

# Predictably Unequal

## The Effects of Machine Learning on Credit Markets

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# Summary

Machine learning

= better prediction of creditworthiness

= different prediction of creditworthiness

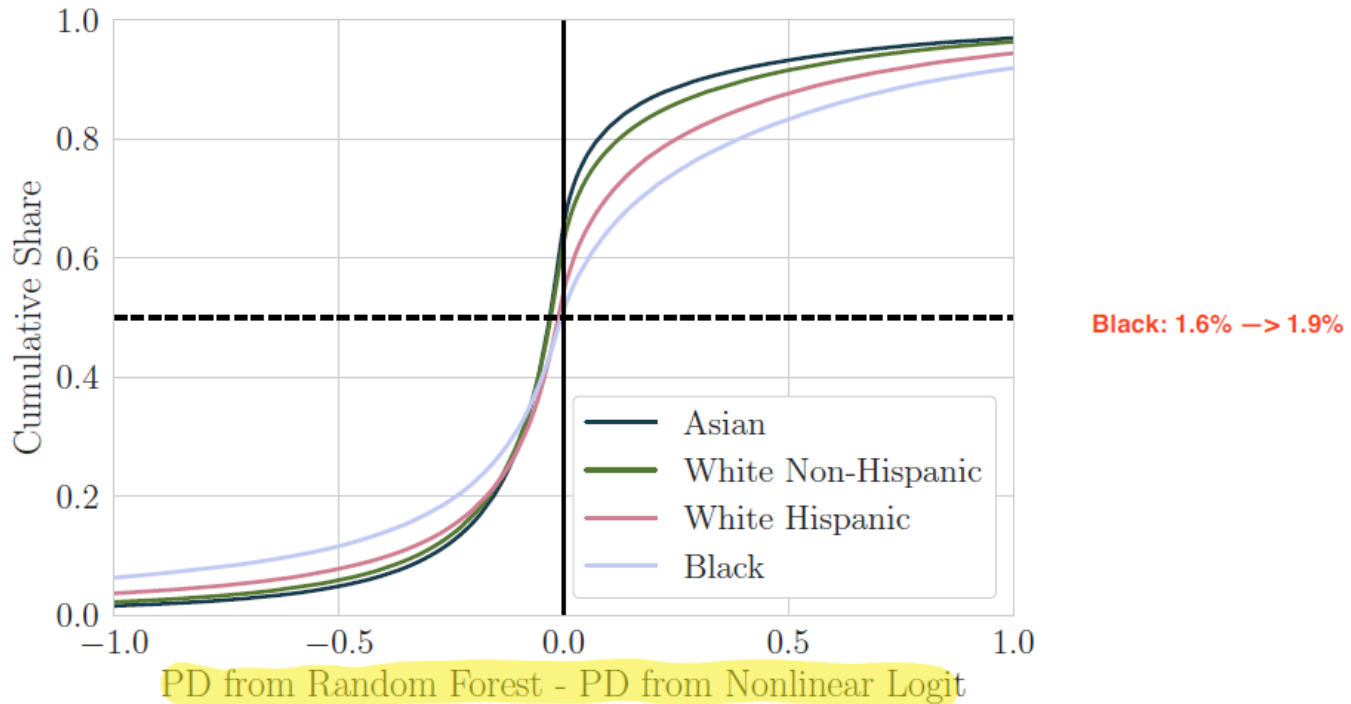
→ Who benefits/who loses?

Using U.S. mortgage data from 2009-2013

- Black and Hispanic borrowers less likely to gain
- Attributable to flexibility, not triangulation

# Dispersion PD $\uparrow$ , Black-PD $\uparrow$

Figure 5: Comparison of Predicted Default Probabilities Across Models, by Race Groups



- General: Dispersion in PD increases
- Black borrowers: PD: 1.6%  $\rightarrow$  1.9% (mean PD increases)

# Equilibrium model: Black acceptance rate $\uparrow$ , black rates $\uparrow$

Table 7: Equilibrium Outcomes

	Accept (%)		Mean SATO (%)		SD SATO (%)	
	(1)	(2)	(3)	(4)	(5)	(6)
	NL	RF	NL	RF	NL	RF
Asian	92.4	93.3	-0.108	-0.123	0.274	0.322
White Non-Hispanic	90.3	91.1	-0.083	-0.090	0.296	0.356
White Hispanic	85.6	86.4	-0.031	-0.008	0.333	0.414
+1.6PP Black	77.7	79.3	0.022	0.060	4bps	161
Other	88.9	89.5	-0.083	-0.088	0.296	0.360
+0.9PP Population	89.8	90.7	-0.081	-0.086	-0.5bps	360
Cross-group SD	2.165	2.098	0.020	0.029		

Results are not black and white: Rejected blacks benefit from larger variance of prediction

# What I like about the paper

- FinTech-Lending
  - More/better data
  - Better methodology
- Host of papers on effects of more/better data
- Little known about effects of better methodology
- New topic, important question, large market
- Fundamental insight beyond specific setting:
  - Conceptual framework
  - Illustration of equilibrium effects

