Disparities in Mortgage Lending: A Statistical Analysis of Race and Gender Bias in New York State

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The Mortgage Lending Process

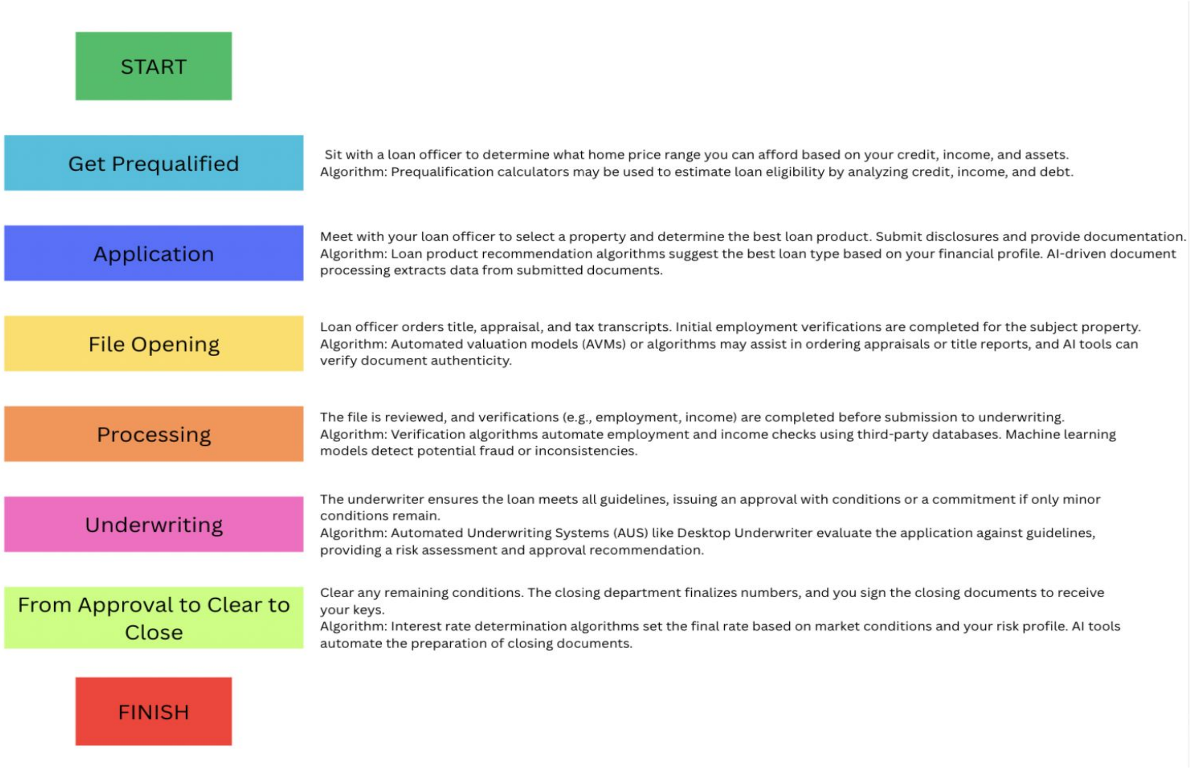


Fig. 2. Diagram of Loan Application and Approval Process.

Motivations & Context

- **Homeownership** = **key path to wealth**, especially for historically excluded groups like Black Americans
- **Rent up, income stagnant** ➔ Ownership more crucial than ever
- **Systemic barriers** persist: undervaluation of homes in Black neighborhoods, higher mortgage rejection rates
- Shift from **human underwriters to algorithmic decision-making**
- Algorithms aim for consistency, but often **replicate existing biases**
- **The Markup (2021):**
  - Black applicants **more likely denied** than white peers with similar finances
  - **High-income Black applicants** sometimes rejected **more than** white applicants with higher debt
- Algorithms risk **reinforcing inequalities** they were built to solve

Research Questions

- How do loan-approval algorithms impact **approval rates** across different identities and locations?
- Are there significant disparities in approval rates based on **race and gender**?
- Do **interest rates** vary across demographic groups despite similar financial profiles?
- How can we design a **fairer credit-scoring model** that balances **equity and accuracy**?

