Discussion of

From Man vs. Machine to Man + Machine: The Art of AI and Stock Analyses

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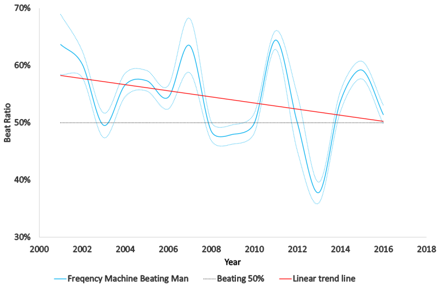
AI & Big Data in Finance Research Forum

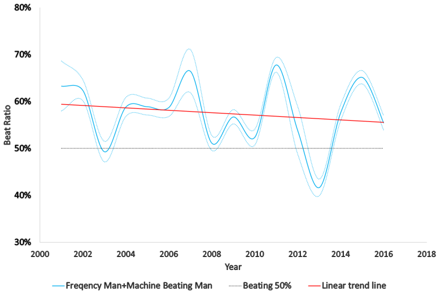
The Paper in One Picture

Forecasting Stocks' Target Prices: Man and Machine (AI, ML methods)

Man vs. Machine



Man + Machine



- Man vs. machine (left): each is better at times!
- Man + machine (right): better than man only (and machine only)
- Bottom line:
  understand why, when, and how man or AI provides better earnings predictions

Assessment and Plan for Comments

- My plan for comments:

  1. Assessing the **contribution**: Why is this a FinTech paper?
  2. Using ML to understand the **economic channels** behind forecasting
  3. **Man vs. Machine**: From forecasting to recommendations
  4. **Man + Machine** vs. Super-Analysts

What is FinTech Research?

Is FinTech about *Any* Technology in Finance?

Is FinTech About Any Technology in Finance?

First ever example of fiat money: *jiaoqao*, Yuan dynasty (1300s)

Although current currency name is renminbi, still colloquial: yuan.

Is FinTech About Any Technology in Finance?

First ever ATM: US, 1969

What is FinTech?

- D'Acunto and Oh (2021, *in preparation*):
  FinTech as Big and Open Data in Finance: A Survey

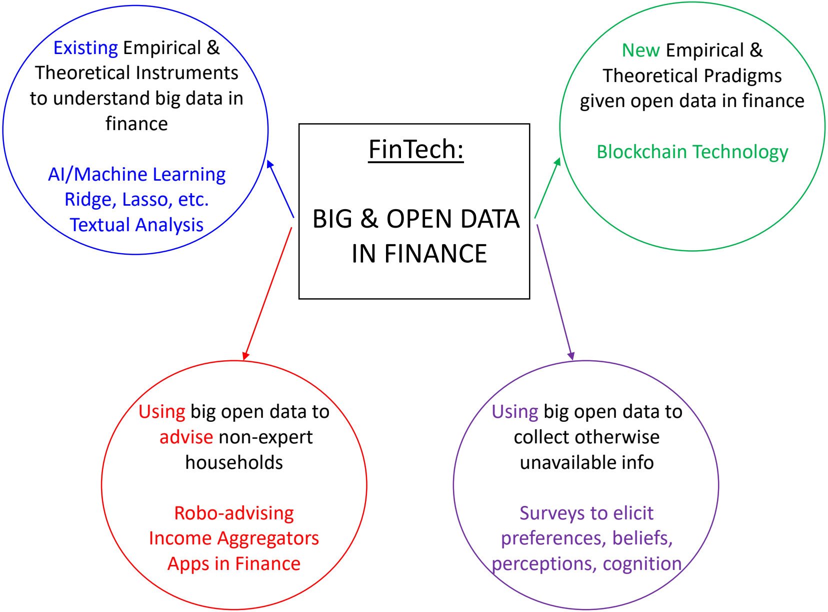
- FinTech as an area of research (and practice) is not about *any* technology in the financial domain

- Defining feature and why FinTech is recent:

  Big and Open Data

- The Four Rings of FinTech

FinTech as Big & Open Data in Finance



This Paper: Blue Ring AND Red Ring

- One of the first papers bringing together two rings of FinTech
- Blue Ring: Using Existing Methods to Analyze Big Data in Finance
- Red Ring: Using Big Data to Provide Better Predictions to Agents (*Robo-Advising*)
- Robo-Advising: *any* algorithmic-based automated advice to economic agents

  D'Acunto and Rossi, 2020: Robo-Advising
  Handbook of Technological Finance (eds. R. Rau and L. Zingales)

