

# “Predictably Unequal? The Effects of Machine Learning on Credit Markets”

by Tarun Ramadorai, Paul Goldsmith-Pinkham, Andreas Fuster, and Angsar Walther

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Discussion by:

**Adair Morse**  
**University of California, Berkeley**

**June, 2019, WFA**


# Context


- This paper speaks to what the potential discrimination implications might be when using machine learning to credit score applicants

## (My) Results Summary

- Main – Predicting default estimations
  - Machine learning does a little better in predictive power, but only a little
  - Small predictive power of race on default using application vars (important)
- Interim, building off this
  - Winners-vs-Losers, Flexibility-vs-Triangulation
- Main – Equilibrium model with pricing and technology that can infer borrower's preferences leading to the potential for default
  - Incredibly important insight in modelling what technology does!

June 10, 2019

  
Elizabeth Warren  
United States Senator

  
Doug Jones  
United States Senator

Dear Chairman Powell, Comptroller Otting, Chairman McWilliams, and Director Kraninger:

1. What is your agency doing to identify and combat lending discrimination by lenders who use algorithms for underwriting?
2. What is the responsibility of your agency with regards to overseeing and enforcing fair lending laws? To what extent do these responsibilities extend to the FinTech industry or the use of FinTech algorithms by traditional lenders?
3. Has your agency conducted any analyses of the impact of FinTech companies or use of FinTech algorithms on minority borrowers, including differences in credit availability and pricing? If so, what have these analyses concluded? If not, does your agency plan to conduct these analyses in the future?
4. Has your agency identified any unique challenges to oversight and enforcement of fair lending laws posed by the FinTech industry? If so, how are you addressing these challenges?

Table 2: Variable List

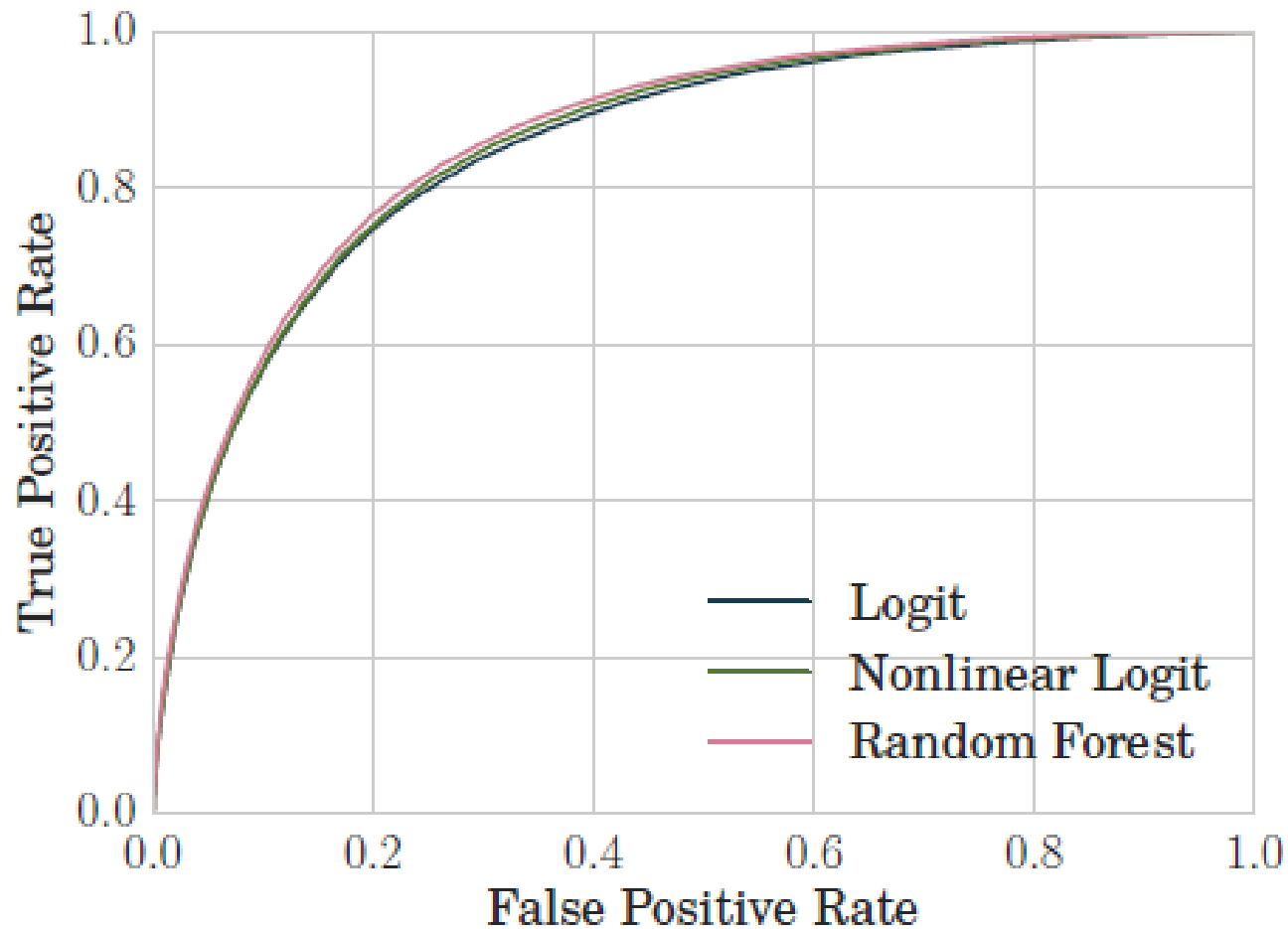
<i>Logit</i>	<i>Nonlinear Logit</i>
Applicant Income (linear)	Applicant Income (25k bins, from 0-500k)
LTV Ratio (linear)	LTV Ratio (5-point bins, from 20 to 100%; separate dummy for LTV=80%)
FICO (linear)	FICO (20-point bins, from 600 to 850;) separate dummy for FICO<600)
(with dummy variables for missing values)	
<i>Common Covariates</i>	
Spread at Origination “SATO” (linear)	
Origination Amount (linear and log)	
Documentation Type (dummies for full/low/no/unknown documentation)	
Occupancy Type (dummies for vacation/investment property)	
Jumbo Loan (dummy)	
Coapplicant Present (dummy)	
Loan Purpose (dummies for purchase, refinance, home improvement)	
Loan Term (dummies for 10, 15, 20, 30 year terms)	
Funding Source (dummies for portfolio, Fannie Mae, Freddie Mac, other)	
Mortgage Insurance (dummy)	
State (dummies)	
Year of Origination (dummies)	

