# Disparities in Consumer Credit: The Role of Loan Officers in the FinTech Era

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# Motivation

Recent debate on the use of machine learning models in the consumer credit market

- Regulatory concerns about loan officers' discretionary lending practice
    - Extensive literature on racial discrimination (e.g., Giacoletti, Heimer, and Yu, 2022; Bhutta, Hizmo, and Ringo, 2021)
    - Regulation Z aiming to reduce steering and discriminatory lending

$\Rightarrow$ Machine may help remove behavioral biases

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  $\Rightarrow$ Machine may help remove behavioral biases

- Growing literature on statistical discrimination
  - Black applicants have noisy hard credit information (e.g., Fuster et al., 2020; Blattner and Nelson, 2021)

  $\Rightarrow$ Loan officers may have soft information, which can disproportionately benefit minorities

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    $\rightarrow$ separating equilibrium if races are matched; pooling if races are unmatched

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    → separating equilibrium if races are matched; pooling if races are unmatched

    → use of machine limits soft information

- New data: Mortgage loan officer registration linked to confidential HMDA
  - Observe borrower races and infer loan officer races using full names

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- more likely to get a loan
- higher interest rate conditional on approval $\rightarrow$ soft information to fairly price
- interest rate is a stronger predictor of default after controlling for hard info; not more likely to default conditional on interest rate
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Results hold in 2SLS settings

- IV: changes in lending institutions' loan officer composition affect the matching likelihood

# Preview of Results - Use of Machine

- Automated underwriting system (AUS) is widely adopted in the US mortgage market
- Regression discontinuity: conforming loans are much more likely to use AUS
- The effect of racial proximity is nearly zero for loans going through AUS
  $\rightarrow$ Use of AUS attenuates the effect of racial proximity on loan approval
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- Implications
  - The net effect pf machine depends on the dominant friction: behavioral bias or noisy hard information
  - shortage of minority loan officer supply leads to efficiency losses

# Road Map

- Data
- Role of Loan Officers
  - Racial proximity and loan outcomes
  - Soft information
- Use of Machine
- Conclusion

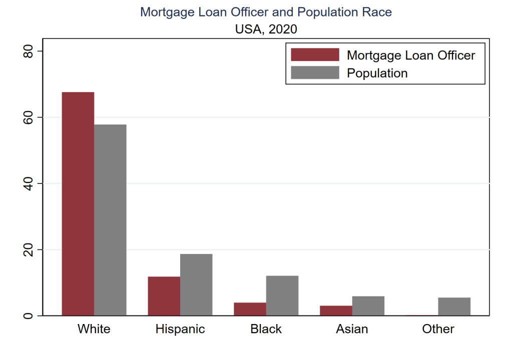
# Data

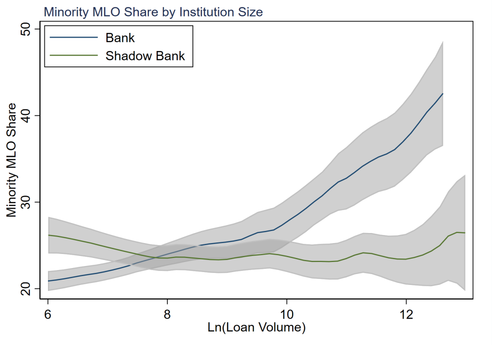
# Main Datasets

- Mortgage loan officer registration data
  - Disclosure required by the Dodd-Frank Act:
    1. every loan officer must be registered with the NMLSR
    2. disclose their unique ID on loan docs they are primarily responsible for
  - Name, registration history, work history, branch location
  - Infer race from surname and refine using first name (Tzioumis, 2018) ◂ Loan Officer Race
  - Coverage: all registered MLOs in the US except for those whose license or registration became inactive before 2015
- Confidential HMDA (2018-2019)
  - Application status (reject/originate), applicant characteristics, loan characteristics, lender identifier, use of AUS, loan officer identifier
  - Merged with MLO registration data using loan officer ID
- McDash: loan delinquency status after origination, reported dynamically

# Minority Loan Officers' Presence

Minority loan officers appear to be under-represented.



