Consumer Lending Discrimination in the Era of FinTech

ROBERT BARTLETT, ADAIR MORSE, RICHARD STANTON, NANCY WALLACE

UNIVERSITY OF CALIFORNIA, BERKELEY

Setting

- Very little is known about discrimination in consumer lending
  - Literature is very scarce relative to that of wage discrimination
    - Munnell, Tootell, Browne, and McEneaney (1996) (application acceptance)
    - Begley and Purnanandam (2017) (quality measures of fit gauged by complaints)
    - New work: Paul Goldsmith-Pinkham & Tarun Ramadorai (2017)
  - Most studies of pricing and acceptance of application are fraught with issues of identification, omitted variables
  - Regulation and courts are very lender-friendly
- Importance now :
  - Growth of algorithms: A need for a re-think on standards and procedures
  - Household debt is $13 trillion: Small degrees of discrimination can have huge consequences on inequality and fairness

Setting

Credit Scoring : Always the first step in loan approval and pricing

- FinTech/Platform lending
  - Use of Big Data algorithms to make scoring more precise with lower costs
- But… Impact on Discrimination?
  - Platforms remove loan officer biases from face-to-face interaction
  - But platforms may use data that induce (illegitimate) statistical discrimination in scoring

What we do

I. **Establish economics of legal "standard of proof"**
II. **Estimate level of ethnic discrimination and by whom**

- Issues are general to all consumer lending, but we study mortgages
  - Setting solves 2 problems in discrimination studies:
    - Ethnicity data
    - Identification (mean conditional independence assumption)

Legal Standing mapped to economic concepts of Statistical Discrimination

Two federal statutes, the **Fair Housing Act of 1968 (FHA)** and the **Equal Credit Opportunity Act of 1974 (ECOA)**, prohibit :

- 1. Refusal to extend credit
- 2. Use different standards in determining whether to extend credit
- 3. Varying the terms of credit offers

… by prohibited status (e.g., ethnicity, gender, etc.)

Issue is not the statute, but the implementation

Legal Standing mapped to economic concepts of Statistical Discrimination

Court standards for successful claims:

- Disparate treatment
- Disparate impact

Legal Standing mapped to economic concepts of Statistical Discrimination

Disparate treatment: requires showing that a lender has treated applicants/borrowers differently because of a protected characteristic.

Two pieces:

1) Explicit bias

2) Redlining

Thus, for economists: two sets of variables are explicitly illegal under disparate treatment

- variables of the protected category (e.g., ethnicity in our case)
- geography.

Legal Standing mapped to economic concepts of Statistical Discrimination

Disparate impact:

- Does not involve any allegation of intentional discrimination
- Prohibited: Lenders apply non-explicit policies more harshly on a protected category

- <u>Hindrance to claims</u>: Lenders can defend the practice (in lender-friendly courts) as justified by a *legitimate business necessity*

Legal Standing mapped to economic concepts of Statistical Discrimination

Statistical Discrimination

- Structural variables exist for scoring repayment risk
  - Life cycle variables of income, wealth, debt, cost of borrowing (credit score), expense levels (local cost of living), age
- Scoring explicitly on these variables is legitimate

- Problem: some variables are unobservable
  - Statistical discrimination is solution to signal extraction problem
  - Use proxy variables that correlate with structural variables (note: more and more as we move into Big Data)

Legal Standing mapped to economic concepts of Statistical Discrimination

Statistical Discrimination

- Disparate Impact: Justified within *legitimate business necessity*
  - Imagine lender cannot see wealth.
  - Lender sees the name of the high school attended, correlated with wealth.

  - *Under disparate impact:* **High School is allowable as a variable if it is only disparately impacting the pool of applicants through its sorting on wealth** (or other unobserved structural variables)

- All other statistical discrimination is illegitimate

Methodology Overview1: **Better data**

- Overcome weaknesses of prior literature:
  - Inadequate data matching loan-level HMDA ethnicities to data
    - Necessary to properly score each loan to assess reasonable comparison groups
  - Four important data sets (2008–2012):
    - **HMDA-** ethnicity and income local geography but not address
    - **DataQuick** – origination, performance and exact location
    - **McDash** – detailed contract terms and performance
    - **Equifax** – consumer debt
  - Solution (multi-year project): Merge data sets using <u>performance strings</u>

Methodology Overview 2: **Decomposition**

- Overcome weaknesses of prior literature in which estimates of discrimination suffer from omitted variables and confounding factors

- **Labor literature** (Oaxaca (1973); Blinder (1973))
  - Ethnic differences in outcome variable are decomposed into
    - Component "explained" by differences in structural covariates
    - Component that is "unexplained" (**discrimination**)
- **Program evaluation literature** ((Fortin et al., 2011; Kline, 2011))
  - Modern implementation of Oaxaca-Blinder in treatment tradition
    - Benefit: clearly lay out the assumptions needed for identification

Oaxaca-Blinder Decomposition: Assumptions

Assumption 1 (Simple Counterfactual for Treatment): Credit scoring of an ethnic minority household would be the same as control group scoring (blinded scoring) if households were not identified to be in the ethnic treatment group.

