SCHOLARLY REVIEW

Disparity or Not: An Exploration of Mortgage-Lending Practices and Solutions For Minorities

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Author Biography

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Abstract

Despite the implementation of various housing policies such as the Fair Housing Act (FHA), Home Mortgage Disclosure Act (HMDA), and Equal Credit Opportunity Act, disturbing reports of mortgage lending disparities among minorities persist, particularly African-American communities. This study investigates the prevalence of such disparities in recent mortgage-lending practices through quantitative research. Initially hypothesizing no disparity for minorities, sophisticated statistical methods like logistic regression to analyze a vast dataset comprising 14 million nationwide mortgage applications were utilized. Many believe racial disparities in mortgage-lending are due to differences in income level and loan amount. To examine whether there is merit in this belief, this study employs a multivariate method by taking 10 related economic factors into consideration which exposes a higher declination rate for African-American borrowers even after accounting for these factors. Consequently, the study substantiates the existence of significant systemic racial disparities within mortgage lending. In a step towards addressing these disparities, an application was developed that integrates insights from the above-mentioned advanced machine learning model and the research of Harvard Professor Kosuke Imai using fully Bayesian Improved Surname Geocoding (fBISG). The overarching goal of this application is to empower borrowers, particularly those from African-American communities, by providing assistance in navigating mortgage expectations and enhancing their probability of success in securing loans.

Keywords: Housing, Race/Ethnicity, Minority, disparity, mortgage-lending, Black Disparity Index

Introduction

The accessibility of fair and equitable mortgage lending is crucial for fostering economic stability and promoting social equity. Regrettably, violations within financial institutions have persisted over time, casting doubt on the integrity of the lending process. Historical instances such as the Drexel Mortgage Corporation in 1975 and Freddie Mac's secondary-market practices in the 1990s exemplify long standing issues within the industry. Recent cases involving Chase in 2017, Citigroup in 2020, and Wells Fargo in both 2012 and 2024 (Son, H., 2023) further underscore the prevalence of such violations. All of these instances all point to the same issue – minority groups are routinely subjected to discriminatory lending practices, especially black borrowers. Racial group categorization adopted in this study aligns with definitions set by the U.S. Census Bureau. Black borrowers, or African Americans borrowers are categorized as both the descendants of enslaved people but also African and Caribbean immigrants who identify culturally or ethnically as African American.

The fundamental question arises: are these cases isolated incidents or symptomatic of systemic issues within the financial sector? Has there been tangible improvement over time with heightened regulatory scrutiny, and are there discernible geographical disparities in lending practices? This study seeks to explore these inquiries by analyzing nationwide mortgage data collected under the Home Mortgage Disclosure Act (HMDA) from lending institutions across the U.S. market. By examining this comprehensive dataset, we aim to illuminate whether instances of discrimination in mortgage lending are sporadic or indicative of systemic challenges within the industry.

Data

HMDA (CFPB, 2024) data from over 4,400 U.S. financial institutions is used in this study. It is the most comprehensive and unbiased dataset available to the public since any institutions with loan origination of 200 or more open-end lines of credit in the United States are all required to report their data, including banks, savings associations, credit unions, and mortgage companies. There are 110 data fields containing applicant and loan information, excluding credit data, to uphold privacy protection standards. The dataset includes critical borrower, loan, property, and lender information, such as demographic details, loan type and purpose, property characteristics, and occupancy status. It provides a comprehensive view of mortgage lending practices across the United States.

Methodology

Data processing

There are missing and illegitimate values such as _, / for the 110 fields in the dataset. To ensure data quality, we first removed fields with high missing rates. The remaining data was cleansed by replacing missing values with the value NA. dplyr package from R studio is the main tool employed in this step.

Exploratory Analyses - Is the disparity an isolated phenomenon?

One may argue that the discriminatory mortgage-lending practices might be institute-specific rather than systematic. That is, certain financial institutions impose additional overlays, or stricter lending standards, even on loans guaranteed by the government (e.g., FHA loans), due to concerns over potential litigation or defaults. Even though these overlays might disproportionately impact minority borrowers, the practice is institution-specific rather than industry-wide. Such overlays are often justified as business necessities to mitigate risk, which could imply that disparities arise only in isolated cases rather than being a systemic issue (Bhutta N., Hizmo A., & Ringo D, 2022).