# Role of Loan Officers

# Empirical Design

$$\begin{aligned} Reject_{i,j,c,l,t} =& \beta_1 SameRace_{i,j} + \beta_2 MLO\_Race_j + \Gamma X_i \\ &+ \alpha_c Borr\_Race_i + \tau_t Borr\_Race_i + \eta_{c,t} + \zeta_{c,l} + \epsilon_{i,j,c,l,t} \end{aligned}$$

- $\beta_2 MLO\_Race_i$: racial difference in loan officer approval rate (quality or standard difference)
- $\Gamma X_i$: hard information (fico, ltv, dti, squared-terms, loan type, loan purpose)
- $\alpha_c Borr\_Race_i + \tau_t Borr\_Race_i$: unobservable creditworthiness for different borrower races
- $\eta_{c,t}$: local unobservables
- $\zeta_{c,l}$: loan supply

# IV for Matching

- Endogeneity: unobserved borrower characteristics $\longleftrightarrow$ same-race matching
- IV: Changes in lending institutions' racial composition of loan officers covering a region
- Identifying assumptions: (1) borrowers' choices of lending institutions $\perp$ loan officer race; (2) short-run minority loan officer supply $\perp$ minority borrower mortgage demand

# IV: Relevance

$$\mathbf{1}_{\text{MLO j is of Race R}} = \beta_1 IV_{\text{MLO j is of Race R}} + \sum_{R' \neq R} \theta_{R'} IV_{\text{MLO j is of Race } R'} + \Gamma X_i$$

$$+\alpha_c Borr\_Race_i + \tau_t Borr\_Race_i + \eta_{c,t} + \zeta_{c,l} + \epsilon_{i,j,c,l,t}$$

| | Non-White MLO | Black MLO | Asian MLO | Hispanic MLO |
|---|---|---|---|---|
| $IV_{\text{Non-White MLO}}$ | 0.922*** | | | |
| | (0.00) | | | |
| $IV_{\text{Black MLO}}$ | | 0.389*** | 0.003* | 0.030*** |
| | | (0.01) | (0.00) | (0.00) |
| $IV_{\text{Asian MLO}}$ | | 0.003 | 0.479*** | 0.019*** |
| | | (0.00) | (0.02) | (0.01) |
| $IV_{\text{Hispanic MLO}}$ | | 0.006*** | 0.008*** | 0.479*** |
| | | (0.00) | (0.00) | (0.01) |
| Loan Characteristics Controls | Fixed Effects: County-Month, County-Borrower Race Borrower Race-Month, Lender-County | | | |

# Racial Proximity and Loan Approval

$$Reject_{i,j,c,l,t} = \beta_1 SameRace_{i,j} + \beta_2 MLO\_Race_j + \Gamma X_i + \alpha_c Borr\_Race_i + \tau_t Borr\_Race_i + \eta_{c,t} + \zeta_{c,l} + \epsilon_{i,j,c,l,t} \;;$$

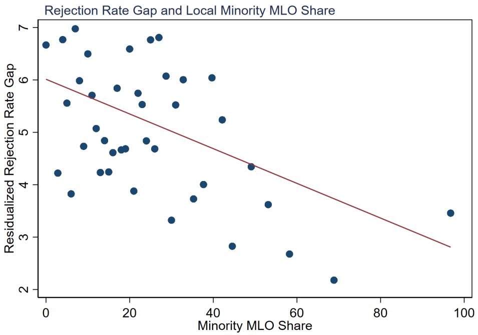
$$\begin{aligned} Reject_{i,j,c,l,t} = & \beta_1 SameRace_{i,j} + \beta_2 SameRace_{i,j} \times MinorBorr_i + \beta_3 MLO\_Race_j + \Gamma X_i + \alpha_c Borr\_Race_i \\ & + \tau_t Borr\_Race_i + \eta_{c,t} + \zeta_{c,l} + \epsilon_{i,j,c,l,t} \end{aligned}$$