Assumption 2 (Linearity in Structural Variables): *Outcomes* Y_{Ti} *and* Y_{Bi} *are linearly related to the structural variables, denoted* X *where* X *is the vector* $(X_i = [X_{i1}, ..., X_{iK}])$:

$$Y_{Ti} = \beta_{T0} + \sum_{k=1}^{K} X_{iTk}\beta_{Tk} + \varepsilon_{Ti}$$
$$Y_{Bi} = \beta_{B0} + \sum_{k=1}^{K} X_{iBk}\beta_{Bk} + \varepsilon_{Bi}.$$

- The difference Δ in outcomes can be decomposed as follows:

$$\Delta = \underbrace{\sum_{k=1}^{K} \left(\overline{X}_{Tk} - \overline{X}_{Bk}\right)\widehat{\beta}_{Bk}}_{\text{explained}} + \underbrace{\left(\widehat{\beta}_{T0} - \widehat{\beta}_{B0}\right) + \sum_{k=1}^{K} \overline{X}_{Tk}\left(\widehat{\beta}_{Tk} - \widehat{\beta}_{Bk}\right)}_{\text{unexplained}}.$$

Assumption 3 (Overlapping Support)*: Each possible treated realization of $X_i = x$ and $\varepsilon_i = e$ must be in the common support; i.e., $0 < \Pr[i \subseteq T \mid X_i = x,\ \varepsilon_i = e] < 1$.*

Assumption 4a (Conditional Independence)*: Applicants' unobserved life cycle characteristics are independent, conditional on observed covariates. $E(\varepsilon \mid X) = 0$.*

Kline (2011) establishes that a lighter version of Assumption 4a is all that is necessary in this setting.

Assumption 4b (Ignorability)*: Any selection based on unobservables must be the same for the treated and control. Unobservables do not need to be independent of X, but their distributions conditional on X is the same for both ethnic groups. Denoting the distribution function by $g(\cdot)$, $g(\varepsilon \mid X, i \subseteq T) = g(\varepsilon \mid X, i \subseteq B)$.*

GSEs (Fannie & Freddie) help on identification

(1) Reject/Accept outcome

a) GSEs dictate acceptability through their underwriting system based on observables: credit score, LTV, debt servicing ability

- No role for unobservables in acceptance

b) GSE guarantee mortgages. Only concern for lenders is put-back risk

- But put-back risk is just about documentation risk, i.e., only about observables.

- Punchline: in accept/reject decisions:
  - There is no *legitimate business necessity* grounds for acceptable disparate impact.
  - All differences in decomposition results thus are illegitimate discrimination

