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Exploring Gender and Racial Disparities in Mortgage Pricing: A Comprehensive Analysis of Risk-Based Lending Practices

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ABSTRACT

Objective - This study examines whether risk-based mortgage pricing in the U.S. is neutral with respect to borrower gender and race/ethnicity, and whether any observed pricing gaps persist after controlling for borrower credit risk and loan characteristics using a nationally representative dataset.
Methodology/Technique – Using the National Survey of Mortgage Originations (NSMO) Public Use File covering originations from 2013–2020, we evaluate demographic disparities in mortgage rate spreads and default outcomes through a unified empirical framework. Specifically, we employ exact matching and propensity score matching to compare observably similar borrowers, interaction regression models to test whether standard risk factors are priced differently across demographic groups, and residual-based diagnostics to assess unexplained pricing components after conditioning on observable risk factors.
Finding – Across methods, female borrowers face higher mortgage rate spreads than comparable male borrowers, despite exhibiting similar or lower observed default risk. Racial disparities are more nuanced: Black and Hispanic borrowers exhibit higher raw loan costs and higher default rates, but conditional rate-spread differences largely attenuate after controlling for observable risk factors, whereas Asian borrowers consistently receive more favorable pricing. Interaction effects indicate that the marginal pricing of key risk variables differs across demographic groups, and residual analysis highlights a persistent unexplained gender pricing component.
Novelty – The paper contributes by combining a uniquely rich dataset that links borrower demographics with detailed credit quality and performance measures and by integrating matching, interaction modeling, and residual diagnostics within one unified framework to evaluate both level differences and differential marginal pricing in mortgage rates.

Type of Paper: Empirical
JEL Classification: G21; G28; C21; D63; J15
Keywords: Mortgage Pricing; Demographic Disparities; Gender Bias; Racial Bias; Machine Learning; Fair Lending; Propensity Score Matching; Financial Regulation; Credit Risk; Algorithmic Fairness

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1. Introduction

Advancements in machine learning and data analytics have revolutionized the financial industry, particularly in mortgage lending. Banks and financial institutions increasingly rely on sophisticated risk-based pricing models to evaluate borrowers' creditworthiness and set interest rates that reflect the perceived risk of default (Kau et al., 2019).

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These models consider numerous variables, thereby enabling a more accurate and individualized approach to mortgage pricing. However, despite these technological advancements, systemic biases and disparities in mortgage lending practices remain a persistent concern, particularly along lines of gender and race (Wyly & Ponder, 2011) (Nickerson, 2022). Research has shown that minority borrowers often face disproportionately higher mortgage costs, as structural inequalities embedded within data and algorithms exacerbate these disparities (Smith & Daniels, 2018) (Deng & Gabriel, 2006).

Moreover, while risk-based pricing models aim to be objective, flaws in underlying data or modeling techniques can unintentionally perpetuate these biases. Studies continue to highlight disparities in loan approval rates and interest rates across demographic groups (Bartlett et al., 2022) (Bhutta & Hizmo, 2021), but they often suffer from limited control of confounding variables, a narrow focus on isolated aspects of lending, or reliance on incomplete datasets. Critical factors like detailed credit profiles and loan performance metrics are frequently missing, hindering a comprehensive understanding of systemic biases. Additionally, the complex interactions between demographic characteristics—such as gender, race, and ethnicity—are often inadequately addressed. These gaps underscore the urgent need for both advancements in technological frameworks and updates to regulatory policies to ensure fairness and equity in mortgage lending (Gerardi et al., 2023).

Our study aims to address these gaps by leveraging the comprehensive dataset from the National Survey of Mortgage Originations (NSMO), which uniquely integrates borrower demographics, such as gender and race, with detailed credit-quality and loan-performance metrics. Unlike commonly used datasets such as the Home Mortgage Disclosure Act (HMDA) data, which include demographic information but lack credit scores and loan performance details (Avery et al., 2007) (Bhutta & Hizmo, 2021) (Loya, 2023a) (Loya, 2023b) (Loya, 2024), or Fannie Mae and Freddie Mac datasets, which provide extensive performance data but exclude demographic variables (Bocian et al., 2008) (Liang & Zhao, 2024). The NSMO provides a comprehensive overview of the mortgage lending process. This richness enables us to overcome key limitations in prior research and provides a robust foundation for examining disparities in mortgage lending practices.

By employing advanced analytical techniques, including machine learning models and propensity score matching, we explore whether risk-based pricing in mortgage lending is genuinely neutral with respect to gender and race. Specifically, we aim to identify and quantify any disparities in mortgage costs and default rates that cannot be explained by traditional risk factors, such as credit quality or loan characteristics.

Our research makes a significant contribution to the discourse on equity in financial services by providing a nuanced and data-rich analysis of how demographic factors influence mortgage outcomes. The findings offer critical insights for policymakers, regulators, and industry stakeholders, providing evidence to promote fair lending practices and mitigate systemic biases in the mortgage market. By addressing the limitations of prior studies and utilizing a uniquely comprehensive dataset, this study underscores the importance of integrating demographic and performance data to ensure fairness in mortgage lending.

To clarify the paper's contributions, we emphasize three ways this study advances the literature. First, we exploit the National Survey of Mortgage Originations (NSMO), which uniquely links borrower demographics to detailed credit quality and subsequent loan performance, enabling a cleaner separation of pricing differences from realized default risk. Second, we develop a unified empirical framework that triangulates disparities using exact matching, propensity score matching, interaction regression, and residual-based diagnostics, thereby allowing us to assess both average gaps and heterogeneous pricing across risk factors. Third, we document a robust gender-related pricing gap: women face higher rate spreads even when they exhibit equal or lower default risk than comparable men; racial patterns are more nuanced, including systematically favorable pricing for Asian borrowers.

We next situate these empirical patterns in the broader literature on discrimination and algorithmic decision-making.

2. Literature Review

A large empirical literature documents demographic disparities in mortgage markets, including differences in approval rates, pricing, and loan performance. Commonly used sources, such as HMDA data, provide broad coverage and demographic information but lack key risk variables, such as credit scores and detailed performance outcomes, which can obscure whether observed pricing gaps reflect differential treatment or unobserved risk. Prior work, therefore, often relies on partial controls or indirect proxies. By contrast, the NSMO combines demographic characteristics with credit-quality measures and subsequent performance, enabling a more direct comparison of mortgage pricing and default outcomes among borrowers that are observable and similar.

Conceptually, several mechanisms can generate demographic differences in loan pricing. In taste-based discrimination, lenders (or agents within lending institutions) may be willing to pay a cost to avoid transacting with certain groups, leading to higher prices for otherwise comparable borrowers (Becker, 1957). In statistical discrimination, group membership can enter pricing as a proxy for unobserved risk when lenders face imperfect information, so differences may persist even after extensive controls if some relevant risk factors remain unobserved (Phelps, 1972) (Arrow, 1971). More recently, algorithmic and machine learning-based underwriting can reproduce or amplify disparities when models are trained on historical outcomes, incorporate proxy variables, or optimize objectives that do not directly encode fairness considerations (Barocas & Selbst, 2016). Fairness frameworks such as equality of opportunity emphasize that prediction errors and decision thresholds should be comparable across groups, which may be violated even when models appear accurate on average (Hardt et al., 2016).