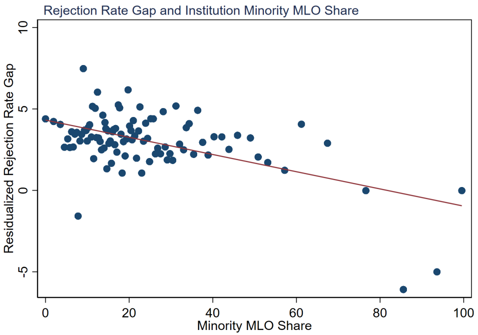
| | OLS | OLS | 2SLS IV | 2SLS IV |
|---|---|---|---|---|
| Same-Race | -2.335*** | -0.858*** | | |
| | (0.13) | (0.29) | | |
| Same-Race × Non-White Borrower | | -2.951*** | | |
| | | (0.54) | | |
| $\widehat{\text{Same-Race}}$ | | | -8.922*** | -1.684 |
| | | | (0.60) | (1.75) |
| $\widehat{\text{Same-Race}}$ × Non-White Borrower | | | | -14.190*** |
| | | | | (3.17) |
| Loan Characteristics Controls | Fixed Effects: County-Month, County-Borrower Race, Borrower Race-Month | | | |

- Racial proximity leads to lower rejection likelihood, especially for minority borrowers

# Minority Loan Officers and Racial Gap

The share of minority loan officers is negatively related to the racial gap in mortgage rejection




◂ Evidence for loan officer discretion

# Soft Information

- Better information to price early-default risk
  $\rightarrow$ Expand credit provision + fairly priced risk $\rightarrow$ high interest rate

- Not more likely to default conditional on interest rates

- Loan size dispersion is bigger
  - More precise signals of creditworthiness $\rightarrow$ increase loan size dispersion (Cornell and Ivo, 1996)

# Rejection Likelihood for Minority Borrowers: 2SLS

$$Reject_{i,j,c,l,t} = \beta_1 MinorBorr_i \times \widehat{MLO\_Race_j} + \beta_2 \widehat{MLO\_Race_j} + \Gamma X_i$$
$$+ \alpha_c Borr\_Race_i + \tau_t Borr\_Race_i + \eta_{c,t} + \zeta_{c,l} + \epsilon_{i,j,c,l,t}$$

| Borrower Sample | All | White & Black | White & Asian | White & Hispanic |
|---|---|---|---|---|
| Non-White Borrower × Non-White MLO | -6.774*** | | | |
| | (2.17) | | | |
| Black Borrower × Black MLO | | -3.222 | | |
| | | (2.03) | | |
| Asian Borrower × Asian MLO | | | -35.209*** | |
| | | | (2.04) | |
| Hispanic Borrower × Hispanic MLO | | | | -16.873*** |
| | | | | (0.93) |
| Loan Characteristics Controls | Fixed Effects: County-Month, County-Borrower Race Borrower Race-Month | | | |

- Benchmarking on white borrowers, minority borrowers having same-race loan officers enjoy lower rejection likelihood — credit expansion

# Interest Rate

$$Interest\ Rate_{i,j,c,l,t} = \beta_1 MinorBorr_i \times \widehat{MLO\_Race_j} + \beta_2 \widehat{MLO\_Race_j} + \Gamma X_i$$
$$+ \alpha_c Borr\_Race_i + \tau_t Borr\_Race_i + \eta_{c,t} + \zeta_{c,l} + \epsilon_{i,j,c,l,t}$$

| Borrower Sample | All | White & Black | White & Asian | White & Hispanic |
|---|---|---|---|---|
| Non-White Borrower × Non-White MLO | 26.377*** | | | |
| | (6.66) | | | |
| Black Borrower × Black MLO | | 14.746** | | |
| | | (6.40) | | |
| Asian Borrower × Asian MLO | | | 39.890*** | |
| | | | (6.23) | |
| Hispanic Borrower × Hispanic MLO | | | | 24.477*** |
| | | | | (2.99) |
| Loan Characteristics Controls | Fixed Effects: County-Month, County-Borrower Race Borrower Race-Month | | | |

- Conditional on approval, racial proximity is associated with higher interest rates for minority borrowers — significant effect on pricing

