j=-5}^{35} \gamma_j \; ROBO_{i,j,t} + \delta \; X_{i,t} + \epsilon_{i,t},$$



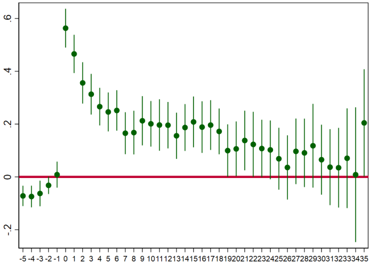
(a) Total (Days with Logins per month)

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

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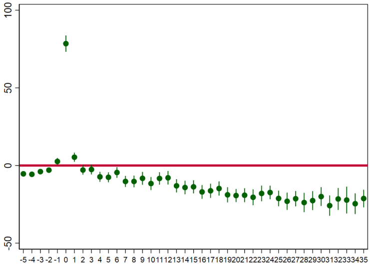
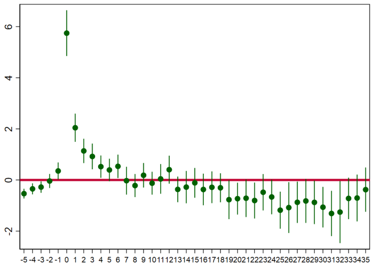


(a) Attention Through Desktop Computer

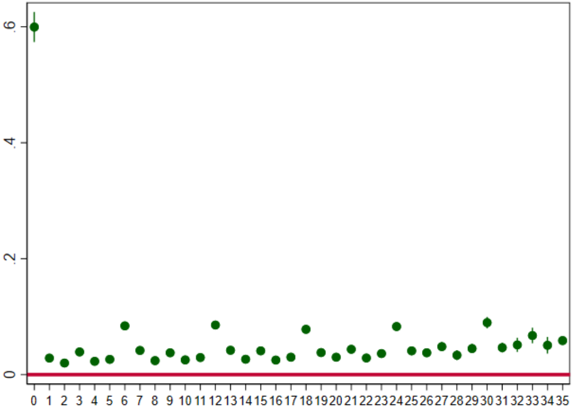


(b) Attention Through Mobile App

Attention is measured as “Minutes” per month

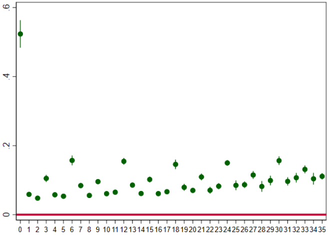
Interaction with Human Advisors

$$\text{Interaction}_{i,t} = \alpha_i + \beta_t + \sum_{j=0}^{35} \gamma_j \ \text{ROBO}_{i,j,t} + \delta \ X_{i,t} + \epsilon_{i,t},$$