GSEs (Fannie & Freddie) help on identification

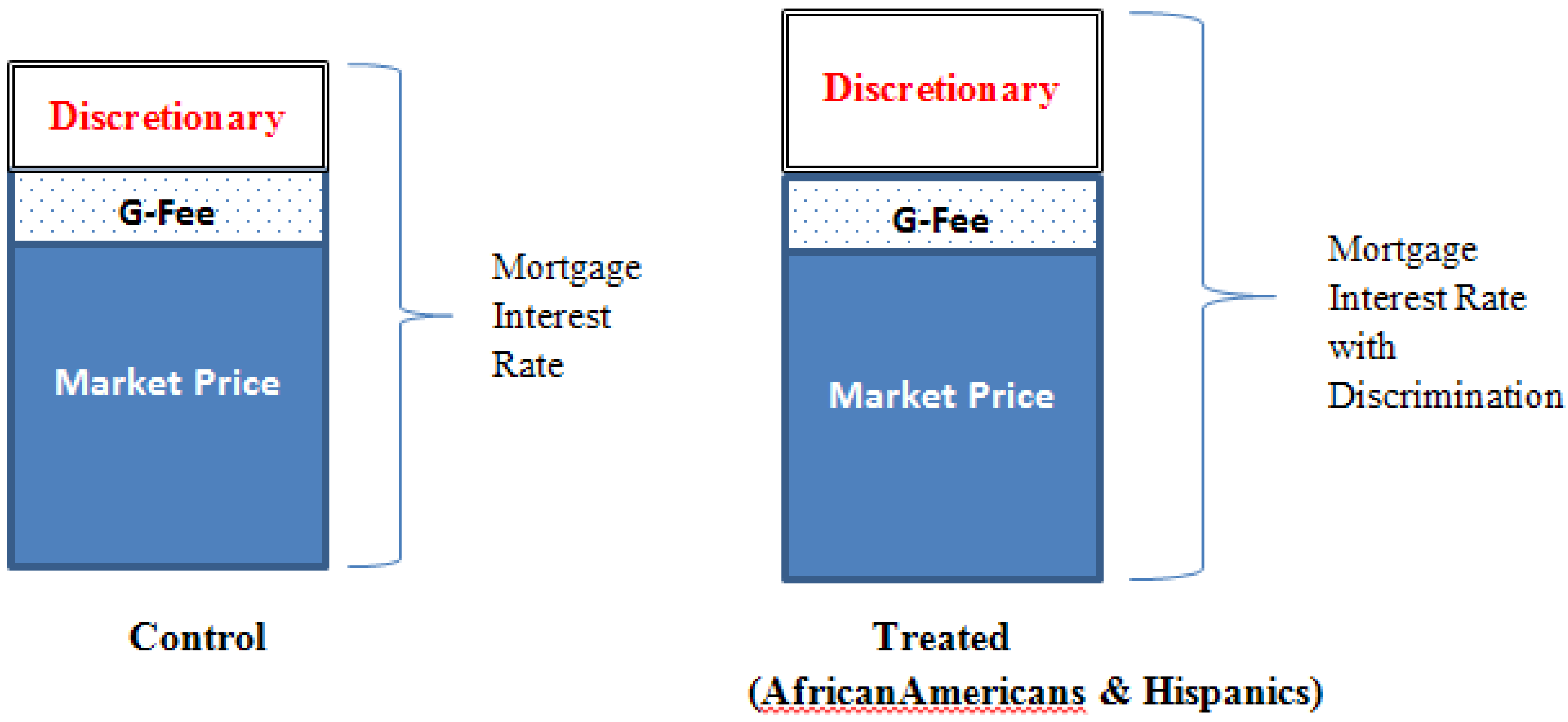
(2) Interest rate outcomes

At what interest rate do lenders price loans?

= Market rate

+ Expected cost of default/prepayment (credit risk)

+ Discretionary part for lender profits & strategic incentives



GSEs (Fannie & Freddie) help on identification

Credit risk part == dictated by Loan Level Performance Adjustments (LLPA) grid

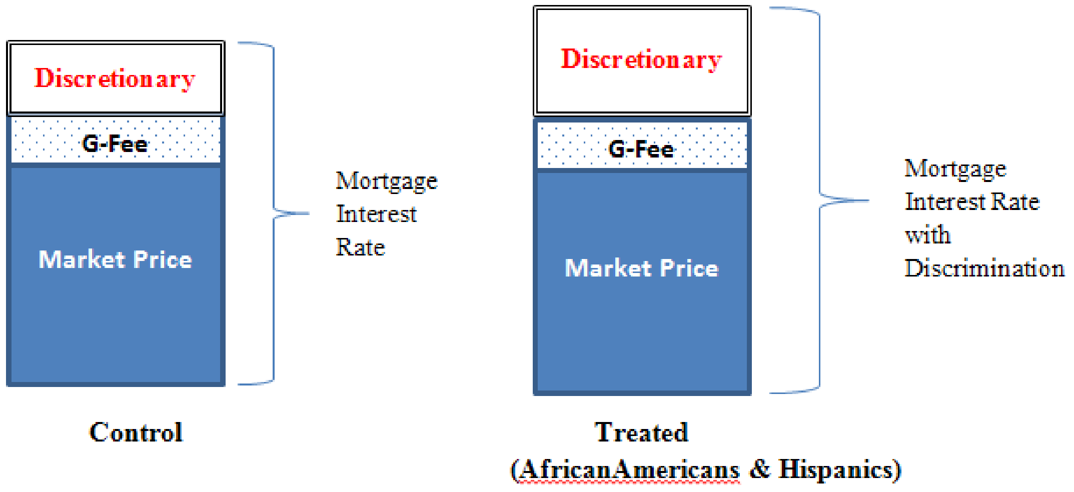
Table 2: All Eligible Mortgages (Excluding MCM): LLPA by Credit Score/LTV

PRODUCT FEATURE	LLPAs by LTV Range								
	≤ 60.00%	60.01 – 70.00%	70.01 – 75.00%	75.01 – 80.00%	80.01 – 85.00%	85.01 – 90.00%	90.01 – 95.00%	95.01 – 97.00%	SFC
Representative Credit Score	Applicable for all mortgages with greater than 15 year terms For whole loans purchased on or before March 31, 2011, or loans delivered into MBS pools with issue dates of March 1, 2011 or earlier								
≥ 740	-0.250%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	N/A
720 – 739	-0.250%	0.000%	0.000%	0.250%	0.000%	0.000%	0.000%	0.000%	N/A
700 – 719	-0.250%	0.500%	0.500%	0.750%	0.500%	0.500%	0.500%	0.500%	N/A
680 – 699	0.000%	0.500%	1.000%	1.500%	1.000%	0.750%	0.750%	0.500%	N/A
660 – 679	0.000%	1.000%	2.000%	2.500%	2.250%	1.750%	1.750%	1.250%	N/A
640 – 659	0.500%	1.250%	2.500%	3.000%	2.750%	2.250%	2.250%	1.750%	N/A
620 – 639	0.500%	1.500%	3.000%	3.000%	3.000%	2.750%	2.750%	2.500%	N/A
< 620 (1)	0.500%	1.500%	3.000%	3.000%	3.000%	3.000%	3.000%	3.000%	N/A

GSEs (Fannie & Freddie) help on identification

(2) Interest rate for accepted

At what interest rate do lenders price loans?