# 60+Day Delinquency

$$
\begin{aligned}
Default_{i,j,c,l,t} =& \beta_1 Interest\ Rate_{i,j,c,l,t} + \beta_2 MinorBorr_i \times \widehat{MLO\_Race}_j + \beta_3 \widehat{MLO\_Race}_j + \Gamma X_i \\
&+ \alpha_c Borr\_Race_i + \tau_t Borr\_Race_i + \eta_{c,t} + \zeta_{c,l} + \epsilon_{i,j,c,l,t}
\end{aligned}
$$

| Borrower Sample | All | White & Black | White & Asian | White & Hispanic |
|---|---|---|---|---|
| Non-White Borrower × Non-White MLO | -1.412 | | | |
| | (1.81) | | | |
| Black Borrower × Black MLO | | 0.490 | | |
| | | (3.16) | | |
| Asian Borrower × Asian MLO | | | 2.992 | |
| | | | (4.04) | |
| Hispanic Borrower × Hispanic MLO | | | | -0.174 |
| | | | | (1.65) |
| Interest Rate | 0.014*** | 0.013*** | 0.012*** | 0.012*** |
| | (0.00) | (0.00) | (0.00) | (0.00) |
| Loan Characteristics Controls | Fixed Effects: County-Month, County-Borrower Race<br>Borrower Race-Month | | | |

- No significant difference in default, but interest rates strongly predict defaults — informative pricing

# Size Dispersion

| | Percentile Value of Loan Size (Logarithm) | | | | |
|---|---|---|---|---|---|
| | P5 | P10 | P50 | P90 | P95 |
| Non-White MLO | -0.062*** | -0.075*** | -0.076*** | -0.090*** | -0.096*** |
| | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) |
| Non-White MLO × Non-White Borrower | -0.056*** | -0.021*** | 0.016*** | 0.041*** | 0.058*** |
| | (0.01) | (0.01) | (0.00) | (0.00) | (0.01) |
| Observations | 1,280,358 | 1,280,360 | 1,280,367 | 1,280,367 | 1,280,367 |
| Adjusted $R^2$ | 0.515 | 0.518 | 0.633 | 0.578 | 0.562 |
| Fixed Effects: County-by-lender-by-time & County-by-borrower race-by-time | | | | | |

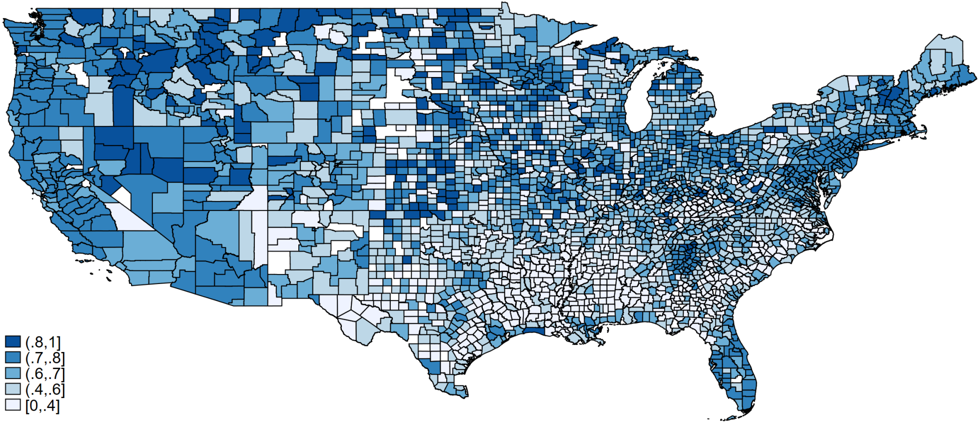
- Sample: MLO-county-borrower race-month
- Minority loans processed by minority MLO have more dispersed size distribution
  - $5^{th}$ percentiles are 5.6% smaller on average
  - $95^{th}$ percentiles are 5.8% larger on average

