Consumer-Lending Discrimination in the FinTech Era

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Setting: Household debt

- Latinx & African-American ethnic groups hold $2.25 trillion of the $13 trillion of U.S. household debt. (Most is housing debt – our focus.)
  - Any interest rate discrimination is material:
    - A 1 basis point (0.01%) higher mortgage rate => minorities pay $160 million extra in interest per year
  - Any rejection rate discrimination is material: In 2017, homeownership rates:
    - Majority ethnicities (72.4%), Latinx (48.4%), African-American (43.0%)
      - If any of this disparity is due to discrimination => welfare inequalities caused by financial services

Our goal

When we started this project…

- Wanted to estimate discrimination
- Also wanted to understand what fin-technology means for discrimination going forward
  - Platforms: Quicken, largest GSE counterparty by volume
  - Non-platforms: Of 2,098 largest issuers, 945 were fully algorithmic by 2018
- Ex ante: Unclear whether technology lessens discrimination:
  - Platforms remove loan officer biases from face-to-face interaction
  - But platforms increasingly use more data in statistical discrimination
    - Fuster, Goldsmith-Pinkham, Ramadorai, and Walther (2018): Machine-learning results in differential loan provision to minority borrowers.

What we do

- Establish an economic basis for the legal “standard of proof”.
  - In an era of Big Data, how can a court distinguish between legitimate and illegitimate discrimination?

    - Disparate treatment vs. disparate impact
- Estimate level of ethnic discrimination (if any) and by whom
  - Study mortgages to address the two empirical challenges of data and identification
  - Identification aided by pricing rules of Fannie Mae and Freddie Mac
    - Allows us to avoid “omitted-variable” problem.

Legal Standard

Two U.S. Federal statutes prohibit discrimination in mortgage processes

- Fair Housing Act of 1968 (FHA)
- Equal Credit Opportunity Act of 1974 (ECOA)

Issue is not the statutes, but how to implement them in the courts.

Legal Standard

- Imagine a lender cannot see wealth
- **Court**: Lenders can use proxy variables (read: Big Data)…

1. Proxies are allowable:
   - If lender can show that these variables have a *legitimate business necessity.*
     - where *legitimate business necessity* is the act of scoring credit risk.
2. Proxies are not allowable:
   - If variables are used for other purposes, including a lender's efforts to earn higher *markup above costs* on a minority group