This conceptual framing guides our empirical design. Matching and propensity score methods compare borrowers with similar observable risk profiles to test whether pricing differences remain after conditioning on key financial characteristics. Interaction regressions examine whether lenders' pricing of standard risk factors (e.g., CLTV, DTI, income, and credit scores) differs across demographic groups, consistent with heterogeneous risk weights or differential treatment. Finally, residual-based diagnostics quantify the portion of rate spreads not explained by observable risk factors, which is informative about persistent gaps but must be interpreted cautiously because it may reflect both unmeasured risk and potential discrimination or algorithmic bias.

3. Methodology

To better analyze the complex interplay between gender and racial disparities in mortgage lending practices, this study employs data from the National Survey of Mortgage Originations (NSMO). The Public Use File (PUF) provided by NSMO encompasses information on loans originated from 2013 through 2020. This dataset includes comprehensive details on loan characteristics, borrower demographics, loan performance, and financial metrics, enabling in-depth analysis of mortgage lending practices across demographic groups.

Panel A of Table 1 presents summary statistics for key variables segmented by gender and race. The average Credit scores (VantageScore 3.0 score) exhibit notable differences across racial groups: Asian borrowers have the highest average score (761.02), followed by White borrowers (743.32), while Black borrowers have the lowest average Credit score (702.74). Income levels also vary significantly, with Asian borrowers reporting the highest average income ($129,590), whereas Black and Hispanic borrowers report lower average incomes ($96,240 and $96,250, respectively).

Rate spreads and default rates further highlight racial disparities. Black borrowers face the highest default rate (2.972%) and higher average rate spreads (0.226%) compared to White borrowers, who have a default rate of 0.786% and a rate spread of 0.194%. Hispanic borrowers also experience elevated default rates (1.264%) and rate spreads (0.214%) relative to White and Asian borrowers.

Panel B of Table 1 uncovers disparities in the types of mortgage loans and features utilized by different demographic groups. Notably, Black and Hispanic borrowers have higher engagement rates with government-sponsored enterprise (GSE) loans, which are typically designed to facilitate homeownership among lower-income families. Furthermore, the use of adjustable-rate mortgages is disproportionately high among Asians, suggesting greater tolerance for or preference for variable borrowing costs.

The disparities highlighted in Panels A and B underscore a complex array of factors influencing mortgage lending and financial health across different demographic groups. These disparities may reflect broader socioeconomic conditions, such as historical inequalities in access to credit, differences in financial literacy, and varying levels of trust in financial institutions.

Figure 1 illustrates variations in default rates and rate spreads across borrower credit scores for each demographic group. While males and females exhibit similar rate spreads across credit score ranges, Black and Hispanic borrowers consistently face higher default rates and loan costs compared to White and Asian borrowers, suggesting the persistence of racial inequities even among borrowers with comparable credit profiles.

In addition to credit scores, supplementary analyses in Appendix Figures A1–A4 demonstrate that the patterns of demographic disparity in mortgage pricing persist across key financial dimensions. Specifically, higher CLTV (Appendix A1) and DTI ratios (Appendix A3) are associated with higher rate spreads and default rates across all groups, whereas larger loan amounts (Appendix A2) and higher income levels (Appendix A4) are associated with lower costs and risks. However, across all dimensions, female, Black, and Hispanic borrowers consistently experience less favorable pricing outcomes than male, White, and Asian borrowers with similar financial characteristics, thereby reinforcing the robustness of the main findings.

4. Results and Discussion

4.1 Exact Matching

To better understand whether the observed disparities are driven by differences in borrower characteristics or other factors, we conducted exact matching analyses to isolate the impact of demographic attributes while controlling for multiple financial variables. While Figure 1 considers only credit score, our matching analyses incorporate a broader range of characteristics, including the Combined Loan-to-Value (CLTV) ratio, Debt-to-Income (DTI) ratio, income level, and loan amount, thereby enabling comparisons between borrowers with similar profiles. Female borrowers were matched with male borrowers with comparable financial characteristics, and, in cases of multiple matches, one male borrower was randomly selected for each female borrower to ensure unique pairs and reduce bias; a similar approach was applied to race matching.

Table 2 presents the results of exact matching analyses. In the gender-matching (Panel A), females have a slightly higher rate spread (0.01%, p-value = 0.02) and a lower default rate than males, although the difference in default rates is not statistically significant.

In the racial matching (Panel B), differences in rate spreads between minority groups and White borrowers are generally small and not statistically significant for Black and Hispanic borrowers. However, Asian borrowers receive more favorable terms, with a significantly lower rate spread compared to White borrowers (difference of -0.04%, p-value < 0.01), suggesting preferential pricing even when matched on key financial variables.

4.2 Propensity Score Matching

In addition to exact matching, we conduct propensity score matching (PSM) as a complementary approach to validate our findings. While exact matching requires borrowers to have identical financial characteristics, this method often reduces sample size and representation, potentially overlooking subtle differences. PSM addresses these limitations by estimating the probability of group membership (e.g., gender or race) from covariates, thereby enabling the creation of balanced samples with more observations. By controlling for multiple covariates simultaneously, PSM effectively reduces confounding and enhances robustness. The combination of both methods strengthens our analysis, ensuring consistency and reinforcing the validity of the results.

We estimate the propensity score P(X)P, defined as the probability of belonging to a treatment group (e.g., a specific racial group), given covariates X, using logistic regression:

$$P(X) = \frac{e^{(\alpha_0 + \sum \alpha_i X_i)}}{1 + e^{(\alpha_0 + \sum \alpha_i X_i)}}$$

Borrowers from different demographic groups are matched based on their propensity scores using the nearest neighbor method, minimizing the distance between propensity scores to create comparable groups.

The results of the propensity score matching analysis are presented in Table 3. Panel A shows that female borrowers have a higher mean rate spread (0.223%) compared to male borrowers (0.199%), with the difference being statistically significant (t-statistic = 3.897, p-value < 0.001). This finding aligns with the results from exact matching (Table 2A), further supporting the robustness of the observed gender disparity.

Panel B of Table 3 examines racial groups and shows that Asian borrowers have a significantly lower mean rate spread (0.110%) compared to White borrowers (0.145%), with a statistically significant difference (t-statistic = -2.209, p-value = 0.027). However, the differences in rate spreads between Black or Hispanic borrowers and White borrowers are not statistically significant, suggesting that observable financial characteristics may account for these disparities in rate spreads.

