Predictably Unequal? The Effect of Machine Learning on Credit Markets

A. Fuster, P. Goldsmith-Pinkham, T. Ramadorai, and A. Walther
SNB, FRBNY/Yale SOM, Imperial College
The views expressed do not necessarily reflect the position of the Federal Reserve Bank of New York, the Federal Reserve System, or the Swiss National Bank.
Winners and Losers

Convex quadratic: “extreme” x lose, others gain
Two groups: “blue” borrowers lose due to high variance
Sources of Unequal Effects

- Previous example could arise from

\[ y = P(x) + \varepsilon, \]

where \( P \) is nonlinear and \( g \) does not matter for \( y \).

\( \Rightarrow \) Winners/losers arise from additional \textbf{flexibility} of new technology. Effects across \( g \) depend on functional form of new technology, and the differences in distribution of characteristics.
Sources of Unequal Effects

- Previous example could arise from

\[ y = P(x) + \varepsilon, \]

where \( P \) is nonlinear and \( g \) does not matter for \( y \).

\( \Rightarrow \) Winners/losers arise from additional **flexibility** of new technology.

Effects across \( g \) depend on functional form of new technology, and the differences in distribution of characteristics

- Alternative:

\[ y = \beta \cdot x + \gamma \cdot g + \varepsilon, \]

i.e. true relationship is linear, but \( g \) predictive of default.

\( \Rightarrow \) Effects of new technology arise due to “**triangulating**” \( g \)
No linear correlation between $x$ and $g$ $\rightarrow$ linear model simply recovers average
- Blue borrowers more likely to have extreme $x \rightarrow$ nonlinear model penalizes.
US Mortgage Data

HMDA
- Application date, applicant income, loan type, size, purpose,
- race, ethnicity, gender

McDash (Black Knight)
- Underwriting, contract and performance: e.g. FICO, LTV, interest rate, default status

Linked Dataset
- 9.4m mortgage loans from 2009-2013
- Portfolio and GSE loans, < $1m
- Default: 90+ days delinquent within 3 years of origination
Unequal Effects of New Technology: Population

Cumulative Share

- Asian
- White Non-Hispanic
- White Hispanic
- Black

Log(PD from Random Forest) - Log(PD from Nonlinear Logit)
Flexibility versus Triangulation

Decomposition of model improvements:

1. Add race as an explanatory variable to Logit
2. Allow use of ML technology to the model with race
   (i.e. "add" nonlinear functions / interactions of x as explanatory variables)
Flexibility versus Triangulation

Decomposition of model improvements:

1. Add race as an explanatory variable to Logit

2. Allow use of ML technology to the model with race
   (i.e. ”add” nonlinear functions / interactions of x as explanatory variables)

<table>
<thead>
<tr>
<th></th>
<th>Race</th>
<th>Technology</th>
</tr>
</thead>
<tbody>
<tr>
<td>ROC-AUC</td>
<td>5.88</td>
<td>94.12</td>
</tr>
<tr>
<td>Precision</td>
<td>7.90</td>
<td>92.10</td>
</tr>
<tr>
<td>R2</td>
<td>2.04</td>
<td>97.96</td>
</tr>
</tbody>
</table>

⇒ Improved performance mostly due to flexibility, not triangulation

NB: Order of decomposition matters; but our qualitative conclusion is robust
Conclusion

Improvements in statistical technology creates
- Greater predictive power and gains for producers
- Increased disparity in outcomes for consumers

Framework for unequal effects: Flexibility and Triangulation

Empirical assessment in the US mortgage market
- Unequal effects along racial lines
- Appear to be driven by flexibility