Outcomes of discrimination

I. **Pricing Decisions**

II. **Accept/Reject Decisions**

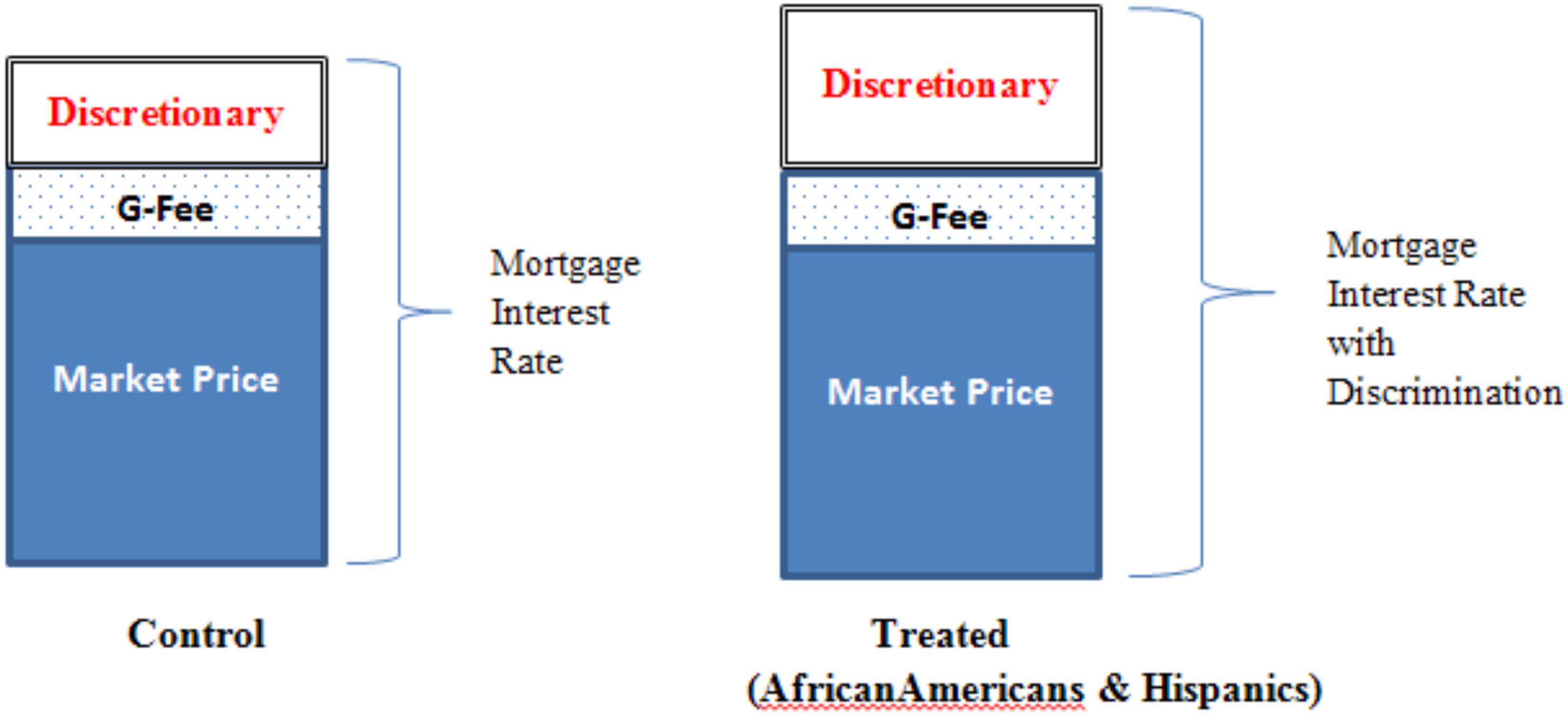
GSEs help on Identification: Pricing of Loan