Discretionary part:

- Lender profits and strategic objectives are <u>not</u> *business necessity of credit risk*

Thus, any difference in rates charged by ethnicity are disparate impact

- Examples: charging higher rates to customers less likely to shop around (monopoly rents, financial servicer deserts, preying on behavioral biases)

Panel A: Rejected Applications (N = 2,970,922)

	Mean	Standard Deviation	Minimum	Median	Maximum
Interest Rate %	--	--	--	--	--
Loan Amount $	197,163	122,407	20,000	169,000	793,000
Applicant Income $	85,268	69,700	10,000	69,000	999,000
Loan-to-Value	0.859	0.201	0.388	0.876	1.300
Credit Score	689	36	359	690	825
FinTech	0.041				
Top 25	0.497				
African_American/Hispanic	0.220				
Purchase=1; Refinance=0	0.157				

Panel B: Accepted Applications without Equifax match (N = 3,570,267)

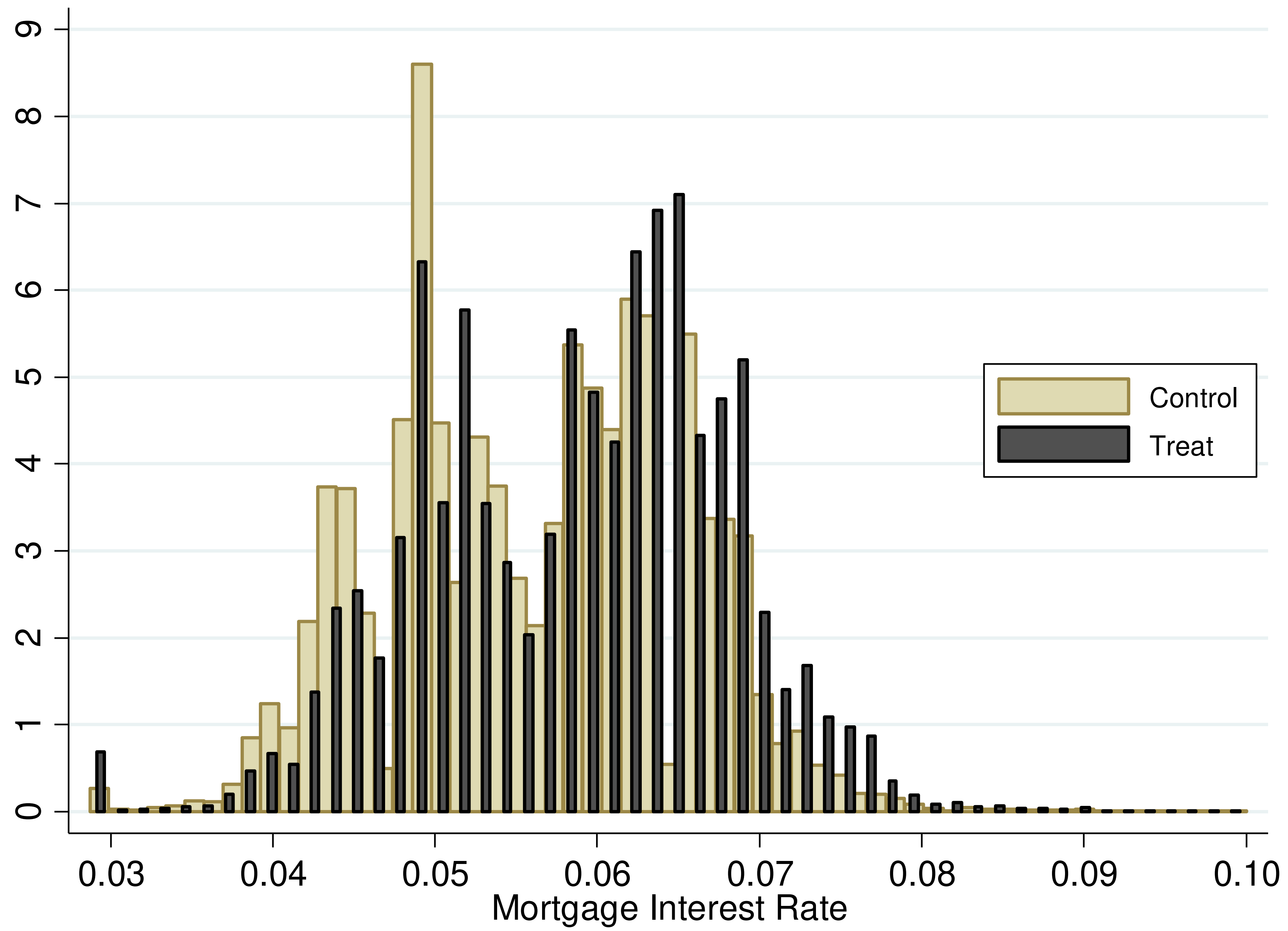
	Mean	Standard Deviation	Minimum	Median	Maximum
Interest Rate %	0.052	0.008	0.029	0.050	0.100
Loan Amount $	225,194	117,659	7,000	203,000	793,000
Applicant Income $	104,867	76,137	10,000	87,000	999,000
Loan-to-Value	0.764	0.196	0.190	0.785	1.300
Credit Score	717	75	359	725.5	850
FinTech	0.029				
Top 25	0.501				
African_American/Hispanic	0.132				
Purchase=1; Refinance=0	0.335				