# Use of Machine

# Adoption of AUS in Mortgage Origination

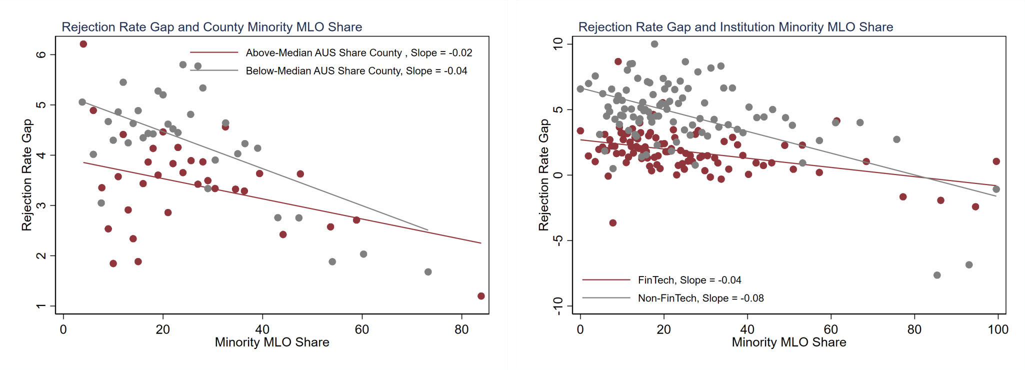
Automated Underwriting Systems (AUS) are widely adopted in the U.S. AUS pre-processes applicants' credit profile (i.e., hard information only) and provides a recommended decision, where the algorithm is based on the database of previous loans.

Regional Distribution of AUS Usage



# Use of AUS Weakens the Importance of Minority Loan Officers

The involvement of FinTech significantly reduces the extent to which minority loan officers' presence narrows the racial gap in mortgage rejection.



# AUS Weakens Effects of Racial Proximity

$$Reject_{i,j,c,l,t} = \beta_1 SameRace_{i,j} + \beta_2 SameRace_{i,j} \times AUS_{i,j,c,l,t} + \sum_{R' \neq R} \theta_{R'} \cdot \mathbf{1}_{\text{MLO j is of Race}R'}$$

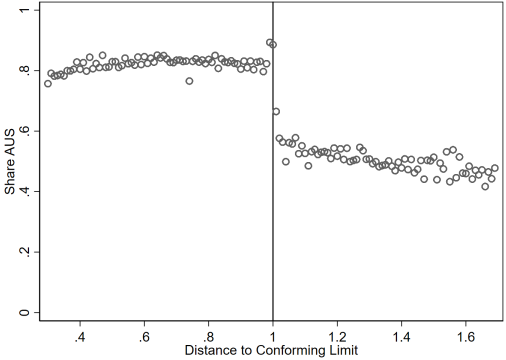
$$+ \sum_{R' \neq R} \lambda_{R'} \cdot \mathbf{1}_{\text{MLO j is of Race}R'} \times AUS_{i,j,c,l,t} + \Gamma X_i + \eta_{c,t} + \epsilon_{i,j,c,l,t} \text{ ; | Borrower i is of race R.}$$

| | Binary Race Definition | | Race Defined Individually | | |
|---|---|---|---|---|---|
| Borrower Sample | White | Non-white | Black | Asian | Hispanic |
| Same-Race MLO | -4.204*** | -3.675** | -1.174* | -11.279*** | -4.054*** |
| | (0.26) | (0.50) | (0.61) | (0.80) | (0.62) |
| Same-Race MLO × AUS | 1.310*** | 3.448*** | 2.375*** | 8.352*** | 3.140*** |
| | (0.24) | (0.45) | (0.61) | (0.73) | (0.55) |
| AUS | -11.987*** | -17.938*** | -18.657*** | -13.989*** | -19.222*** |
| | (0.32) | (0.39) | (0.56) | (0.52) | (0.38) |
| Observations | 8,585,250 | 3,002,148 | 883,874 | 723,989 | 1,374,635 |
| Adjusted $R^2$ | 0.177 | 0.218 | 0.253 | 0.216 | 0.211 |
| Loan Characteristics Controls, Other Race indicators & Other Interactions; County-Month FE | | | | | |

# Use of AUS by Distance to Conforming Loan Limit

- Conforming loans are more likely to use AUS

  "Use of Desktop Underwriter, Fannie Mae's automated credit risk assessment platform, is required for all Fannie Mae sellers."