4.3 Interaction Effects Analysis

To assess the differential impact of financial variables on mortgage rate spreads across gender and race, we employ two separate linear regression models with interaction terms.

$$Y = \beta_0 + \beta_1\, Gender + \beta_2\, Race$$

$$+ \sum (\beta_{3i}\, FinancialVariable_i \,+\, \beta_{4i}\, Gender \,\times F\text{inancialVariable}_i) \,+ \epsilon \quad (1)$$

$$Y \,=\, \beta_0 \,+\, \beta_1\, Gender \,+\, \beta_2\, Race$$
$$+ \sum (\beta_{3i}\, FinancialVariable_i \,+\, \beta_{4i}\, Race \times F\text{inancialVariable}_i) \,+ \epsilon \qquad (2)$$

Where:

- Y represents the mortgage rate spread.
- **Gender** and **Race** are control variables.
- $FinancialVariable_i$ represents individual financial predictors such as CLTV, income, loan amount, DTI, and Credit scores.
- $Gender \,\times F\text{inancialVariable}_i$ are interaction terms that show how the effect of financial variables on rate spread varies by gender.
- ϵ is the error term.

Model 1 (Panel A, Table 4) examines gender interactions, while Model 2 (Panel B, Table 4) focuses on racial interactions. Significant interaction terms, tested using t-tests, indicate differential effects of financial variables on rate spreads by demographic group.

In Panel A of Table 4, the gender interaction model examines how financial variables interact with gender to influence mortgage rate spreads. The results indicate that the impact of some financial factors on rate spreads varies by gender. For instance, the interaction between gender (female) and CLTV is negative and significant (coefficient = -0.001, $p < 0.01$), indicating that as CLTV increases, the rate spread rises less for females than for males. Similarly, the interaction between gender and income is negative and significant (coefficient = -0.000, $p<0.01$), suggesting that higher income levels lead to a greater reduction in rate spreads for females than for males. In contrast, the interaction between gender and loan amount is positive and significant (coefficient = 0.000, $p < 0.001$), indicating that as loan amounts increase, the rate spread increases more for females than for males. These findings reveal that, although females may face slightly higher rate spreads overall, certain financial factors, such as higher income and CLTV, can mitigate these disparities.

In Panel B of Table 4, the race interaction model evaluates how financial variables interact with race to influence mortgage rate spreads. The results reveal significant differences in how financial factors affect borrowers across racial groups. For Black borrowers, the interaction between race (Black) and CLTV is negative and significant (coefficient = -0.003, $p < 0.001$), indicating that as CLTV increases, the rate spread declines less for Black borrowers than for White borrowers. This finding suggests that Black borrowers may face less severe penalties for higher CLTV ratios. In contrast, for Asian borrowers, the interaction between race (Asian) and CLTV is positive and significant (coefficient = 0.003, $p < 0.001$), indicating that as CLTV increases, the rate spread increases more for Asian borrowers than for White borrowers. Additionally, the interaction between race (Asian) and DTI is positive and significant (coefficient = 0.003, $p < 0.01$), suggesting that higher DTI ratios are associated with larger increases in rate spreads for Asian borrowers than for White borrowers.

Beyond documenting statistically significant interaction terms, the results have substantive implications for how pricing models translate risk into interest rate spreads across groups. In a standard risk-based pricing framework, the "same" financial characteristic should carry a similar marginal pricing penalty for observationally similar borrowers unless lenders or models intentionally apply different weights, or unless the characteristic proxies differently for unobserved risk across groups. The interaction patterns, therefore, give rise to three non-mutually exclusive interpretations.

First, the interaction terms may reflect differences in **algorithmic weighting** or underwriting rules that are implicitly group-contingent, even when group indicators are not explicitly used. In practice, machine-learning or rule-based models can embed group differences through correlated proxies, nonlinearities, or threshold effects. If features such as CLTV, DTI, or loan amount are used in ways that interact with other borrower or product characteristics correlated with gender or race, the model's effective marginal pricing of these variables can differ across groups even without conditioning on protected-class status. Under this interpretation, the interaction coefficients provide evidence that the mapping from observables to prices is not uniform across groups and may raise concerns about model governance, feature engineering choices, and transparency in automated pricing systems.

Second, the interaction terms may reflect **lender behavior or market structure**, including differential product steering, negotiation dynamics, or differential reliance on "soft information." Even when CLTV or DTI are measured identically, lenders may perceive risk differently across groups due to institutional practices, differential documentation, or the use of additional signals not captured in the dataset. If unobserved contract features or pricing adjustments (e.g., discount points, fees rolled into rates, rate-lock terms, or broker-related add-ons) vary systematically across groups, then interaction patterns can emerge because the observed covariates correlate differently with these unobserved pricing components.

Third, the results may be consistent with **statistical discrimination**, in that lenders treat certain observable variables as more informative about default or prepayment risk for some groups than for others. For example, a higher DTI might be interpreted as more predictive of repayment stress in one group if lenders believe income volatility or liquidity buffers differ, even if those beliefs are imperfect or shaped by historical data. This interpretation emphasizes that differential marginal pricing is meaningful because it implies different "risk translation rules," which can generate disparate outcomes even when average rates are similar after controls.

Importantly, these interpretations have different policy implications. If interaction patterns reflect model design choices or proxy-driven weighting, then transparency, auditing, and governance of automated pricing systems become central. If they reflect steering or negotiation, consumer protection and enforcement targeting origination practices may be more effective. In either case, the interaction estimates help move beyond mean differences to show that disparities may arise through the **structure of pricing**, not only through average pricing levels.

These findings indicate that the relationship between financial variables and mortgage pricing varies significantly by race, pointing to potential differential treatment or systemic factors affecting minority borrowers. Overall, the interaction terms underscore that both gender and race play a critical role in shaping how financial variables impact mortgage rate spreads, highlighting disparities that suggest unequal treatment across demographic groups.

4.4 Residual Analysis

To investigate whether the disparities in mortgage rate spreads are fully explained by financial characteristics or if additional unobserved factors contribute, we conduct a residual analysis. This approach helps isolate the portion of rate spreads not accounted for by observable financial variables, providing insights into potential systemic biases or unmeasured influences. The regression model excludes race and gender, allowing us to focus on the unexplained components:

$$\mathrm{Y} = \beta_0 + \sum(\beta_i \mathrm{FinancialVariable_i}) + \epsilon$$

Where:

- Y is the mortgage rate spread.
- $FinancialVariable_i$ includes predictors such as CLTV, income, loan amount, DTI, and Credit scores.
- ϵ_i represents the residuals or the unexplained portion of the mortgage rate spread after accounting for the financial variables.

Residuals (ϵ_i) are calculated as:

$$\epsilon_i = Y_i - \widehat{Y_i}$$

where $\mathrm{Y_i}$ is the predicted rate is spread based on the regression model. We then compare mean residuals across gender and racial groups to identify potential disparities not attributable to financial factors. Results are summarized in Table 5.

In Panel A of Table 5, the analysis shows that the mean residual for females is 0.0128, which is significantly higher than that for males (-0.0102). The t-statistic of 4.283 ($p < 0.001$) confirms that this difference is statistically significant. This suggests that females experience a higher unexplained rate spread than males after controlling for financial variables, pointing to potential non-financial contributors to the observed disparities.