  D'Acunto and Rossi, 2020: New Frontiers of Robo-Advising
  Machine Learning in Financial markets: A Guide to Contemporary Practice

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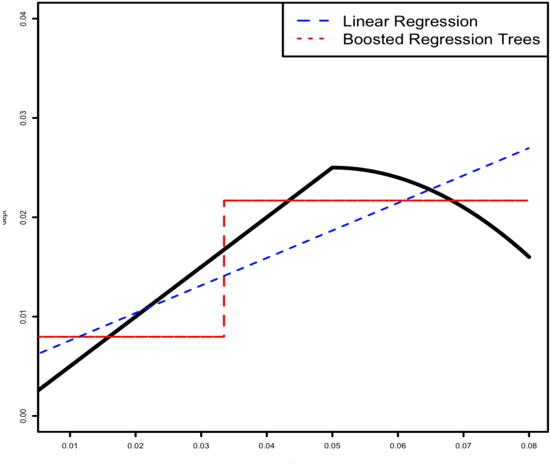
Levering ML for Economic Intuition: What and How Matters for Forecasting Earnings?

- Common prejudice: ML methods are a black box. We don't get economic intuition
- WRONG! Instead, we can lever the properties of ML procedures to understand what, how matters for forecasting outcome variable
- This is because, contrary to traditional methods like OLS, ML accounts for non-linearities...
  - for ease of statistical modeling, we mostly assume relationships are linear
  - by doing so, we miss important economic intuition coming from the non-linearities of statistical relationships
  - ML methods allow a vivid and clear description of these non-linearities (some methods more than others...)