Interest rate pricing

= Market rate

+ Expected cost of default (credit risk= G-Fee)

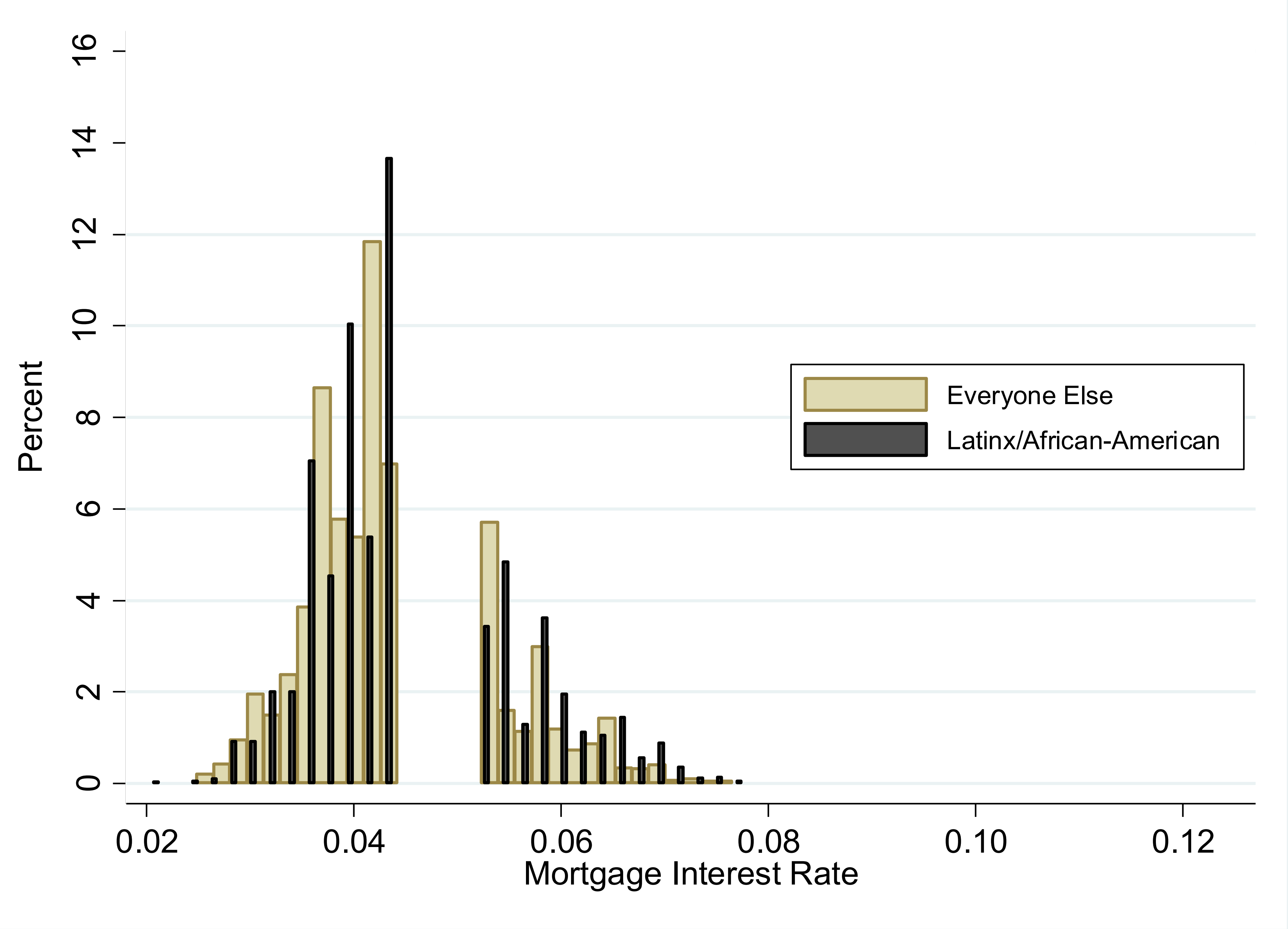
+ Discretionary part for lender profits & strategic incentives