Panel A: Rejected Applications (N = 2,970,922)

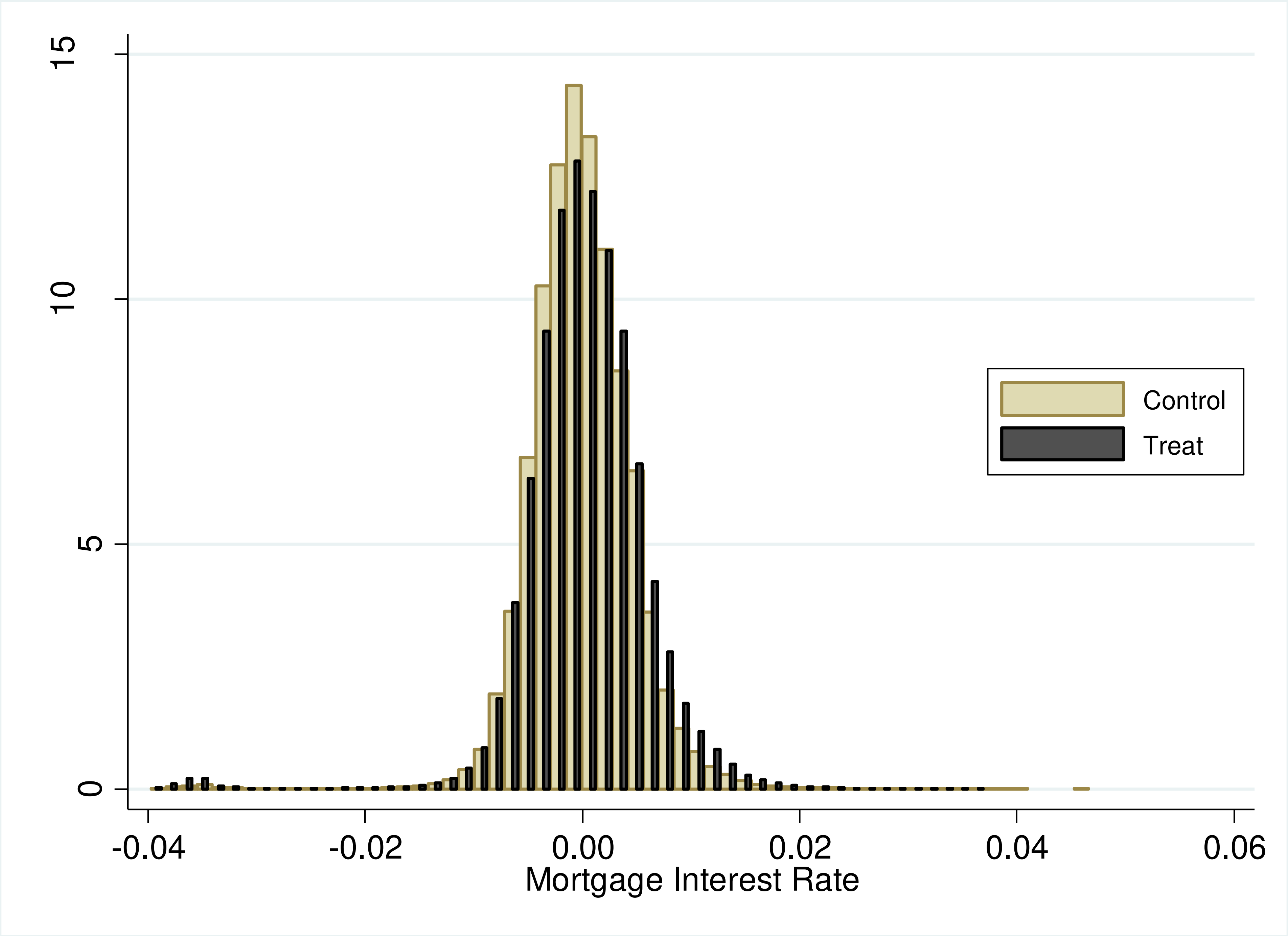
	Mean	Standard Deviation	Minimum	Median	Maximum
Interest Rate %	--	--	--	--	--
Loan Amount $	197,163	122,407	20,000	169,000	793,000
Applicant Income $	85,268	69,700	10,000	69,000	999,000
Loan-to-Value	0.859	0.201	0.388	0.876	1.300
Credit Score	689	36	359	690	825
FinTech	0.041				
Top 25	0.497				
African_American/Hispanic	0.220				
Purchase=1; Refinance=0	0.157				