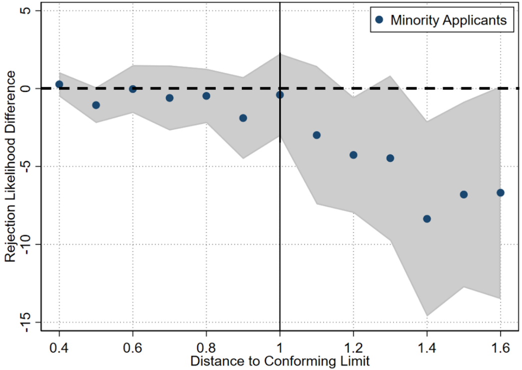


# Rejection RDD

$$
\begin{aligned}
Reject_{i,j,c,l,t} =& \beta_1 MinorMLO_j + \beta_2 MinorBorr_i \times MinorMLO_j \\
& + \Gamma X_i + \alpha_{race,t} + \tau_{race,c} + \eta_{c,t} + \gamma_{l,t} + \epsilon_{i,j,c,l,t}
\end{aligned}
$$

- Estimate for each loan size/conforming ratio bucket, plot $\beta_2$
- The effect of racial proximity is bigger for jumbo loans

  $\rightarrow$ Use of AUS attenuates the effect of loan officer racial proximity

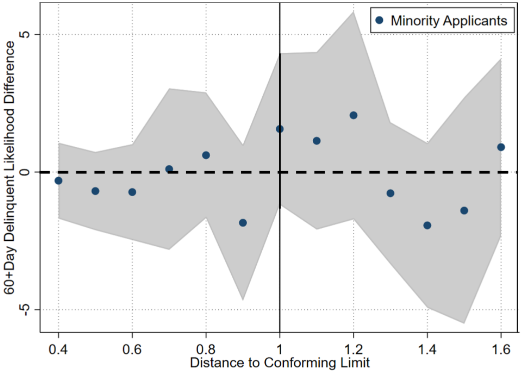


# Default RDD

$$
\begin{aligned}
Default_{i,j,c,l,t} = &\beta_1 MinorMLO_j + \beta_2 MinorBorr_i \times MinorMLO_j \\
&+ \Gamma X_i + \alpha_{race,t} + \tau_{race,c} + \eta_{c,t} + \gamma_{l,t} + \epsilon_{i,j,c,l,t}
\end{aligned}
$$

- Estimate for each loan size/conforming ratio bucket, plot $\beta_2$
- Jumbo loans processed by minority MLO is not significantly more likely to default

  $\rightarrow$ Use of AUS limits minority loan officers' soft information



# Conclusion and Discussion

# Conclusion and Discussion

- Compared to minority applications processed by white loan officers, minority applications processed by minority loan officers have lower rejection likelihood, lower interest rates upon approval, and lower default rate

- Results attributable to minority loan officers having better soft information about minority borrowers due to racial proximity

- The use of algorithmic underwriting attenuates the effect of racial proximity on loan approval by limiting soft information

- Implications
  - The net effect pf machine depends on the dominant friction: behavioral bias or noisy hard information
  - shortage of minority loan officer supply leads to efficiency losses

# Appendix

# Loan Officer Race

- Step 1: Get race and ethnicity probabilities from the surname list of the 2010 U.S. Census
- Step 2: Refining our categorization using racial information of first names provided by Tzioumis (2018)

$$P(r|s,f) = \frac{P(r|s) \cdot P(f|r,s)}{\sum_r P(r|s) \cdot P(f|r,s)}$$

◂ Return

## Loan Officers' Discretion

Does loan officers' discretion matter for mortgage decisions? We follow Bertrand and Schoar (2003) and estimate the extent to which loan-officer fixed effects improve the fit (adj. R-squared) of a linear model for two outcomes: (1) rejection; and (2) interest rates.

| Fixed Effects | Rejection | Interest Rate |
|---|---|---|
| M+C+L | 0.488 | 0.370 |
| M+C+L+O | 0.582 | 0.566 |
| | | |
| Loan Officer F-stat | 10.630 | 17.670 |
| P-value | 0.000 | 0.000 |
| C-by-M+L-by-M | 0.317 | 0.480 |
| C-by-M+L-by-M+O | 0.359 | 0.601 |
| | | |
| Loan Officer F-stat | 3.881 | 12.560 |
| P-value | 0.000 | 0.000 |

◂ Return