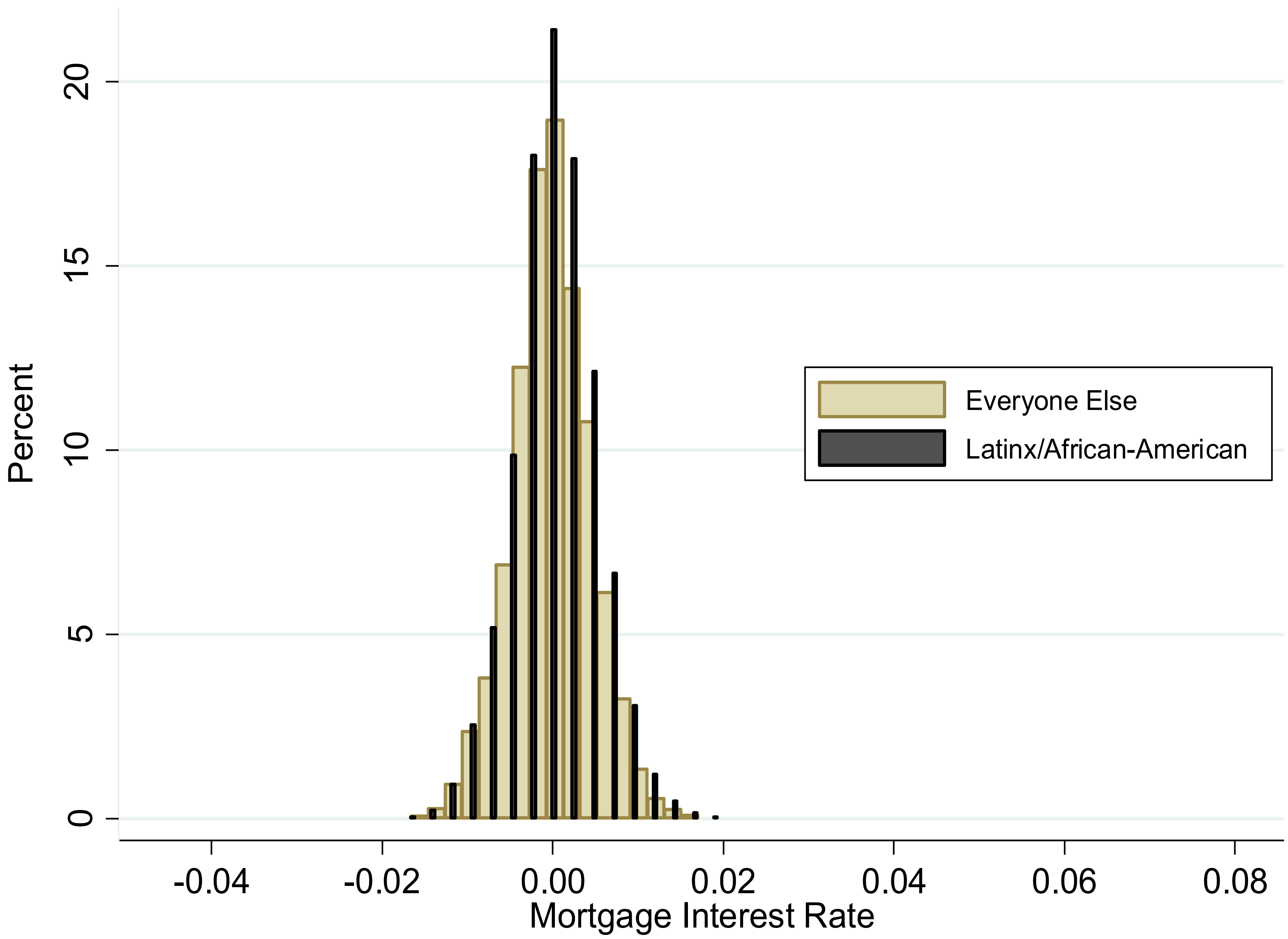
G-Fees

G-Fees are 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



Raw Interest Rates



Interest Rates Adjusted for GSE Grid

Data

- Focus on mortgages – because HMDA has ethnicity
  - Focus on 30-year fixed for comparability & conforming for GSE process

- Datasets (2008–2015):
  - **HMDA**- ethnicity and income local geography but not address
  - **ATTOM** – origination, performance and exact location
  - **McDash** – detailed contract terms and performance
  - **Equifax** – consumer debt

- Merge using performance strings

Pricing Results

Interest Rate Discrimination

	Dependent Variable: Mortgage Interest Rate			
	Purchase Mortgages		Refinance Mortgages	
	(1)	(2)	(3)	(4)
Latinx/African-Americans	0.000903***	0.000792***	0.000299***	0.000356***
	[0.000101]	[3.09e-05]	[7.96e-05]	[2.96e-05]
Observations	1,480,186	1,480,186	2,068,453	2,068,271
R-squared	0.003	0.729	0.000	0.693
Year-Month FE	N	Y	N	Y
GSE Grid FE	N	Y	N	Y

- Minorities pay 9 basis points (bps) more in purchase interest rates. (3bps in refis)
  - Incorporating the credit risk model (time differences and GSE grid effects = R-square >0.70) discrimination remains.
- Discrimination: 7.92 bps in purchases, 3.56 in refis
  - Is 7.92 bps worth talking about?
  - Mortgage Bankers Association: **Average mortgage makes 50 bps in profit.**
  - **Together, $748 million more interest paid by minorities annually on existing stock of mortgages**

Interest Rate Discrimination –Issuances by FinTechs

Dependent Variable: Mortgage Interest Rate

	Purchase Mortgages		Refinance Mortgages	
	FinTech	FinTech + Algorithm	FinTech	FinTech + Algorithm
Latinx/African-Americans	0.000534***	0.000680***	0.000200**	0.000249***
	[4.36e-05]	[5.50e-05]	[6.34e-05]	[3.08e-05]
Observations	41,832	354,680	110,870	348,833
R-squared	0.731	0.607	0.707	0.65
Year-Month FE	Y	Y	Y	Y
GSE Grid FE	Y	Y	Y	Y

- FinTechs & Algorithm-Based Lenders Discriminate almost as much as traditional lenders
  - FinTechs cannot see borrowers.
  - Thus, it must be that the algorithms build in discrimination into their pricing strategies. Even if unintentional, this is still illegal.
  - Pricing for low shopping behavior, financial deserts, etc… correlated with ethnicity

Omitted Variables - Costs vs Profit Margins

Which costs?