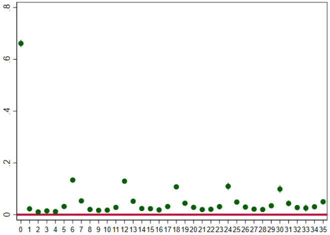


(a) Any Interactions

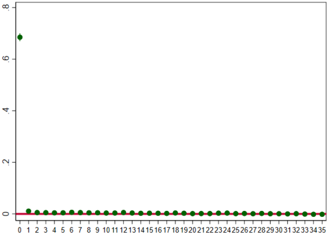
Interaction with Human Advisors



(a) Level 3

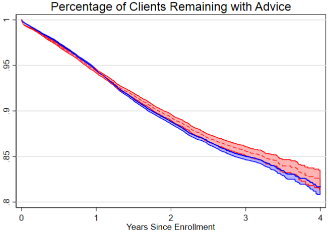


(b) Level 2

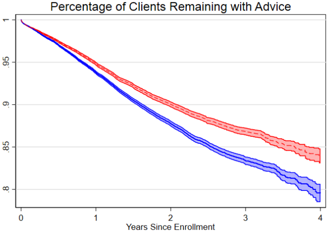


(c) Level 1

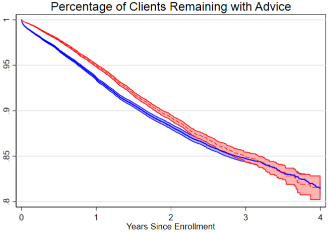
Attrition



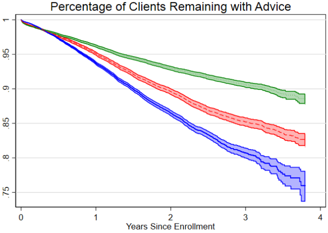
(a) Female; Male



(b) Long-tenure; Short-tenure



(c) Slow to Enroll; Quick to Enroll



(d) Level 3; Level 2; Level 1

Additional Results

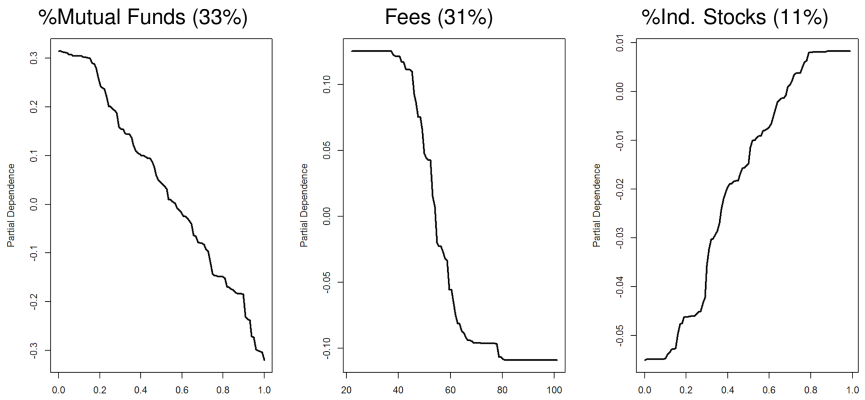
In the paper, additional results on

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

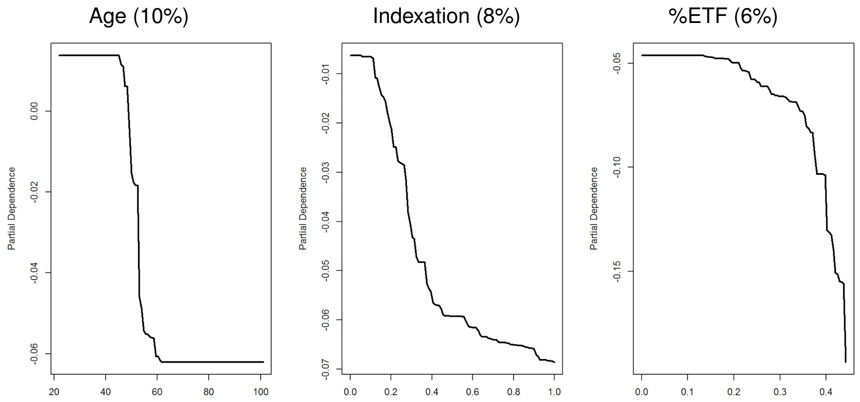
Conclusions

- 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



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

	NON-PAS		PAS	
Rank	**Ticker**	**Pct of Assets**	**Ticker**	**Pct of Assets**
1	VTSAX	16%	VTSAX	28%
2	VFIAX	7%	VTIAX	18%
3	VBTLX	7%	VBTLX	16%
4	VTIAX	5%	VTABX	11%
5	VWIUX	4%	VFIDX	6%
	Total	39%	Total	79%

PAS & Performance Changes (Identification Strategy)

Problem

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

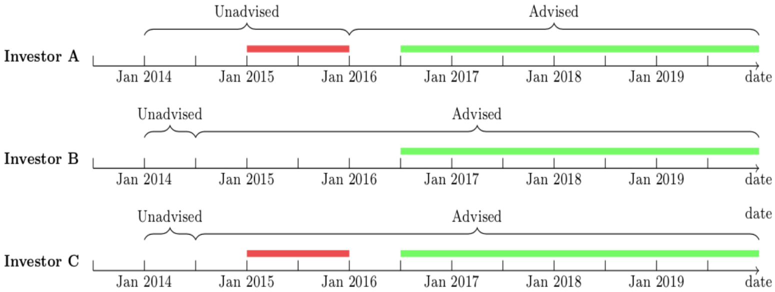
People who do poorly may be the one who sign-up
$\rightarrow$ Performance improvement may be overstated