Table 1

Denial Rate by Racial Group

HMDA Race Code	Denial Rate	Application Count %
5 - White	11.27%	85.58%
3 - Black or African American	18.90%	7.17%
2 - Asian	11.58%	6.04%
1 - American Indian or Alaska Native	17.74%	0.76%
4 - Native Hawaiian or Other Pacific Islander	16.02%	0.46%
Grand Total	11.91%	100.00%

*HMDA data , 2010-2017

Our analysis of the HMDA data from over 4,400 U.S. financial institutions can be found in Table1 above. There are only three ethnicities with credible application counts, White, Black and Asian. Denial rate for the Black Group is the highest among the three, 18.9% vs. less than 12% for the other two groups, which is 63% higher.

Exploratory Analyses - Has the gap been improved over time?

Since the Fair Housing Act was introduced in 1968, there have been several significant efforts made to mitigate disparities in mortgage lending practices especially for minority borrowers, including legislative and regulatory reforms including 2010 HMDA amendment on data collection as increased scrutiny and reporting requirements. These efforts have contributed to some progress in mitigating disparities. As indicated in a research by Atlanta Fed, the average processing time for home purchase mortgages generally decreases more drastically for Blacks and Hispanics after the year 2003 than for Asians and whites (Wei, B., Zhao, 2022).

However, does it mean that the discriminatory disadvantage for the Black group diminished?

Table 2

Denial Rate From 2010 to 2017

Application Denial Rate Comparison:

Year	Denial Rate(Black)	Denial Rate(All)	Black Disparity Index
2010	20.28%	12.68%	1.60
2011	22.20%	12.81%	1.73
2012	21.38%	12.05%	1.77
2013	20.56%	12.00%	1.71
2014	20.65%	11.97%	1.72
2015	17.67%	10.25%	1.72
2016	15.15%	9.03%	1.68
2017	15.60%	9.27%	1.68
Grand Total	**18.90%**	**11.26%**	**1.68**

Table 2 above explores denial rate for Black and for all applicants as well as the Black Disparity Index, which is defined as

Black Disparity Index = Denial Rate of Black / Denial Rate of All Applicants in the same year

Note. Index created by author.

The results show that loan rejection rates have gradually declined for all applicants, including African American applicants, since 2011. However, improvement in the Black Disparity Index was not observed until 2016, with the rate of denial for Black applicants decreasing slightly from over 70% higher than average to 68% higher compared to all applicants.

Does the disparity vary by regions?

There have been some beliefs that discrimination may vary by regions, e.g. be less prevalent in geographies where the general population displays a greater degree of racial animus (Bhutta N., Hizmo A., & Ringo D, 2024).

Our study of the collected HMDA data in Table 3 below gives mixed signals on geographic differences of the discriminatory practices for the Black group.

Table 3

Denial Rate By State

State	Denial Rate (Black)	Denial Rate (All)	Black Disparity Index	State	Denial Rate (Black)	Denial Rate (All)	Black Disparity Index
Ohio	27.60%	15.67%	1.76	Vermont	16.65%	11.10%	1.50
Pennsylvania	25.75%	12.71%	2.03	Delaware	16.60%	11.38%	1.46
New York	24.11%	14.87%	1.62	Texas	16.56%	11.17%	1.48
District of Columbia	23.45%	11.86%	1.98	Minnesota	16.31%	9.26%	1.76
West Virginia	22.78%	15.22%	1.50	Iowa	16.10%	8.21%	1.96
Michigan	22.77%	11.91%	1.91	Massachusetts	16.00%	8.07%	1.98
Illinois	22.66%	11.65%	1.94	South Dakota	15.62%	8.13%	1.92
Wisconsin	22.37%	10.32%	2.17	Arkansas	15.60%	8.87%	1.76
Nebraska	21.54%	8.26%	2.61	Mississippi	15.25%	10.15%	1.50
Florida	21.16%	14.26%	1.48	Oklahoma	15.04%	9.54%	1.58
New Jersey	21.10%	13.28%	1.59	North Dakota	14.97%	7.56%	1.98
South Carolina	20.34%	12.66%	1.61	Montana	14.71%	8.57%	1.72
Indiana	19.71%	11.86%	1.66	New Mexico	14.54%	13.48%	1.08
Connecticut	19.66%	12.05%	1.63	California	14.34%	10.46%	1.37
Rhode Island	19.32%	10.58%	1.83	New Hampshire	14.25%	10.56%	1.35
Georgia	18.90%	12.00%	1.57	Alaska	13.40%	9.05%	1.48
North Carolina	18.76%	11.82%	1.59	Washington	13.37%	9.43%	1.42
Kentucky	18.41%	12.86%	1.43	Colorado	13.33%	9.10%	1.47
Maryland	18.08%	11.11%	1.63	Nevada	13.15%	10.94%	1.20
Virginia	17.65%	10.35%	1.71	Oregon	13.14%	10.16%	1.29
Missouri	17.53%	8.78%	2.00	Arizona	12.24%	9.62%	1.27
Alabama	17.52%	10.83%	1.62	Idaho	12.04%	10.79%	1.12
Louisiana	17.44%	10.78%	1.62	Utah	11.99%	8.92%	1.34
Tennessee	17.44%	9.98%	1.75	Wyoming	10.61%	9.05%	1.17
Kansas	16.88%	9.21%	1.83	Hawaii	9.82%	10.63%	0.92
Maine	16.71%	11.35%	1.47				
				Grand Total	**18.90%**	**11.26%**	**1.68**