1. Geography: It could be that locations in areas with higher minority populations involve higher costs
2. Lender: It could be that lenders servicing more minorities have higher fixed costs

Interest Rate Discrimination: Results in Purchase Mortgages
Robustness: Costs may vary by geography or by fixed cost of lender

	Dependent Variable: Mortgage Interest Rate			
Latinx/African-Americans	0.000792*** [3.09e-05]	0.000701*** [2.37e-05]	0.000552*** [2.76e-05]	0.000525*** [3.33e-05]
Observations	1,480,186	1,480,170	1,478,947	1,453,606
R-squared	0.729	0.733	0.747	0.758
Year-Month FE	Y	Y	Y	Y
GSE Grid FE	Y	Y	Y	Y
County FE	N	Y	Y	N
Lender FE	N	N	Y	N
County-Lender FE	N	N	N	Y

- Of the nearly 7.9 bps of potential discrimination
  - 0.9 bps might be due to varying location costs,
  - 1.5 bps might be due to varying lender fixed costs
  - **5.25 bps of discrimination is robust (probably more)**
  - Follow-up work: **"The geography of discrimination"**.
  - Our view: what we are identifying is monopoly rent-seeking in financial deserts and other communities known for low shopping. Not allowed under court ruling.

Omitted Variables - Costs vs Profit Margins

Robustness

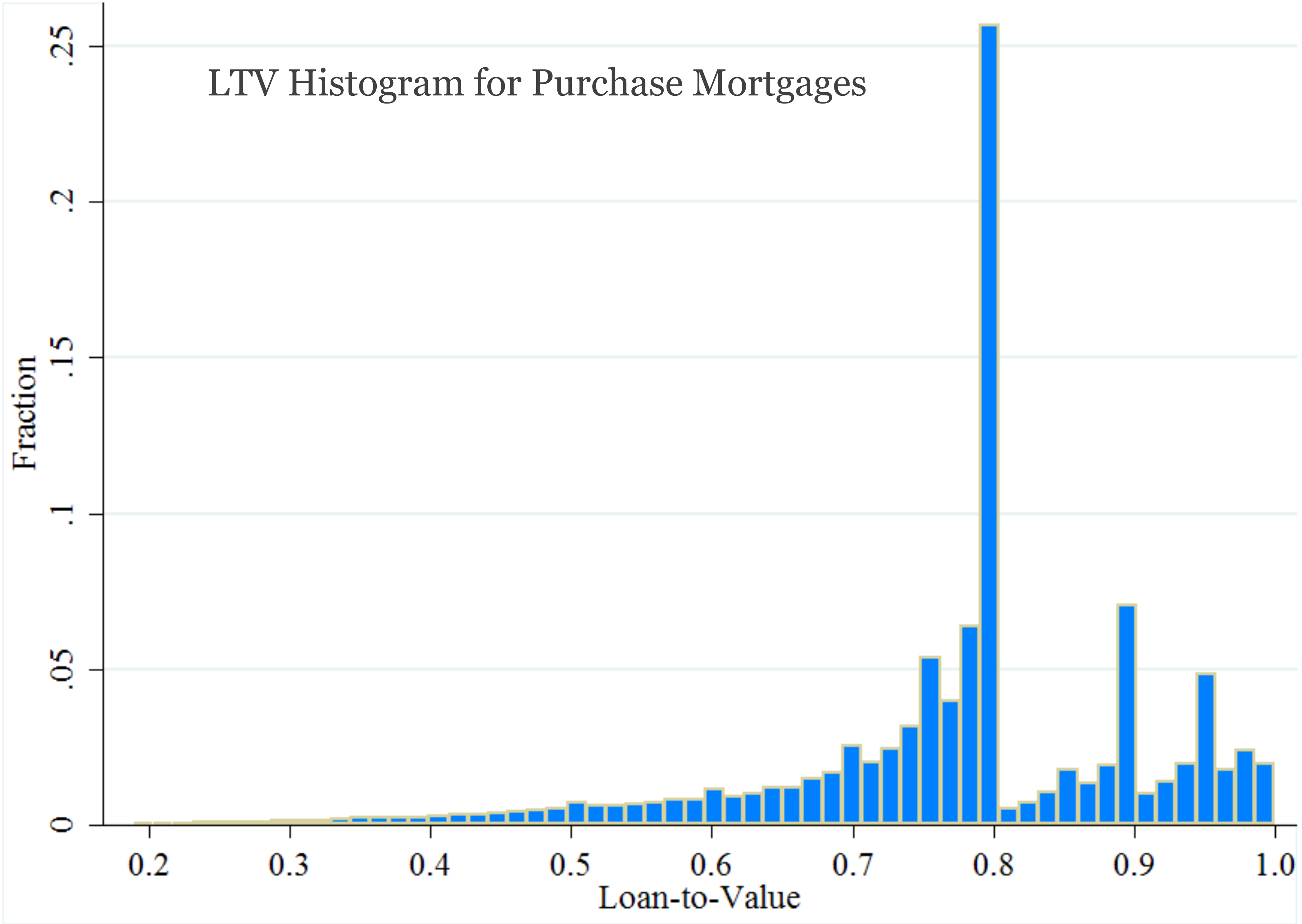
1. Geography: It could be that locations in areas with higher minority populations involve higher costs
2. Lender: It could be that lenders servicing more minorities have higher fixed costs
3. Servicing costs
4. Points