Panel B: Accepted Applications (N = 3,570,267)

	Mean	Standard Deviation	Minimum	Median	Maximum
Interest Rate %	0.052	0.008	0.029	0.050	0.100
Loan Amount $	225,194	117,659	7,000	203,000	793,000
Applicant Income $	104,867	76,137	10,000	87,000	999,000
Loan-to-Value	0.764	0.196	0.190	0.785	1.300
Credit Score	717	75	359	725.5	850
FinTech	0.029				
Top 25	0.501				
African_American/Hispanic	0.132				
Purchase=1; Refinance=0	0.335				



0
1
2
3
4
5
6
7
8
9
0.03
0.04
0.05
0.06
0.07
0.08
0.09
0.10
Mortgage Interest Rate
Control
Treat



15
10
5
0
Control
Treat
-0.04
-0.02
0.00
0.02
0.04
0.06
Mortgage Interest Rate

Rates

Rate Discrimination: Results in Purchase Mortgages

	Dependent Variable: Mortgage Interest Rate				
				Oaxaca Decomposition	
	OLS	OLS	Diff. in Means	Explained	Unexplained
Discrimination	0.00132***	0.000758***	0.00186***	0.00109***	0.000769***
	[2.53e-05]	[1.64e-05]	[2.76e-05]	[2.24e-05]	[1.66e-05]
Loan-to-Value	0.00238***	-0.00146***		-4.96e-05***	0.00131***
	[6.15e-05]	[0.000148]		[4.57e-06]	[0.000397]
Credit Score	-1.12e-05***	2.24e-06***		-3.06e-05***	8.82E-05
	[1.14e-07]	[3.19e-07]		[4.38e-06]	[0.000629]
Log Income	-0.000584***	-0.000389***		6.75e-05***	-0.00428***
	[1.41e-05]	[8.82e-06]		[1.94e-06]	[0.000309]
Observations	785,899	785,899	785,899		
R-squared	0.197	0.696			
Year FE	N	Y	Y		
Bucket FE	N	Y	Y		
Lender FE	Y	Y	Y		

Rate Discrimination: Results in Purchase Mortgages with Equifax Debt Data

	Dependent Variable: Mortgage Interest Rate				
				Oaxaca Decomposition	
	OLS	OLS	Diff. in Means	Explained	Unexplained
Discrimination	0.00127***	0.000822***	0.00167***	0.000836***	0.000833***
	[3.98e-05]	[2.32e-05]	[4.05e-05]	[3.33e-05]	[2.32e-05]
Loan-to-Value	0.00226***	-0.00213***		-4.26e-05***	-0.00119
	[0.000113]	[0.000298]		[6.96e-06]	[0.000775]
Credit Score	-4.38e-05***	-8.41e-06***		7.04e-05***	0.00321
	[4.23e-07]	[1.07e-06]		[9.09e-06]	[0.00235]
Log Income	-0.000585***	-0.000549***		8.99e-05***	-0.00486***
	[2.43e-05]	[1.38e-05]		[3.05e-06]	[0.000453]
Log Debt	0.000259***	7.18e-05***		-1.53e-05***	7.87E-05
	[7.18e-06]	[4.07e-06]		[1.19e-06]	[0.000103]
Observations	315,257	311,911	311,911		
R-squared	0.052	0.707			
Lender F.E.	Y	Y	Y	Y	Y
Year & Bucket FE	N	Y	Y	Y	Y

Interest Rate Discrimination: Results in Refi Mortgages

	Dependent Variable: Mortgage Interest Rate				
				Oaxaca Decomposition	
	OLS	OLS	Diff. in Means	Explained	Unexplained
Discrimination	0.00101***	0.000290***	0.00197***	0.00168***	0.000289***
	[1.87e-05]	[1.26e-05]	[2.11e-05]	[1.71e-05]	[1.28e-05]
Loan-to-Value	0.00259***	0.000585***		3.01e-06***	0.000350**
	[2.77e-05]	[5.59e-05]		[4.41e-07]	[0.000139]
Credit Score	-9.57e-06***	4.27e-06***		-3.28e-05***	0.00580***
	[7.42e-08]	[2.36e-07]		[2.33e-06]	[0.000451]
Log Income	-0.00127***	-0.000717***		0.000122***	-0.00132***
	[9.66e-06]	[6.46e-06]		[1.59e-06]	[0.000249]
Observations	1,354,399	1,354,399	1,354,399		
R-squared	0.24	0.659			
Year FE	N	Y	Y		
Bucket FE	N	Y	Y		
Lender FE	Y	Y	Y		