Nebraska, Wisconsin, Pennsylvania and Missouri are the states with high Black Disparity Index. They all exhibit some degree of racial animus, the level of which often correlates with urban versus rural distinctions and is affected by historical context, socioeconomic conditions, and population diversity. For example, Wisconsin is a state with considerable racial disparities, especially in urban areas like Milwaukee, which has been reported to have some of the highest levels of Black-White segregation in the United States.

Although Wisconsin's larger cities may be politically progressive, the state's rural areas often exhibit more conservative racial attitudes.

New Mexico, Hawaii and Nevada belong to the group with lowest Black Disparity Index. We believe that high population diversity and inclusion policies, strong anti-discrimination laws and active fair housing and lending initiatives contribute to the relatively benign mortgage-lending practices for African American ethnicity.

States like New Jersey, Georgia and Maryland exhibit moderate Black Disparity Index. This could reflect mixed influences—diversity and anti-discrimination efforts may reduce some bias, while persistent socioeconomic disparities maintain a moderate level of denial disparity.

Our analysis does not suggest a direct correlation between the degree of racial animus and the disparity index in mortgage-lending practices. Southern U.S. regions are the ones traditionally associated with high levels of racial animus, such as Mississippi, Louisiana, Alabama, Georgia, and South Carolina. Their Black Disparity Index is relatively moderate though.

A More Holistic Examination of the Problem

Despite the above evidence of persistent and systematic discriminatory lending practices, even with regulatory efforts in place, some may argue that observed disparities in mortgage denial rates are largely due to economic factors such as financial status rather than outright discrimination. To address this perspective, our study delved deeper by incorporating advanced machine learning (ML) methods to analyze these disparities more comprehensively. Machine Learning techniques are proven to be effective in this kind of study since they involve the use of mathematical and computational methods to process vast amounts of data and make predictions. Logistic regression model out of the machine learning field is chosen in this research.

Logistic regression is a statistical method used for binary classification tasks to predict the probability that an instance belongs to a particular class. During the training process, the model's parameters (coefficients) are estimated using techniques such as maximum likelihood estimation, i.e. finding the parameter values that maximize the likelihood of observing the actual outcomes given the predictor variables.

In this study, a logistic regression model is trained and tested on the 2017 HMDA data.

Methodology

Data processing

The model training dataset is the 2017 HMDA dataset obtained from the Consumer Financial Protection Bureau (CFPB), consisting of 14 million records. To ensure the data's quality and relevance for modeling, fields with high rates of missing values or those likely to introduce information leakage, such as loan pricing details and purchase type (e.g., loans related to secondary mortgage market investors or aggregators like Fannie Mae), were excluded. Information leakage, in this context, refers to inadvertently including future or external data in the training process, leading to overly optimistic model performance estimates. Excluding these fields ensured that the model predictions remained accurate and generalizable.

For interpretability, we reclassified some fields. For example, races like American Indian, Native Hawaiian were grouped as "Others".

Encoding

We use one-hot encoding technique for categorical variables. It is a method of representing categorical variables as binary vectors, where each category is represented by a vector of binary values. For example, the race of African American is encoded as 1 while all other races are set to 0.

Feature Engineering and Feature Selection

Logarithm transformations are performed for all features in order to improve the model performance and to meet the assumptions of the model.

Univariate Feature Selection via exploratory data analysis and Forward/Backward Stepwise Selection are employed for feature selection where adding or removing features from the model based on their individual contributions to model performance.
Model Building

The dataset is randomly split into two parts, where 70% of the records are used to train the model while the rest 30% are used for testing. The training dataset contains 9.8 million records. Logistic regression model using Maximum Likelihood Estimation objective function (finding the parameter values that maximize the likelihood of observing the given data) and logit link function is built on the training data as seen in Figure 1 below.

Figure 1
Logistic Model Specification

Note. Figure created by author.