Robustness Concerns

Robustness Concern:	Points	Residual Risk via Servicing or MBS Holding	Ethnicity Designation
Sub-Sample:	0.795 < LTV <0.801	Small Lenders	Only use HMDA-Classified Ethnicity Observations
Reasoning:	At budget constraint	Unlikely to service the loans or hold as MBS on balance sheet	Eliminate software errors in classification

Points: It could be that we are picking up non-minority borrowers lowering interest rates by paying points

- Solution: Down-payment behavior
  - Many borrowers do whatever they can to get the house they want
  - Right at LTV of 0.80, borrowers have scraped to meet down-payment (Avoid paying insurance cost above 0.80)
  - Limit to sample LTV = 0.80 (see histogram)



LTV Histogram for Purchase Mortgages
Fraction
0
.05
.1
.15
.2
.25
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1.0
Loan-to-Value

Robustness Concerns

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Residual Risk: It could be that discrimination we show reflects residual risk for lenders exposed to default risk, not in the loan default, but in additional costs of servicing loans that are delinquent

- Solution: Eliminate large lenders

Robustness Concerns

Robustness Concern:	Points	Residual Risk via Servicing or MBS Holding	Ethnicity Designation
Sub-Sample:	0.795 < LTV <0.801	Small Lenders	Only use HMDA-Classified Ethnicity Observations
Panel A: Purchases			
Latinx-/African-American	0.000944*** [4.21e-05]	0.000868*** [3.49e-05]	0.000814*** [3.23e-05]
Observations	327,355	833,579	1,356,670
R-squared	0.739	0.730	0.729
Month-Year FE	Y	Y	Y
GSE Grid FE	Y	Y	Y