Magnitude of Rates Results

- Hispanics/African Americans pay, 8 bps (purchases) or 4 bps (refis) extra
  - Profit margin on a mortgage is 50bps (Mortgage Brokers Association).
    - 8 bps is very material
  - Back of the envelope aggregation:
    - In all HMDA mortgages in the U.S., 15% are African-American or Hispanic
    - Applying these magnitudes (8 bps and 4 bps) conservatively to this float implies that:

African-Americans and Hispanics pay over $500 million EXTRA in interest (without compounding) every year because of illegitimate discrimination

Rate Discrimination: Results in Purchase Mortgages by FinTech versus Traditional

	Dependent Variable: Mortgage Interest Rate					
	Traditional Lenders			FinTech Lenders		
	Oaxaca Decomposition			Oaxaca Decomposition		
	Diff. in Means	Explained	Unexplained	Diff. in Means	Explained	Unexplained
Discrimination	0.00189***	0.00113***	0.000768***	0.00140***	0.000685***	0.000717***
	[2.79e-05]	[2.28e-05]	[1.68e-05]	[0.000141]	[0.000100]	[0.000104]
Loan-to-Value		-4.88e-05***	0.00139***		-5.76E-05	-0.00013
		[4.57e-06]	[0.000401]		[3.95e-05]	[0.00282]
Credit Score		-3.25e-05***	0.000415		5.78E-06	-0.0113**
		[4.42e-06]	[0.000636]		[2.27e-05]	[0.00461]
Log Income		6.60e-05***	-0.00421***		0.000133***	-0.00685***
		[1.95e-06]	[0.000313]		[1.58e-05]	[0.00191]
Observations	768,408			17,491		
Lender FE	Y			Y		
Year&Bucket FE	Y			Y		

Interest Rate Discrimination: Results in Refi Mortgages by FinTech versus Traditional

	Dependent Variable: Mortgage Interest Rate					
	Traditional Lenders			FinTech Lenders		
	Oaxaca Decomposition			Oaxaca Decomposition		
	Diff. in Means	Explained	Unexplained	Diff. in Means	Explained	Unexplained
Discrimination	0.00199***	0.00170***	0.000296***	0.000737***	0.000605***	0.000132**
	[2.15e-05]	[1.74e-05]	[1.30e-05]	[9.75e-05]	[7.90e-05]	[6.02e-05]
Loan-to-Value		2.80e-06***	0.000332**		6.67E-06	0.00102
		[4.46e-07]	[0.000142]		[5.53e-06]	[0.000709]
Credit Score		-3.65e-05***	0.00595***		4.84E-06	-0.000902
		[2.46e-06]	[0.000460]		[4.11e-06]	[0.00231]
Log Income		0.000123***	-0.00140***		7.67e-05***	6.58E-05
		[1.63e-06]	[0.000254]		[7.50e-06]	[0.00128]
Observations	1,300,245			54,154		
Lender FE	Y			Y		
Year&Bucket FE	Y			Y		

Rate Discrimination: Results in Purchases by Top 25 Volume Lenders versus Small Lenders

	Dependent Variable: Mortgage Interest Rate					
	Top 25 Lenders			Small Lenders		
	Oaxaca Decomposition			Oaxaca Decomposition		
	Diff. in Means	Explained	Unexplained	Diff. in Means	Explained	Unexplained
Discrimination	0.00224***	0.00142***	0.000819***	0.00151***	0.000812***	0.000694***
	[3.83e-05]	[3.07e-05]	[2.29e-05]	[4.07e-05]	[3.37e-05]	[2.46e-05]
Loan-to-Value		-7.56e-05***	0.00163***		-1.47e-05**	0.000993*
		[6.26e-06]	[0.000547]		[6.72e-06]	[0.000590]
Credit Score		-2.80e-05***	0.00162*		-3.04e-05***	-0.00163*
		[6.90e-06]	[0.000890]		[5.34e-06]	[0.000923]
Log Income		5.95e-05***	-0.00471***		7.30e-05***	-0.00344***
		[2.49e-06]	[0.000428]		[3.05e-06]	[0.000459]
Observations	412,530			355,886		
Lender FE	Y			Y		
Year&Bucket FE	Y			Y		

Rate Discrimination: Results in Refi by Top 25 Volume Lenders versus Small Lenders

	Dependent Variable: Mortgage Interest Rate					
	Top 25 Lenders			Small Lenders		
	Oaxaca Decomposition			Oaxaca Decomposition		
	Diff. in Means	Explained	Unexplained	Diff. in Means	Explained	Unexplained
Discrimination	0.00165***	0.00128***	0.000373***	0.00257***	0.00210***	0.000467***
	[2.58e-05]	[2.04e-05]	[1.59e-05]	[3.73e-05]	[3.03e-05]	[2.18e-05]
Loan-to-Value		4.03e-06***	0.000485***		1.80E-07	0.000242
		[8.02e-07]	[0.000173]		[1.77e-07]	[0.000249]
Credit Score		-1.55e-05***	0.00570***		-8.24e-05***	0.00768***
		[3.24e-06]	[0.000576]		[4.91e-06]	[0.000753]
Log Income		0.000129***	-0.00133***		0.000130***	-0.00240***
		[2.15e-06]	[0.000303]		[2.63e-06]	[0.000441]
Observations	739,530			560,718		
Lender FE	Y			Y		
Year&Bucket FE	Y			Y		