In Panel B of Table 5, the mean residuals across racial groups do not differ significantly from those of White borrowers. These results suggest that, after accounting for financial variables, there is no significant unexplained difference in rate spreads across racial groups in the residuals. However, given the persistent disparities in rate spreads and default rates, unobserved factors or systemic issues may contribute to these differences.

The residual analysis is informative because it isolates the portion of rate spreads not explained by the observed risk factors included in the baseline pricing model. The finding of a persistent positive, unexplained component among female borrowers is particularly important because it is consistent with a pricing wedge that persists after conditioning on standard measures of borrower risk and loan structure. Substantively, this "unexplained" component can arise from at least three channels.

One channel is unobserved contract terms and price components that are not fully captured by the spread measure or by the covariates used in the regression. For example, lenders may adjust pricing through points and fees, discounting practices, broker compensation, or rate-lock terms, and these may vary systematically across borrowers. If such terms differ by gender and are correlated with the observed spread, they can generate residual differences even when observable risk is similar.

A second channel is differential treatment or negotiation dynamics during origination. Mortgage pricing frequently involves some scope for discretion, and if bargaining power, search costs, or the quality of financial advice differ systematically, outcomes can differ even with identical risk profiles. Under this interpretation, the residual gap highlights potential frictions relevant to consumer protection policies, disclosure requirements, and oversight of intermediary practices.

A third channel is algorithmic or statistical discrimination, where models trained on historical outcomes or institutional data encode patterns that produce systematically different pricing for observationally similar borrowers. This can occur through proxies and interactions that effectively shift pricing, even when protected-class variables are omitted. In this sense, the residual gap does not by itself prove discrimination, but it is consistent with concerns that pricing models may amplify historical inequities or incorporate group-correlated signals in ways that generate disparate outcomes.

These mechanisms also clarify why the residual results matter for policy. If unexplained gender pricing differences persist in settings where default risk is not higher, then purely "risk-based" justifications become less compelling, and stronger emphasis may be warranted on (i) model audits and documentation of pricing drivers, (ii) routine disparate-impact monitoring, and (iii) supervisory attention to discretionary pricing channels and add-on charges. At the same time, because residual differences may reflect omitted risk or product features, the results should be interpreted as evidence of persistent, unexplained disparities rather than definitive causal evidence of discrimination.

Taken together, the interaction and residual analyses suggest that disparities may operate not only through average pricing differences but also through the way underwriting systems convert risk signals into prices. This distinction is important for the oversight of automated underwriting and pricing tools: monitoring only average rate gaps can miss disparities arising from differential marginal pricing or persistent, unexplained components. These findings, therefore, motivate regulatory attention to model governance and transparency, including documentation of feature impacts, stability checks across demographic groups, and monitoring for disparate impact at both the level and marginal effects of pricing.

5. Conclusion

Using the National Survey of Mortgage Originations (2013-2020), we evaluate whether risk-based mortgage pricing is neutral with respect to borrower gender and race. Across exact matching, propensity score matching, interaction regressions, and residual diagnostics, female borrowers face higher rate spreads than comparable male borrowers, even when their observed default risk is like or lower than that of male borrowers. Racial disparities are more nuanced: Black and Hispanic borrowers exhibit higher default rates and higher raw loan costs, but rate-spread differences largely attenuate after conditioning on observable risk factors, whereas Asian borrowers consistently receive more favorable pricing.

Interpreted through the lenses of taste-based discrimination, statistical discrimination, and algorithmic bias, these patterns are consistent with either differential treatment or differential use of information across groups. The interaction models indicate that standard risk factors can be priced differently across demographic groups, and the residual analysis highlights a persistent unexplained gender pricing component. At the same time, residual differences may also reflect unmeasured risk factors or contractual features not observed in the data, so the evidence should be interpreted cautiously.

The paper contributes by combining a uniquely rich dataset with a unified empirical framework that can be applied to other credit markets. From a policy perspective, the results underscore the importance of transparency in pricing models, routine monitoring for disparate impact, and continued enforcement of fair-lending rules, particularly as automated underwriting and pricing tools become more prevalent. Future work could incorporate lender-level identifiers, more granular product features, and model-level information to better distinguish discrimination from omitted risk.

Competing Interests

The authors declare that they have no competing interests.

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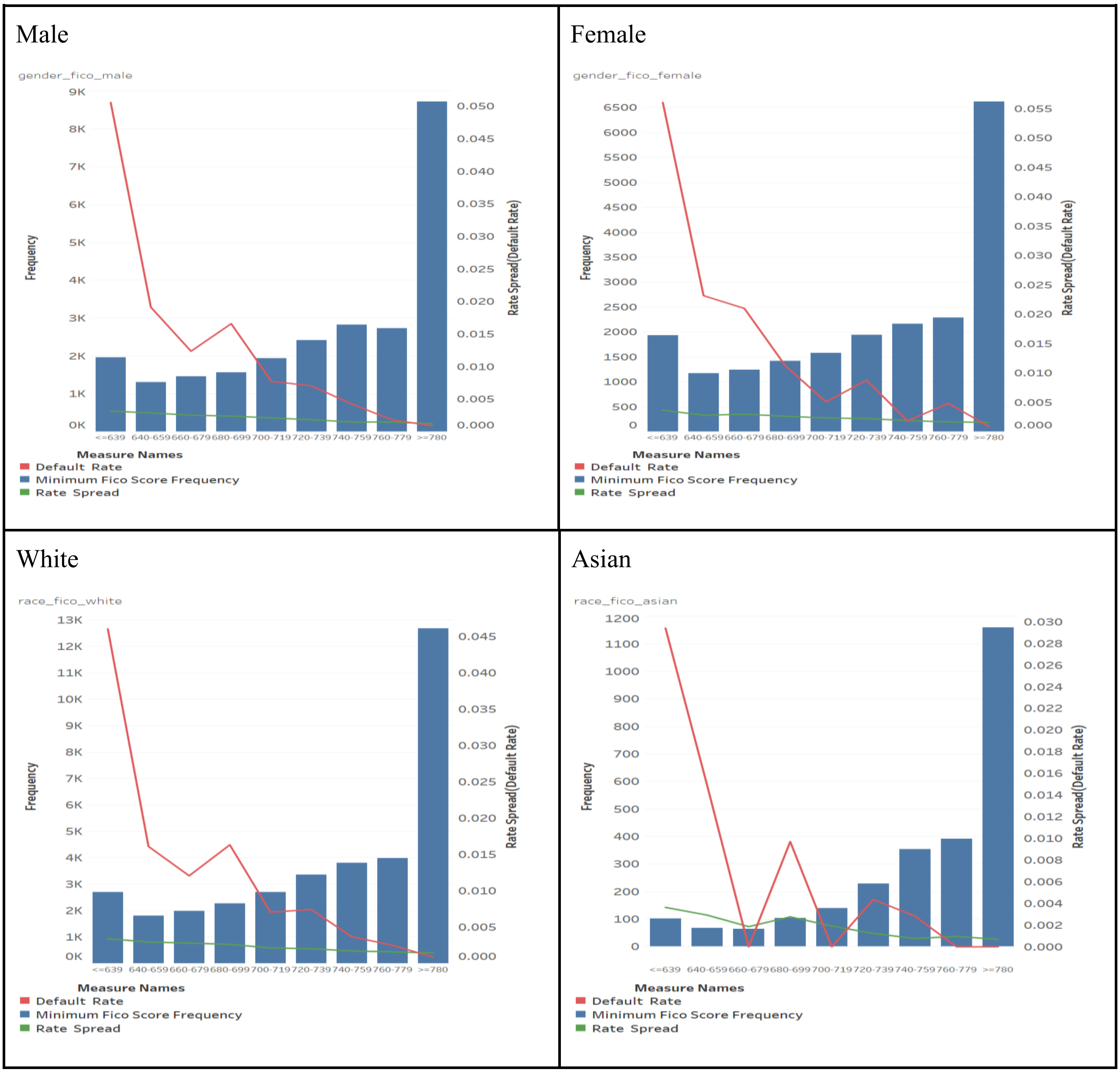
Figure 1: Credit Score Distribution, Rate Spread, and Default Rates