2 Silver Linings for Fin-Technology

1> Time pattern

2> Rejection rates

Rate discrimination is declining

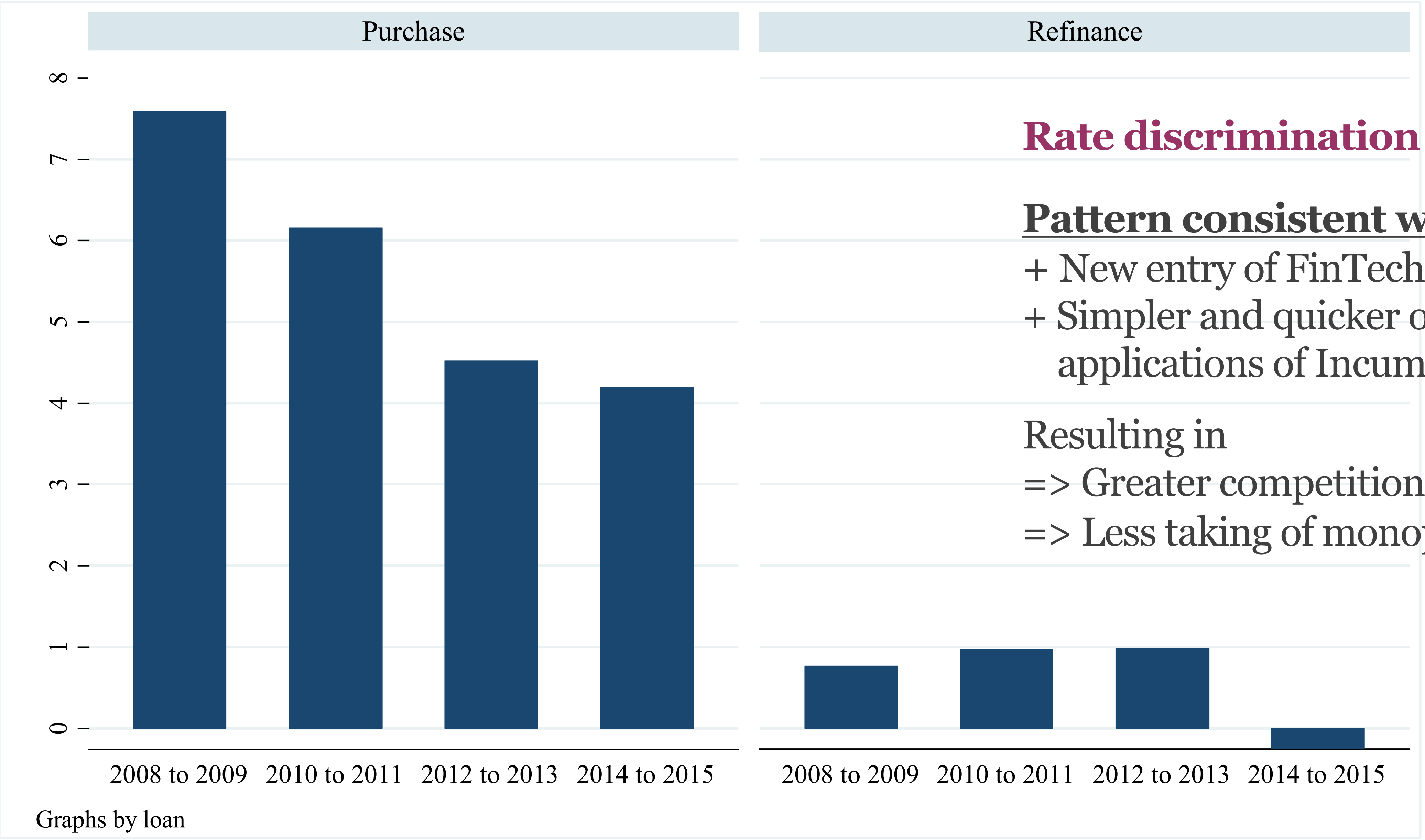
<u>**Pattern consistent with:**</u>

+ New entry of FinTech platforms
+ Simpler and quicker online applications of Incumbents

Resulting in

=> Greater competition

=> Less taking of monopoly rents



	Dependent Variable: Application Rejection								
	Small Lenders			FinTech Lenders: Buchak, et al (2017)			FinTech Lenders with Full Online Application 2018		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Latinx/African-American	0.0934*** [0.00646]	0.0858*** [0.00563]	0.0639*** [0.00266]	0.023 [0.0200]	0.0112 [0]	0.0259** [0.00881]	0.0531*** [0.0160]	0.0496*** [0.0136]	0.0344*** [0.0118]
Observations	2,007,520	2,007,520	2,007,520	116,893	116,893	116,893	926,542	926,542	926,542
R-squared	0.058	0.064	0.329	0.082	0.088	0.301	0.039	0.046	0.345
Application Variable Splines	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Census Tract %iles: LTV, Credit Score	N	Y	Y	N	Y	Y	N	Y	Y
County FE	N	N	Y	N	N	Y	N	N	Y
Lender F.E	N	N	Y	N	N	Y	N	N	Y

- 6.4% extra rejections overall: Consistent with material discrimination.
- Yet (silver lining #2) FinTechs discriminate much less, if at all.

Conclusions

1. This work could provide a tool for regulators and the courts
   - Big data is just starting… lenders may be testing the waters on how courts will handle statistically discriminating variables
2. Back of the envelope: $750 million in extra interest per year. Our estimates are a lower bound, but show that discrimination is happening (sometimes without purpose)
3. Surprise contributions:
   - GSEs may be serving a role in preventing discrimination.
   - Algorithms may be improving competitive landscape
4. Work in progress:
   - The targeting of monopoly rents & the geography of disparate impact