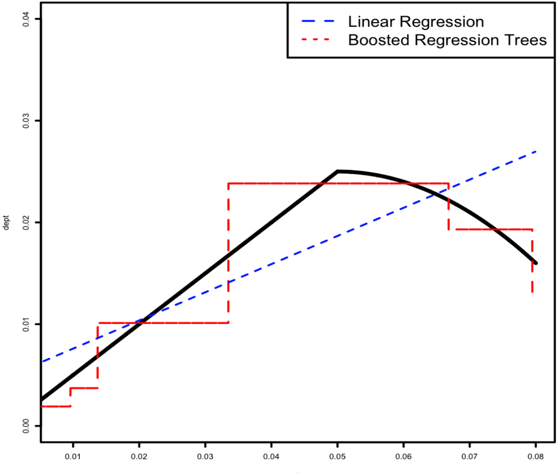
How ML Uncovers Non-linearities

Example: BRT, 1 iteration



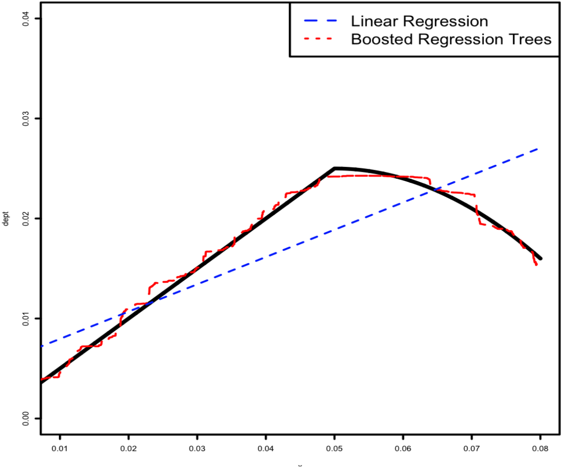
How ML Uncovers Non-linearities

Example: BRT, 5 iterations



How ML Uncovers Non-linearities

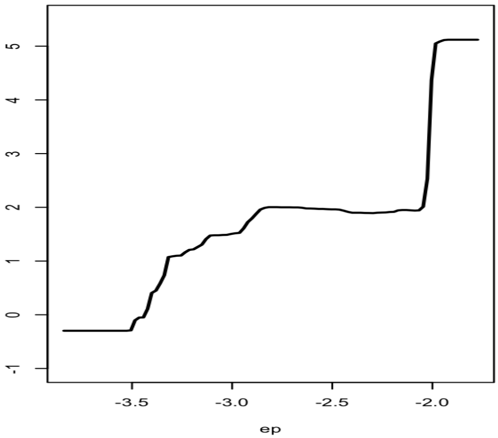
Example: BRT, 10000 iterations



Economic Intuition: Partial Dependence

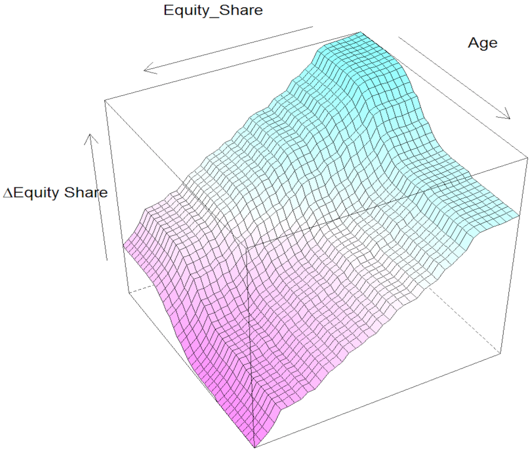
- ML allows estimating *partial dependence*:
  - Which values through the support of each predictor contribute more or less to explain the variation earnings?
  - and hence, if, when, and how is each predictor really relevant?
  - for instance, does illiquidity only matter when very high? Very low?

Example of Partial Dependence: Univariate



Source: "Predicting Stock Market Returns with Machine Learning" (Rossi, 2018)

Example of Partial Dependence: Bivariate



Source: "Who Benefits from Robo-Advising?"
(Rossi and Utkus, 2020)

Partial Dependence: Time Series and Cross Section

Contributions for this paper:

- **“Cross-section”**
  in the full sample, in what way does each proposed predictor matter to predict earnings
  - e.g., does industry concentration only matter when it becomes really high? When it becomes really low?
  - does illiquidity matter only in certain parts of its support?
- **“Time Series”**
  using the rolling windows, assess part. dep. over business cycle
  - does illiquidity matter only in times of crisis? Or high liquidity only in good times? etc.

Partial Dependence: Time Series and Cross Section

Contributions for this paper:

- **"Cross-section"**
  in the full sample, in what way does each proposed predictor matter to predict earnings
- **"Time Series"**
  using the rolling windows, assess part. dep. over business cycle
- **Why important?**
  - Informs the potential economic mechanisms
  - Provides a roadmap for "red flags" in what to pay attention to and when for forecasting
  - Would be virtually impossible to detect in other ways
    - could run survey of actual analysts and ask their opinions about what matters and when. But, biases, inattention, conflicts of interest

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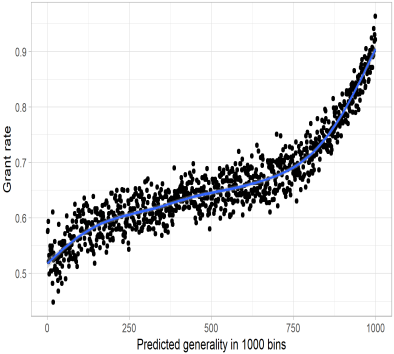
Comparing Forecasting Ability vs. Recommendations

- So far, the paper compares **forecasting abilities** of man vs. machine
  - Very meaningful given that recommendations are not continuous
- BUT, most economic agents care for the **recommendation** in this context
- And, in this application we can easily assess the **quality** of the rec ex post
- Idea:
  Approach the man vs. machine question by also asking who and when make better recommendations

Man vs. Machine: Quality of Multinomial Recommendations

Example: assessing quality patent granting decisions

- Plot by bins avg. grant recommendations (y-axis) vs. pat. quality (x-axis)
- Insight: on average, positive relationship. BUT, human analysts also reject many high quality patents (which ML algo uncovers)



Source: "How Can Innovation Screening be Improved?" (Zheng, 2020)

Man vs. Machine: Quality of Multinomial Recommendations

In the authors' context:

- Sort stocks by target price prediction ML methods (x-axis)
- Average buy recommendation on the y-axis
- To what extent does the resulting cloud depart from a linear relationship?
- Allows to interpret vividly the comparison man vs. machine

Assessment and Plan for Comments

- Very important contribution
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Man + Machine: How and Why?

- The paper shows that man and machines add forecast accuracy in different contexts and both are important (**How**)
- Ultimately, we also care for **Why** this is the case
- Elephant in the room: Skill vs. biases/conflicts of interest
- Good news:
  An ideal test to disentangle these two possibilities exists in this setting!!

Man + Machine: Skill vs. Biases/Conflicts of Interest

- Ideal intervention: Robo-Advising for Experts
(D'Acunto et al., 2021, How Costly Are Cultural Biases? Evidence from FinTech)
- Randomly provide real-world analysts with ML predictions + explanation
- Observe Analysts posted predictions and recommendations
- If **Conflicts of interest**: even with more accurate ML predictions (and explanation why) stick with inaccurate forecast/recommendation
- If **Skill or bias**: after accurate ML predictions move to more accurate forecast/recommendation

Conclusions

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