This figure shows the distribution of FICO scores, rate spreads, and default rates, segmented by gender (Panels A and B) and race/ethnicity (Panels C through F: White, Black, Hispanic, Asian). The figure highlights demographic disparities in mortgage pricing and outcomes.



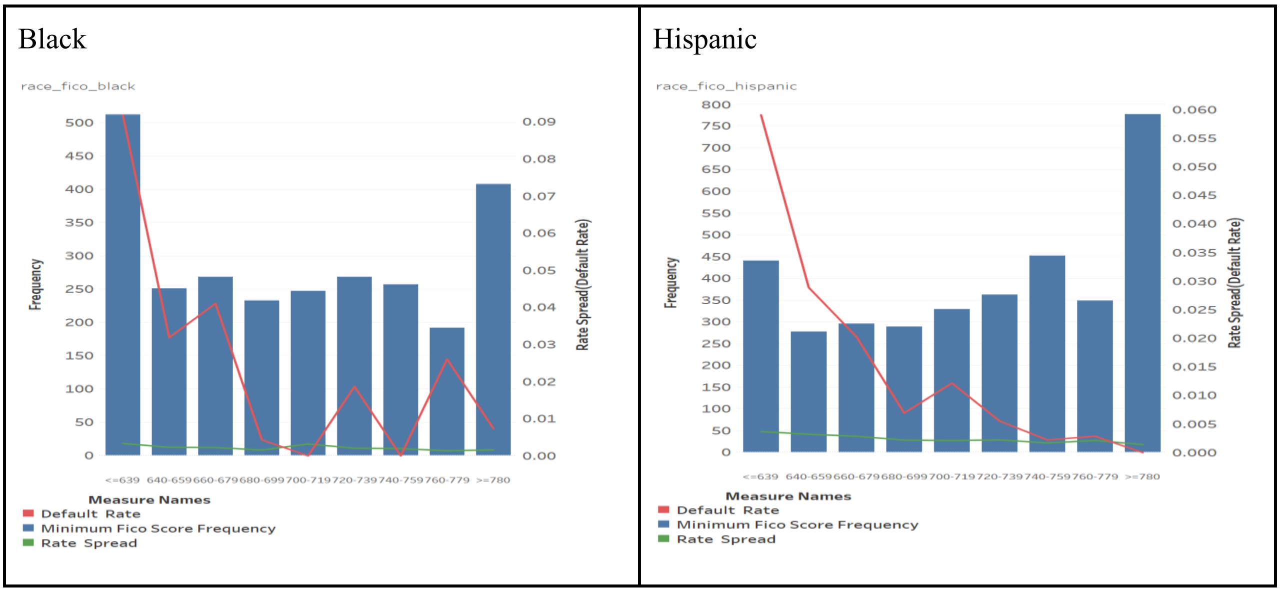


Table 1. Summary Statistics of Financial and Demographic Variables

This table presents descriptive statistics of key financial and demographic variables for the study sample. Panel A includes the mean, median, and standard deviation for continuous variables like credit score, rate spread, default rate, loan amount, income, CLTV, and DTI ratios. Panel B includes percentages for categorical variables, such as loan purpose, loan type, and mortgage characteristics. The data is segmented by gender and race.

Panel A: Summary Statistics of Continuous Financial and Demographic Variables

Variable	Overall Average	Male	Female	White	Asian	Black	Hispanic
Credit Score	739.880	741.620	737.690	743.320	761.020	702.740	721.660
Rate Spread (%)	0.192	0.176	0.213	0.194	0.109	0.226	0.214
Default Rate (%)	0.935	0.869	1.017	0.786	0.283	2.972	1.264
Loan ($, thousands)	221.160	228.870	211.500	216.390	295.250	207.640	222.360
Income($, thousands)	108.000	112.600	102.220	108.520	129.590	96.240	96.250
CombinedLoan-to-Value Ratio(%)	75.390	75.430	75.340	74.700	70.090	83.890	79.050
Debt Service to Income(%)	35.700	35.490	35.970	35.010	35.350	39.910	39.360
N (Number of Observations)	43444	24174	19270	34095	2471	2490	3322

Panel B: Distribution of Categorical Mortgage Loan Features and Demographics

Variables	Overall Average	Male	Female	White	Asian	Black	Hispanic
Refinance Cashout (%)	17.23	16.99	17.54	17.54	10.12	19.56	17.55

Buy Property (%)	47.110	46.560	47.790	46.830	48.320	45.980	50.000
Refinance Noncashout (%)	31.660	32.500	30.610	31.360	39.300	30.960	29.710
Add/Remove Coborrower (%)	0.720	0.600	0.870	0.790	0.240	0.480	0.600
Finance Construction (%)	1.710	1.760	1.650	1.870	0.450	1.200	1.200
New Loan (%)	1.570	1.580	1.550	1.610	1.580	1.810	0.930
Adjustable Rate Mortgage (%)	6.460	7.200	5.530	6.330	13.680	3.780	5.060
Jumbo (%)	4.090	4.890	3.080	4.040	9.630	2.170	2.290
Only One Borrower (%)	46.940	47.680	46.000	44.460	52.250	67.830	51.930
First Mortgage (%)	17.340	16.170	18.800	15.430	24.160	24.340	24.980
Conventional Loan (%)	77.500	76.870	78.280	79.700	92.070	52.530	65.710
GSE Loan (%)	60.630	59.500	62.040	62.020	70.090	41.970	55.420
Prepayment Penalty (%)	2.270	2.170	2.400	2.020	3.930	3.090	2.800
Escrow Account (%)	79.180	78.400	80.150	79.600	65.200	87.710	77.510
Balloon Payment (%)	1.540	1.760	1.280	1.510	2.230	1.490	1.350
Interest Only Payment (%)	3.810	3.880	3.740	3.610	3.520	4.860	4.850
Private Mortgage Insurance (%)	13.120	12.410	14.010	12.620	7.810	20.000	16.230
N (Number of Observations)	43444	24174	19270	34095	2471	2490	3322

Table 2: Exact Matching Analyses Results

Panel A compares matched male and female borrowers on rate spread, default rate, and key financial metrics. Panel B compares racial groups (Black, Hispanic, and Asian) with White borrowers using exact matching. Results show mean differences and statistical significance for each variable.