Who & Why: Rate Discrimination

- Traditional lenders discriminate (slightly) more than FinTech
  - Interesting heterogeneity not yet explored

Mechanism points to strategic pricing or preying on biases or financial deserts

We are working on mapping the geography of discrimination

Anecdotes: Enclaves of ethnic trust = a lack of shopping. Also Financial deserts. Also perhaps less bank-experienced borrowers or those uncomfortable with financial system

Rejections

Rejection Discrimination: Main Results

	Dependent Variable: Rejection				
	(1)	(2)	(3)		
				Oaxaca Decomposition	
Model	OLS	OLS	Difference in Means	Explained	Unexplained
Discrimination	0.0484***	0.0423***	0.152***	0.103***	0.0491***
	[0.000470]	[0.000450]	[0.000524]	[0.000345]	[0.000458]
Loan-to-Value	0.400***	0.451***		0.0178***	0.003
	[0.000865]	[0.00282]		[0.000162]	[0.00635]
Credit Score	-0.00113***	-0.000237***		0.0151***	1.486***
	[3.22e-06]	[1.02e-05]		[0.000247]	[0.0185]
Log Income	-0.0956***	-0.0746***		0.0159***	-0.00217
	[0.000282]	[0.000270]		[7.86e-05]	[0.00790]
Observations	6,177,674	6,177,670	6,177,670		
R-squared	0.27	0.348			
Lender FE	Y	Y	Y		
Year&Bucket FE	N	Y	Y		

Rejection Discrimination: Results by FinTech versus Traditional

	Dependent Variable: Rejection					
	Traditional Lenders Oaxaca Decomposition			FinTech Lenders Oaxaca Decomposition		
	Diff. in Means	Explained	Unexplained	Diff. in Means	Explained	Unexplained
Discrimination	0.157***	0.107***	0.0508***	-0.00682**	0.00238	-0.00920***
	[0.000531]	[0.000350]	[0.000463]	[0.00335]	[0.00208]	[0.00273]
Loan-to-Value		0.0179***	0.00269		0.0100***	0.0949**
		[0.000167]	[0.00642]		[0.000678]	[0.0396]
Credit Score		0.0138***	1.444***		0.0256***	1.646***
		[0.000253]	[0.0187]		[0.00127]	[0.122]
Log Income		0.0161***	-0.0000351		0.00504***	0.047
		[8.04e-05]	[0.00798]		[0.000241]	[0.0517]
Observations	5,951,291			226,379		
Lender FE	Y			Y		
Bucket & Year FE	Y			Y		

Rejection Discrimination: Results by Top 25 Volume Lenders versus Small Lenders

	Dependent Variable: Rejection					
	Top 25 Lenders Oaxaca Decomposition			Small Lenders Oaxaca Decomposition		
	Diff. in Means	Explained	Unexplained	Diff. in Means	Explained	Unexplained
Discrimination	0.145***	0.0885***	0.0567***	0.161***	0.123***	0.0385***
	[0.000709]	[0.000404]	[0.000646]	[0.000749]	[0.000567]	[0.000616]
Loan-to-Value		0.0202***	0.00332		0.0147***	0.00177
		[0.000237]	[0.00904]		[0.000210]	[0.00837]
Credit Score		0.0257***	1.454***		0.00825***	1.497***
		[0.000389]	[0.0281]		[0.000301]	[0.0232]
Log Income		0.0172***	-0.104***		0.0154***	0.139***
		[0.000115]	[0.0111]		[0.000104]	[0.0106]
Observations	3,263,880			3,192,159		
Lender FE	Y			Y		
Bucket & Year FE	Y			Y		

Summary of Rejection results

- Treated are rejected 15 percentage points more often
  - 4.9 percentage points is discrimination.
  - Rejection rate overall is about 50%

  - But NOT FinTechs
    - FinTech firms pick up good borrowers discriminated against by other

  - Mechanism points to facial biases

Conclusions/ Policy

- Contribute to debates on:
  - "Robust statistical" measurement of disparate impact as required by courts
  - Identification of illegitimate discrimination of protected characteristics
  - Big data is just starting… lenders may be testing the waters on how courts will handle more and more statistically discriminating variables
    - Hopefully we provide policy tool
- Contribute to discussion on unwinding GSE's role
  - Note: In this draft we are not (yet) showing what would happen to discrimination for credit risk in a world without GSE role
  - Working on this for non-conforming and private market

More work: Financial deserts and geography of disparate impact