Programming Language

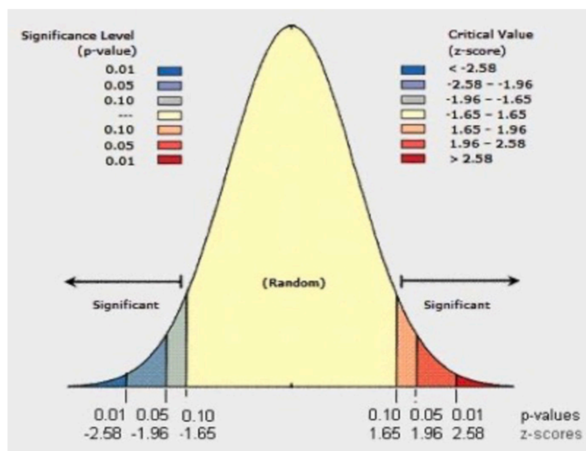
We used R for both data processing and model building. The packages employed include tidyverse and dplyr for data processing, gbm, rpart, caret and pROC for modeling building and evaluation.

Statistical Analyses

We used two main metrics - Area under the curve (AUC) and Receiver Operating Characteristic curve (ROC) to evaluate the model performance in terms of its ability to correctly classify instances into the appropriate classes, i.e. to segment loan rejections vs. approvals in the study. AUC values close to 1 indicate the model can distinguish between loan rejections and approvals very well, while a value around 0.5 suggests that the model is not able to discriminate between the classes effectively and is performing no better than random guessing. AUC is calculated using the trapezoidal rule. It is a simple numerical integration method that approximates the area under the ROC curve by summing the areas of trapezoids formed by adjacent points on the curve.

The other metrics used are coefficients of predictors, Z score and P value. Coefficients in the context of this study represents the change in the log odds of loan rejections associated with a one-unit change in the predictor variable, holding other variables constant. The Z-score for each coefficient is calculated as the coefficient divided by its standard error. It measures how many standard deviations the coefficient estimate is from zero. It helps assess the significance of each predictor variable's contribution to the model. Large Z-scores (in absolute value) indicate that the corresponding coefficient is significantly different from zero, suggesting that the predictor variable has a strong influence on the outcome. P value probability of obtaining test results at least as extreme as the result observed in null-hypothesis significance testing. The p-value is calculated from the Z-score using the standard normal distribution. When p-value is less than 0.01, we are 99% confident to reject the null hypothesis which claims no disparity for minorities in mortgage-lending as seen in the Figure 2 below.

Figure 2
Z Score and P Value



Note. Figure adapted from ArcMap Documentation. (Desktop.arcgi, ArcMap 10.8)

Variables Selected

We employed both forward and backward selection techniques to select features for the logistic regression model, guided by statistical significance (p-value threshold of 0.01). Final selection variables are Gender, Income level, Loan Amount, Loan Purpose, Loan Type, Loan-amt-to-income ratio, Occupancy Type, Property Type, Race group and state.

Model Selection

In developing our logistic regression model, we tested multiple specifications, each incorporating different model selection included goodness-of-fit measures, interpretability, and predictive power across training and testing datasets. Each model specification was assessed using metrics such as Area Under the Receiver Operating Characteristic Curve (AUC), which allowed us to evaluate the trade-offs between complexity and performance, with the goal of selecting a generalizable model that avoided overfitting while maintaining high predictive accuracy.

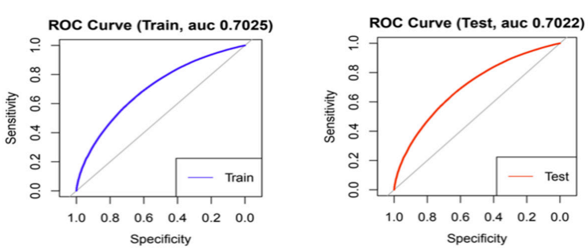
The final model was chosen based on its ability to balance interpretability and predictive strength, demonstrating consistent AUC and ROC curve results between training and testing datasets. This consistency indicated robust generalization and ensured that the model performs well on new data. Additionally, the inclusion of key interaction terms further enhanced the model's explanatory power with deeper insights into the relationships between variables.

Results

ROC Curve and AUC

Figure 3

Final ROC Curve and AUC



Our logistic regression model observes consistent and decent AUC results between training and testing datasets, which indicate a strong generalization capability of the model. This stability suggests that the model is not overfitting, as it performs similarly well on new, unseen data. It also implies that the model's predictive power is robust. Hence, we are able to confidently conclude that significant systemic racial disparities exist for Black borrowers within the mortgage lending process, even after controlling for economic factors such as income and loan amount.