Panel A: Match by gender

Variable	Female	Male	Difference	P value
Rate Spread (%)	0.20	0.19	0.01	0.02
Default Rate (%)	0.97	1.17	-0.2	8.65
Debt Service to Income (%)	34.52	34.61	-0.08	0.1

Combined Loan-to-Value Ratio (%)	75.52	75.83	-0.31	0
CREDIT Score	744.34	744.99	-0.65	0

Panel B: Match by race

Variable	Black	White	Difference	P value
Rate Spread (%)	0.17	0.17	0	0.99
Default Rate (%)	1.79	1.09	0.7	0
Debt Service to Income (%)	33.12	33.08	0.03	0.57
Combined Loan-to-Value Ratio (%)	76.71	76.65	0.06	0.34
CREDIT Score	746.12	748.07	-1.95	0

Variable	Latino	White	Difference	P value
Rate Spread (%)	0.16	0.16	0	0.53
Default Rate (%)	0.67	0.83	-0.15	12.53
Debt Service to Income (%)	33.29	32.91	0.38	0
Combined Loan-to-Value Ratio (%)	73.44	73.75	-0.32	0
CREDIT Score	755.33	756.98	-1.66	0

Variable	Asian	White	Difference	P value
Rate Spread (%)	0.09	0.13	-0.04	0
Default Rate (%)	0.13	0.31	-0.19	0.23
Debt Service to Income (%)	31.19	30.92	0.26	0
Combined Loan-to-Value Ratio (%)	69.19	69.47	-0.29	0
CREDIT Score	776.28	777.38	-1.1	0

Table 3: Propensity Score Matching Results

This table compares treated groups (e.g., female, Black, Hispanic, Asian borrowers) with their respective control groups (male or White borrowers) based on propensity score matching. Mean rate spreads, t-statistics, and p-values are presented to assess disparities.

Treatment Group	Mean Rate Spread (Treated)	Mean Rate Spread (Control)	T-Statistic	P-Value
Female vs Male	0.223	0.199	3.897	0.000
Black vs White	0.241	0.234	0.421	0.674
Hispanic vs White	0.216	0.212	0.259	0.796
Asian vs White	0.110	0.145	-2.209	0.027

Table 4: Interaction Effects of Gender and Race on Rate Spreads

Panel A presents results for gender interaction terms, illustrating how financial variables such as CLTV, income, and loan amount affect rate spreads differently for males and females. Panel B examines race interactions, showing the differential impact of financial variables such as CLTV and DTI across racial groups.

Panel A Gender Interaction Model

Variable	Coefficient	Std. Error
Intercept	1.122***	-0.057
Add or Remove Co-borrower	0.106***	-0.032
Number of Borrowers Modified	0.014**	-0.006
Combined Loan-to-Value Ratio (CLTV)	-0.001***	0.000

Debt-to-Income Ratio (DTI) Construction Loan Financing	0.002*** 0.114***	0.000 -0.021
First Mortgage Rate Modified	-0.036***	-0.008
Gender (Female)	0.186**	-0.081
Female x CLTV Interaction	-0.001**	0.000
Female x DTI Interaction	0.000	0.000
Female x Income Interaction	-0.000**	0.000
Female x Loan Amount Interaction	0.000***	0.000
Female x Minimum Credit Interaction	-0.000*	0.000
Income	0.001***	0.000
Jumbo Loan Modified	-0.068***	-0.015
Loan Amount	-0.001***	0.000
Minimum Credit Score	-0.001***	0.000
Race (Asian)	0.000	-0.012
Race (Black)	-0.004	-0.012
Race (Hispanic)	0.006	-0.01
Cash-Out Refinance	0.018**	-0.008
Non-Cash-Out Refinance	-0.032***	-0.007
New Loan Taken Out	0.177***	-0.022
Adjust Rate Loan	0.091***	-0.011
Observations	42,378	
R-Squared	0.063	
Adjusted R-Squared	0.063	
Residual Std. Error	0.556 (df = 42,354)	
F Statistic	124.248*** (df = 23; 42,354)	

Panel B: Race Interaction Model

Variable	Coefficient	Std. Error
Intercept	1.192***	-0.048
Add or Remove Co-borrower	0.106***	-0.032
Number of Borrowers Modified	0.015***	-0.006
Combined Loan-to-Value Ratio (CLTV)	-0.001***	0.000
Debt-to-Income Ratio (DTI)	0.002***	0.000
Construction Loan Financing	0.114***	-0.021
First Mortgage Rate Modified	-0.035***	-0.008
Gender (Female)	0.023***	-0.005
Income	0.001***	0.000
Jumbo Loan Modified	-0.071***	-0.015
Loan Amount	-0.001***	0.000
Minimum CREDIT Score	-0.001***	0.000
Race (Asian)	-0.388*	-0.204
Race (Asian) x CLTV Interaction	0.003***	-0.001
Race (Asian) x DTI Interaction	0.003**	-0.001
Race (Asian) x Income Interaction	0.000	0.000
Race (Asian) x Loan Amount Interaction	0.000	0.000

Race (Asian) x Minimum CREDIT Interaction Race (Black)	0.000 0.353**	0.000 -0.157
Race (Black) x CLTV Interaction	-0.003***	-0.001
Race (Black) x DTI Interaction	0.000	-0.001
Race (Black) x Income Interaction	0.000	0.000
Race (Black) x Loan Amount Interaction	0.000	0.000
Race (Black) x Minimum CREDIT Interaction	0.000	0.000
Race (Hispanic)	0.087	-0.144
Race (Hispanic) x CLTV Interaction	-0.001**	-0.001
Race (Hispanic) x DTI Interaction	0.000	-0.001
Race (Hispanic) x Income Interaction	0.000	0.000
Race (Hispanic) x Loan Amount Interaction	0.000***	0.000
Race (Hispanic) x Minimum CREDIT Interaction	0.000	0.000
Cash-Out Refinance	0.016*	-0.008
Non-Cash-Out Refinance	-0.031***	-0.007
New Loan Taken Out	0.175***	-0.022
Adjust Rate Loan	0.090***	-0.011
Observations	42,378	
R-Squared	0.065	
Adjusted R-Squared	0.064	
Residual Std. Error	0.555 (df = 42,344)	
F Statistic	88.592*** (df = 33; 42,344)	

Table 5: Residual Analysis of Unexplained Rate Spread Disparities

This table reports the mean residuals for gender (Panel A) and racial groups (Panel B), representing the unexplained portion of rate spreads after controlling for financial variables. Results highlight whether disparities persist beyond observed financial characteristics.