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

	Top Decile	Top 2 Deciles	Top 3 Deciles	All Investors
Difference	-0.069*** (-29.98)	-0.071*** (-30.74)	-0.074*** (-31.60)	-0.072*** (-30.96)
N	297,134	297,134	297,134	297,134

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)

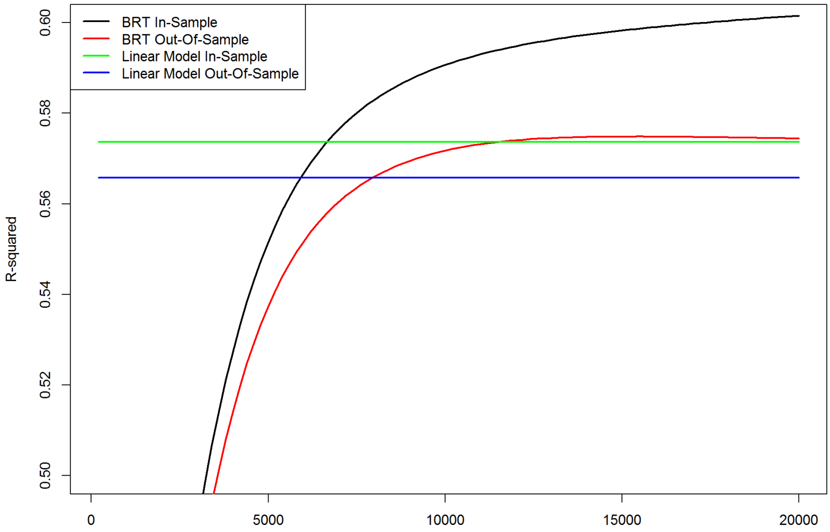
→ Show that BRT easily outperform linear model

Out-of-Sample Performance

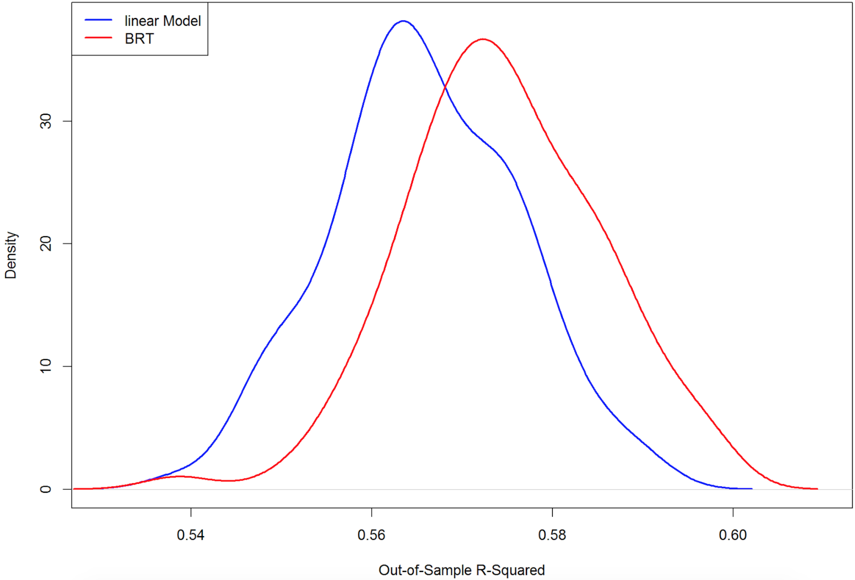
Cross-Validation Exercise:

- 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

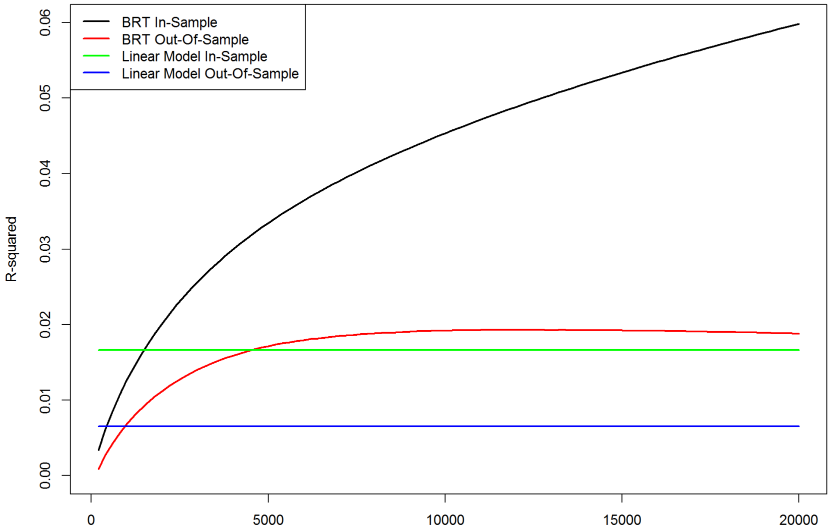
Results for Portfolio Changes



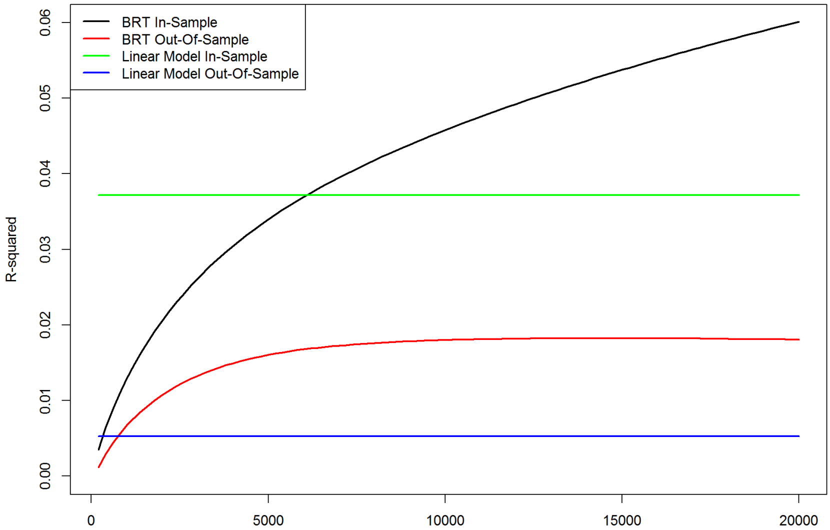
Results for Portfolio Changes



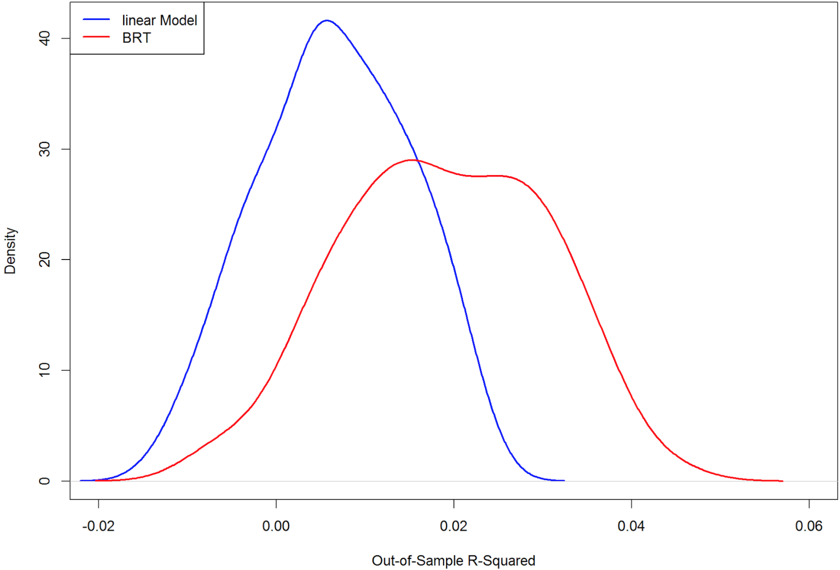
Results for Performance Changes



With Higher Order Terms



Results for Performance Changes



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