The model's odds ratio for Black borrowers relative to White borrowers is 1.69, meaning Black borrowers are 69% more likely to have their loan applications declined compared to White borrowers. Furthermore, our statistical analysis, which employed Z-scores and corresponding P-values below 0.01, confirmed statistically significant disparities affecting minorities in mortgage lending practices. This statistical confirmation highlights that the observed differences are unlikely to be due to random variation and is a strong indicator of underlying inequities in the lending process for minority groups.

Mortgage Loan Approval Predictor (MoLAP) Application

Leveraging insights from our predictive models and research findings on fBISG (Imai, K., Olivella, S., & Rosenman, E., 2022), we developed a MoLAP application to aid borrowers, particularly those from African American communities, in understanding mortgage lending requirements and improving their chances of approval. Borrowers can use the tool to effortlessly monitor important factors affecting loan approval probability and optimize their loan applications. With just a few clicks, underserved borrowers can navigate through the tool, gaining insights and recommendations tailored to their specific circumstances. MoLAP represents a significant step towards creating a more equitable and inclusive mortgage lending environment. It empowers individuals to overcome barriers and achieve their homeownership goals. The MoLAP application demonstrated its utility in providing borrowers with actionable insights to optimize their loan applications, thereby increasing their chances of securing a mortgage loan.

Discussion

The results from our analysis highlight the critical need to tackle systemic inequities present within mortgage lending procedures and to foster lending practices that are fair and inclusive. The MoLAP application marks a substantial advancement toward enabling borrowers from underserved communities and enhancing transparency in loan processing. Nonetheless, additional initiatives are essential to drive significant reforms and expand inclusivity across the mortgage lending sector. Such efforts should involve advocating for new legislative and regulatory actions to mitigate discriminatory practices, alongside promoting diversity and inclusion within lending institutions.

Conclusion

Our analysis using HMDA data from 2010 to 2017 confirms the persistence of on-going racial disparities within mortgage lending, particularly affecting African-American borrowers. The enduring presence is a reminder that disparity in this sector remains unresolved. By developing the MoLAP application, we aim to provide underserved borrowers with valuable insights and tools to navigate the mortgage application process more effectively. The tool leverages advanced predictive modeling and findings from fBISG to deliver customized guidance. It is a modest yet significant step toward a more equitable mortgage lending system.

The findings underscore the limited effectiveness of traditional fair lending regulations in fully addressing these disparities. Thus, while MoLAP enhances borrower empowerment, substantial progress will require broader, systemic efforts. Policies aimed at closing the observed credit risk gaps, possibly through improved risk assessment methods and targeted legislative reform, may prove more effective in reducing racial inequities in mortgage access. These collective efforts, both regulatory and technological, will be critical to achieving a transparent and inclusive lending landscape for all applicants moving forward.

Reference

Bhutta N., Hizmo A., & Ringo D., Federal Reserve Board. (2022), How Much Does Racial Bias Affect Mortgage Lending? Evidence from Human and Algorithmic Credit Decisions, https://www.federalreserve.gov/econres/feds/files/2022067pap.pdf

Bhutta N., Hizmo A., Ringo D. (2024), How Much Does Racial Bias Affect Mortgage Lending? Evidence from Human and Algorithmic Credit Decisions https://www.philadelphiafed.org//media/frbp/assets/working-papers/2024/wp24-09.pdf

Download HMDA data. (n.d.). Consumer Financial Protection Bureau. Retrieved March 11, 2024, from https://www.consumerfinance.gov/data-research/hmda/historic-data/

Imai, K., Olivella, S., & Rosenman, E. (2022). Addressing census data problems in race imputation via fully Bayesian Improved Surname Geocoding and name supplements. Science Advances, 8(49), eadc9824. https://doi.org/10.1126/sciadv.adc9824

Son, H. (2023, December 11). Regulators caught Wells Fargo, other banks in probe over mortgage pricing discrimination, https://www.cnbc.com/2023/12/11/wells-fargo-mortgage-lenders-probed-over-racial-discrimination.html

Wei, B., Zhao, F., Federal Reserve Bank of Atlanta. (2022). Racial Disparities in Mortgage Lending: New Evidence Based on Processing Time https://www.atlantafed.org/-/media/documents/research/publications/wp/2022/01/13/01--racial-disparities-in-mortgage-lending--new-evidence-based-on-processing-time/full-text.pdf

What is a z-score? What is a p-value? – ArcMap Documentation. (n.d.). Desktop.arcgi https: //desktop.arcgis.com/en/arcmap/latest/tools/spatial-statistics-toolbox/what-is-a-z-score-what-is-a-p-value.htm