# #1: Provocative Interpretation

- “Black and Hispanic borrowers are disproportionately less likely to gain from the introduction of machine learning.”
- “The majority of the predictive accuracy gains [...] can be attributed to the increased flexibility” (and not to triangulation)
- Provocative interpretation: Current use of coarse logistic models discriminates against Whites and subsidizes Black and Hispanic Borrowers

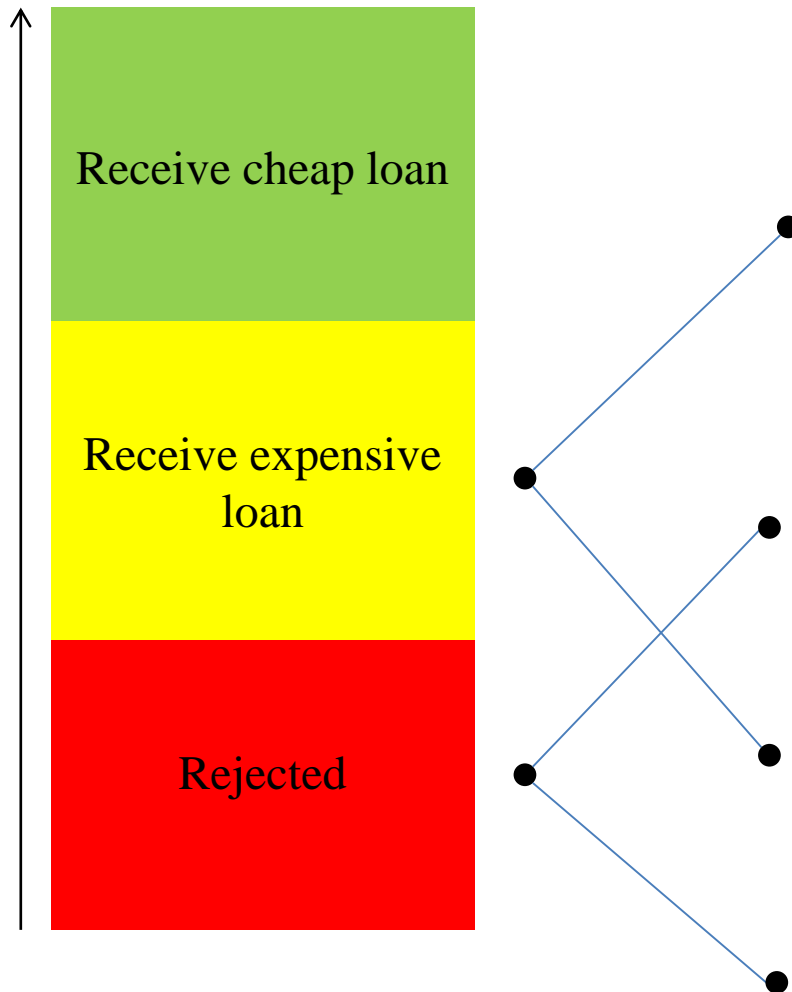
## #2: Should Homer Simpson receive a loan?

- "No Loan Again, Naturally" (Simpsons 2009)
  - Homer throws a party using home equity loan
  - Defaults on his loan, loses house
  - Gets rescued by Ned Flanders
- Deeper question: Worse rating = loser of new rating method?
  - PD=1% for everyone
  - PD=0.9%/1.1% → 1.1%-type = losers of new rating method
  - PD=0%/100% → Are the 100%-PDs really losers? Or saved by new rating method from private bankruptcy?
- Rating method with maximum variance (PD=0/1)
  - Seems hard to argue that there are losers
  - Seems hard to argue that this is bad for risk averse applicants

# #3: Better model = more lending?

Rough signal  
(e.g. FICO)

Better signal  
(e.g. ML)



- Willing to lend at pooling price: Better information → less lending
- Not willing to lend at pooling price: Better information → more lending



# #3: Better model = more lending?

- Pooling price: willing to lend or not?
  - If yes, then better model leads to less lending
  - If no, then better model leads to more lending
  - See Proposition 4 in Pagano and Japelli (1993)
  - See Section 3.2. in Berg et al. (2020), On The Rise in FinTechs. We find more lending for applicants with scarce data after introduction of digital footprint
- Equilibrium price and quantities highly depend on whether pooling price leads to unraveling
- Conceptual discussion in paper is great, with one exception:  
Should discuss implications of Pagano and Japelli (1993), Proposition 4
  - Data set only includes accepted loans = loans where pooling price does not lead to unraveling
  - Statements on quantity and price could be different if you look at full set of applications
  - Currently rejected borrowers should benefit most from better prediction

# Summary

- Important topic, important contribution
- I personally very much enjoyed the conceptual discussion
- It will surely become a very impactful paper
- Suggestion to the audience: Read it!