Dataset

Dataset Overview:

- Sourced from the **2023 Home Mortgage Disclosure Act (HMDA) Loan Application Register (LAR)**
- Mandated by **federal law**, requiring financial institutions to report mortgage application data
- Collected by the **Consumer Financial Protection Bureau (CFPB)**
- Publicly available via the **Federal Financial Institutions Examination Council (FFIEC)**

Data Collection & Reporting:

- Institutions report if they meet criteria based on **asset size, location, and mortgage activity**
- Data is submitted **electronically** and follows a **standardized format**
- CFPB processes, validates, and publishes the data annually

Variables

Applicant demographics: race, ethnicity, gender, age, income

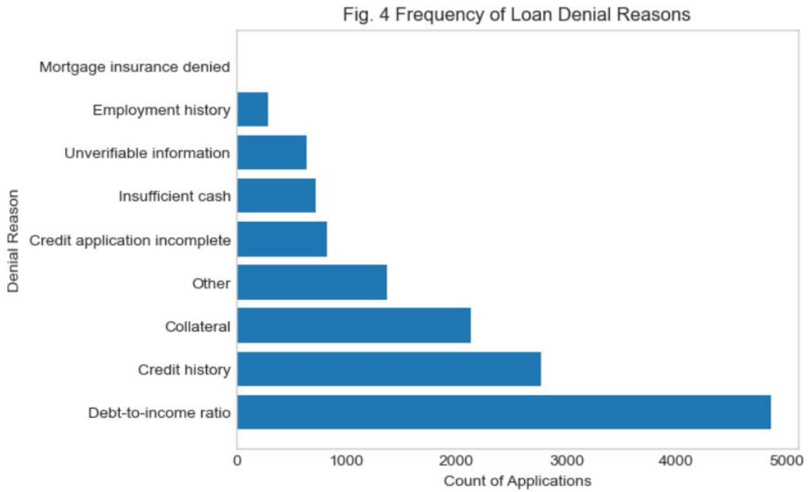
Loan details: loan amount, loan-to-value ratio, interest rate, rate spread, loan type, loan purpose, lien status

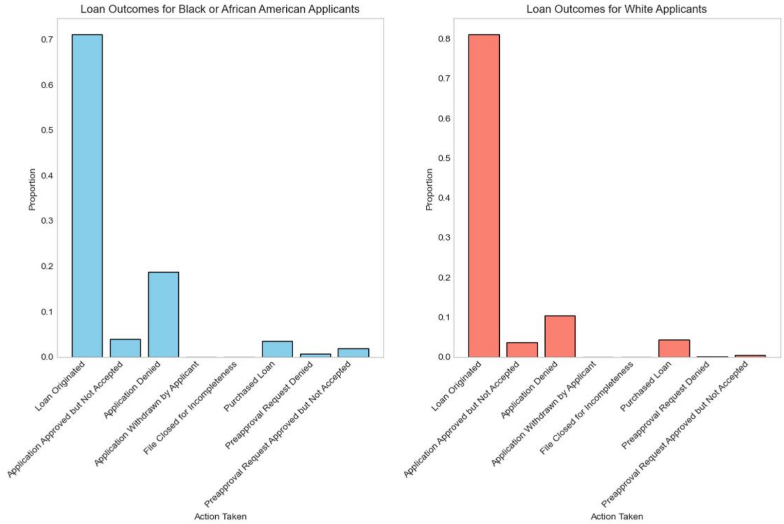
Applicant financials: debt-to-income ratio, credit score type

Other factors: property value, occupancy type, minority population % in census tract

Decision process: action taken, denial reason, automated underwriting system used

EDA Highlights





- Most common loan denial reason is Debt-income-ratio
- African American Applicants have been targeted by historical redlining and zoning and therefore have more unfavorable DTI ratios.

- Denials for African American Applicants is twice is high
- Slightly more pre approval requests were denied, or approved but then not accepted
- The 'Loan Originated' metric indicates whether the applicants actually received the loan, and this value is ~15% lower for Black applicants

Methods

Modeling Approach:

- Built three MLR regression models to assess race/gender effects:
    - **Model 1:** Predicted loan amount
    - **Model 2:** Predicted interest rate
    - **Model 3:** Predicted interest rate spread
- Predictors: demographic (race, sex, age), financial (income, debt-to-income ratio, credit score), loan characteristics (type, purpose, property value).
- **Evaluated** models based on accuracy (how well predicted the data) and fairness (significance of factors, degrees of effect)

Prediction:

- Trained three binary classifiers to predict approval or denial[1] based on key financial factors:
    - Logistic Regression
    - K-Nearest Neighbors
    - Decision Tree
- Compared the **accuracy rates** between white and Black applicants for each model
- Retrained the models to take race as an input, and examined **fairness metrics**

1. Approval = “Loan Originated” or “Application approved but not accepted”
   Denial = “Loan Denied” or “Pre-Approval request denied”

Analysis & Findings of Predictive Approach

Model 1: Predicted loan amount

- R-squared indicates selected predictors did good job of predicting the variance in loan outcome (0.790)
- Race and gender were significant when controlling for other financial, demographic, and loan characteristics (p-value > 0.000), with nearly $16,769 less given to black applicants and $15,570 less given to female applicants