Panel A: Residual by Gender

Gender	Mean Residual	Mean Residual Male	T-Statistic	P-Value
Female	-0.010196	0.012791	4.283	0.000

Panel B: Residual by Race

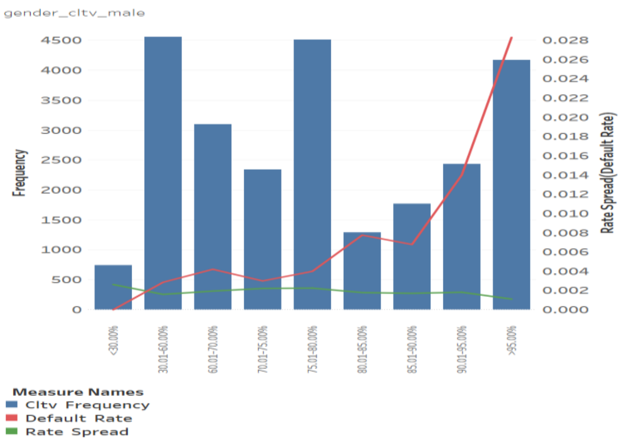
Race	Mean Residual	Mean Residual White	T-Statistic	P-Value
Black	-0.002983	-0.000189	-0.238	0.812
Hispanic	0.00492	-0.000189	0.505	0.614
Asian	-0.001189	-0.000189	-0.086	0.931

Appendix A: Supplemental Analysis of Mortgage Rate Spreads and Default Rates by Financial and Demographic Factors

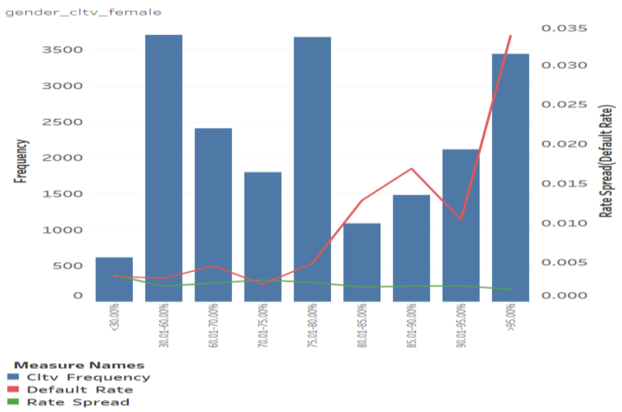
Figure A1: CLTV Ratios, Rate Spread, and Default Rates

This figure examines how combined loan-to-value (CLTV) ratios correlate with rate spreads and default rates, segmented by gender (Panels A and B) and race/ethnicity (Panels C through F: White, Black, Hispanic, Asian).