## Setting the Stage

- The term machine learning is about the algorithmic method
- But the application concern looking forward is generally about “**big data**” variables, not those observable in applications
- **Comment 1: Why Limit?**

# Predicting Default

Figure 3: ROC



Panel A: ROC

- The two technologies predict default almost identically
- **Comment 2: Why not cast this as a main result?**

# Predicting Default: Adding Race

Table 3: Performance of Different Statistical Technologies Predicting Default

Model	ROC AUC		Precision Score		Brier Score $\times 100$		$R^2$	
	(1) No Race	(2) Race	(3) No Race	(4) Race	(5) No Race	(6) Race	(7) No Race	(8) Race
Logit	0.8522	0.8526	0.0589	0.0592	0.7172	0.7171	0.0245	0.0246
Nonlinear Logit	0.8569	0.8573	0.0598	0.0601	0.7146	0.7145	0.0280	0.0281
Random Forest	0.8634	0.8641	0.0630	0.0641	0.7114	0.7110	0.0323	0.0329

- **Adding race to the prediction of default does almost nothing to the predictive power.** This is a pretty important punchline not made by the authors.
- Comment 3: The potential for discrimination is not about manipulating the application variables better.

# Predicting Default: : Curious Interim Steps?

## Next Step 1: Predicting Race

- Then the authors take these variables to predict race.
  - The average African-American has a lower income (e.g.) than the average white, so of course this works.
- **Comment 4: But I think it misguides the reader, because the use of economic/repayment ability variables is legal sorting based on creditworthiness.**

## Next step 2: Speaking to Winners and Losers

Comment 6: How are we as economists to speak to sorting by big data if it is fair or legitimate screening?

- “This means that there will always be some borrowers considered less risky by the new technology, or “winners”, while other borrowers will be deemed riskier or “losers”, relative to their position in equilibrium under the pre-existing technology.



# Predicting Default: Curious Interim Steps?

## Next Step 3:

- Flexibility versus Triangulation
- *“One possibility is that the additional flexibility available to the more sophisticated technology allows it to more easily recover the structural relationships connecting permissible variables to default outcomes.”*
- *Another possibility is that the structural relationship between permissible variables and default is perfectly estimated by the primitive technology, but the more sophisticated technology can more effectively **triangulate the unobserved restricted variables using the observed permissible variables.**”*

**I understand the blue but not the red.**

# Legal Standard for allowable sorting by a protected category (e.g. race)

“Consumer-Lending Discrimination in FinTech Era” [Bartlett, Morse, Stanton, Wallace](#)

- Two U.S. Federal statutes prohibit discrimination (FHA -1968) (ECOA- 1974)
- Issue is not the statutes, but how to implement them in the courts.
  - **Disparate treatment**: Cannot put race in as a variable; cannot redline
  - **Disparate impact**: Cannot use processes that cause an impact disparately by race beyond *legitimate business necessity*.
    - Importantly court has limited *legitimate business necessity* to the act of scoring credit risk.
    - **Comment 7**: Thus, I think all this paper’s triangulation is still allowable because the variables used in this paper are application cash flow risk variables, not proxies

# Equilibrium model!

- Technology can infer applicant's preferences, leading to the potential for default
- **Comment 8:**
- **I cannot over-emphasize how important this modelling idea is.**
  - It would be great to emphasize it more in the paper. This idea is transformational in my mind.
- **Comment 8-i:** In Bartlett, Morse, et al, we show that lenders price mortgages in ways that appears to take advantage of profiling
  - Using additional data sources, presumably.
  - **Your results that technology enables price discrimination of 8-10 bps for African Americans is probably a very lower bound**