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                            OLS Regression Results
==============================================================================
Dep. Variable:            loan_amount   R-squared:                       0.790
Model:                            OLS   Adj. R-squared:                  0.790
Method:                 Least Squares   F-statistic:                     5959.
Date:                Thu, 10 Apr 2025   Prob (F-statistic):               0.00
Time:                        16:26:19   Log-Likelihood:            -8.9893e+05
No. Observations:               66614   AIC:                         1.798e+06
Df Residuals:                   66571   BIC:                         1.798e+06
Df Model:                          42
Covariance Type:            nonrobust
=================================================================================================
                                    coef    std err          t      P>|t|      [0.025      0.975]
-------------------------------------------------------------------------------------------------
const                         -2.143e+05   9240.209    -23.188      0.000   -2.32e+05   -1.96e+05
tract_minority_population_percent 497.8228   32.558     15.290      0.000     434.008     561.637
debt_to_income_ratio            859.3158    175.625      4.893      0.000     515.091    1203.541
income                           45.8630      1.924     23.832      0.000      42.091      49.635
property_value                    0.4421      0.001    395.325      0.000       0.440       0.444
loan_to_value_ratio            3908.5292     44.261     88.306      0.000    3821.777    3995.281
binary_race_1                  1.676e+04   2567.425      6.529      0.000    1.17e+04    2.18e+04
applicant_sex_2               -1.557e+04   1418.140    -10.982      0.000   -1.84e+04   -1.28e+04
```

Snippet of the model showing the selected factors

Model 2: Predicted interest rate

- Sex was not significant
- White applicants predicted to have slightly higher interest rates, 0.0542% (p-value = 0.007)
- Weak model fit (r-squared = 0.171)

Model 3: Predicted interest rate spread

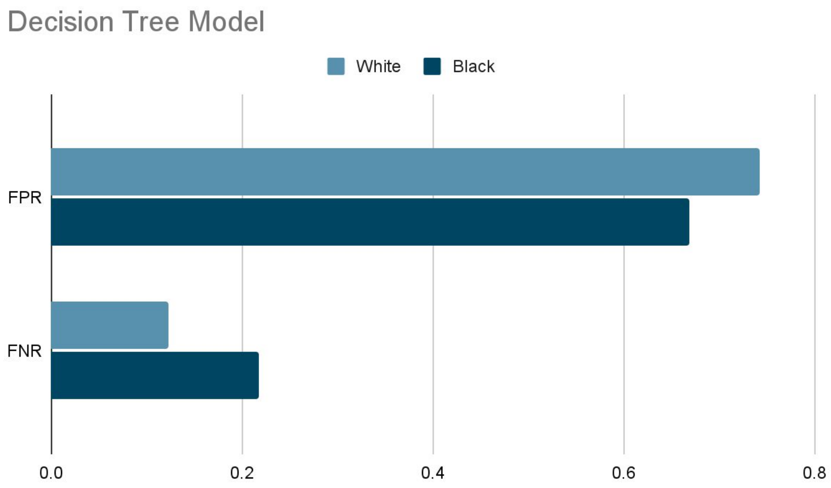
- Neither sex nor race were significant (p-value = 0.110, p-value = 0.611)
- Weak model fit (r-squared = 0.087)

Analysis & Findings

Our models all achieved **>75% accuracy** at predicting the test set outcomes, making them reasonable stand-ins. There were modest but clear indications of **racial bias** in all models trained on this data.

Observed Racial Bias (Accuracy Gap):

- Logistic Regression: **9.13%**
- KNN: **7.95%**
- Decision Tree: **5.02%**



Discussion & Conclusions

Model Insights on Bias:

- **Model 1:** Black female applicants receive lower loan amounts, **even after controls**
  ➜ Consistent with Brookings (2020) findings on **$48K average home devaluation** in Black neighborhoods

- **Model 2:** White applicants charged **0.054% higher rates** than Black applicants
  ➜ Contradicts expectations, raises questions about **algorithmic overcorrection**

- **Model 3:** Rate spread determined mostly by financial indicators, not race
  ➜ Suggests **more standardized pricing** in later loan stages

Dataset concerns:

The bias found in our models suggests that any future development that relies on this dataset for training may inadvertently perpetuate the same systemic inequities

Limitations & Future Work

Data Imbalance:

- Few **rejected applications**, limiting denial pattern analysis
- Majority of applicants are **White**, reducing ability to detect minority disparities

Opaque Lender Models:

- Proprietary **risk scores and underwriting criteria** unknown

Future Work:

- Access the default rate on loans, credit scores
- Conduct the analysis on more regions (other counties, states, etc.)