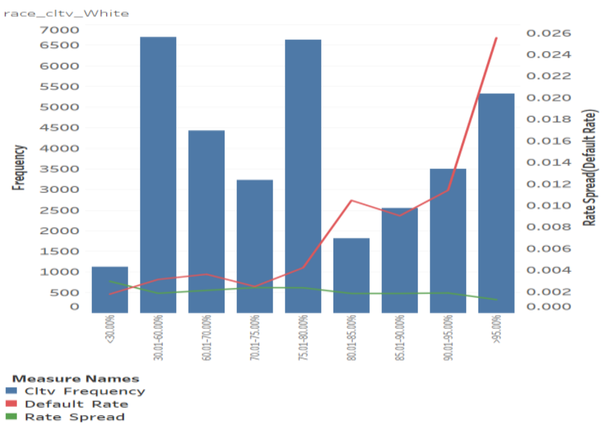
Male



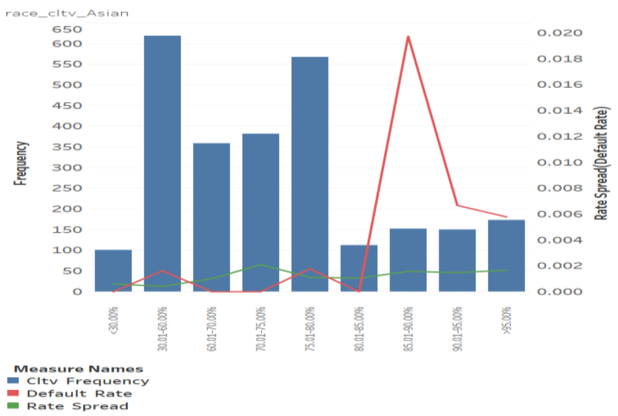
Female



White



Asian



Black

Hispanic

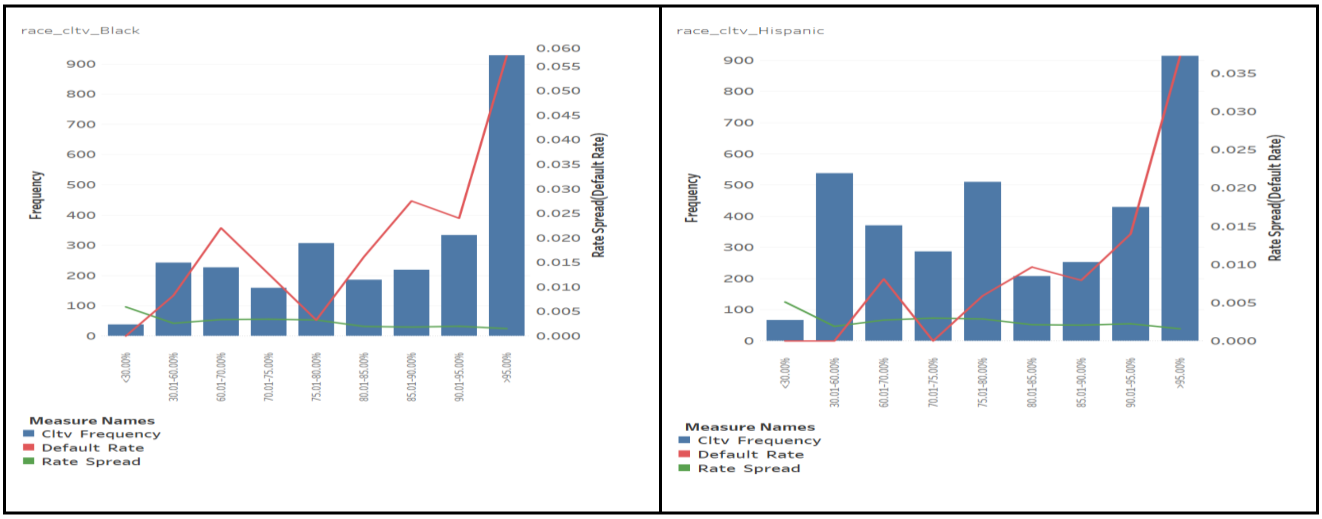
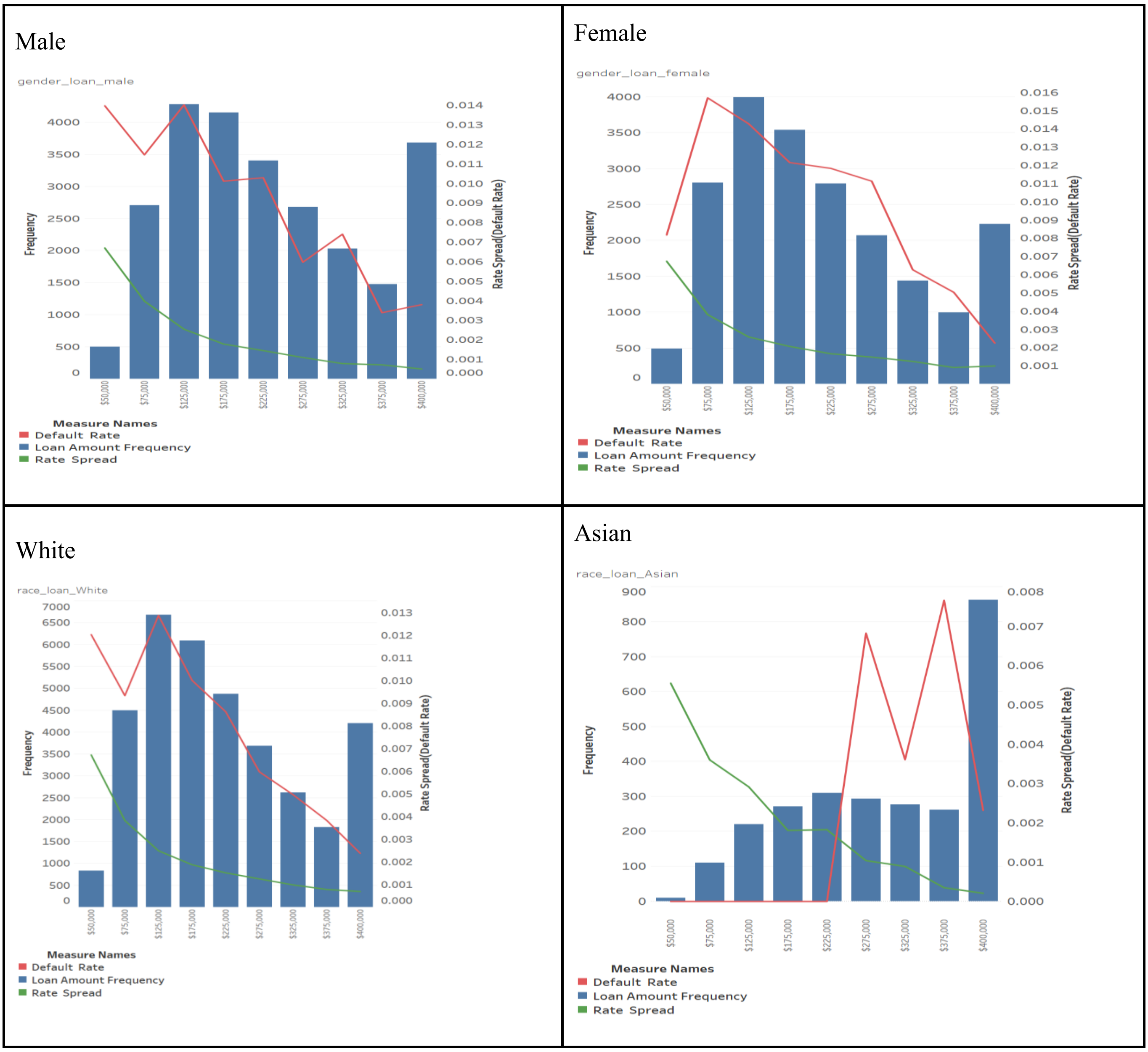
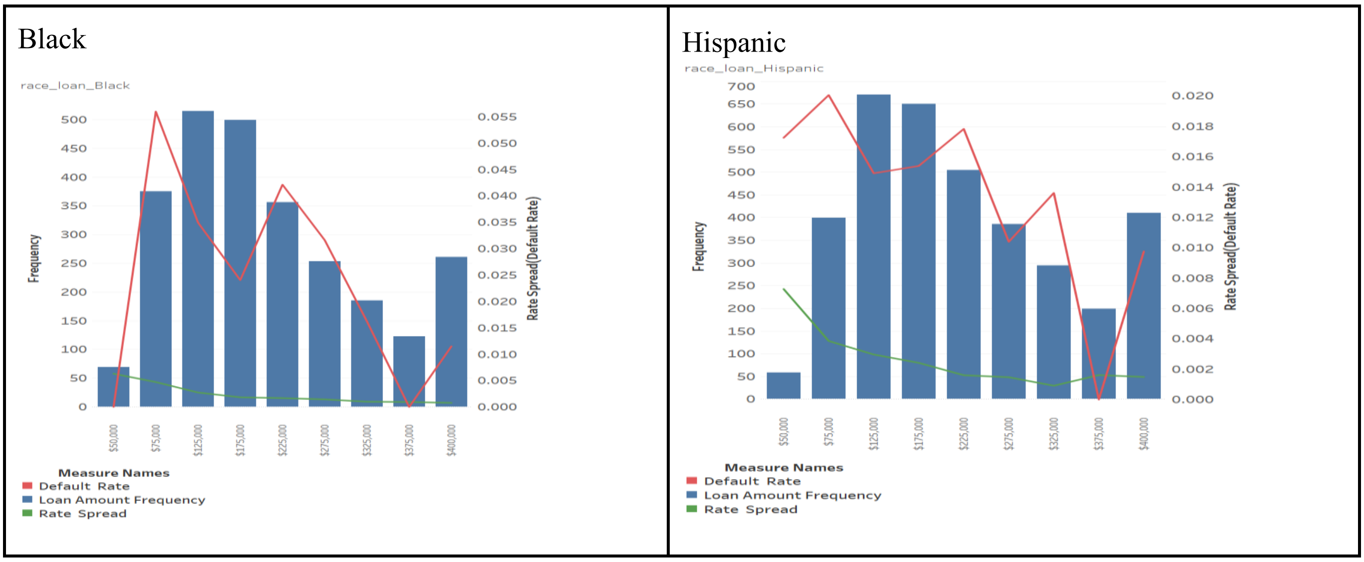

race_cltv_Black
Frequency
Rate Spread(Default Rate)
<30.00%
30.01-60.00%
60.01-70.00%
70.01-75.00%
75.01-80.00%
80.01-85.00%
85.01-90.00%
90.01-95.00%
>95.00%
Measure Names
Cltv Frequency
Default Rate
Rate Spread
race_cltv_Hispanic
Frequency
Rate Spread(Default Rate)
Measure Names
Cltv Frequency
Default Rate
Rate Spread

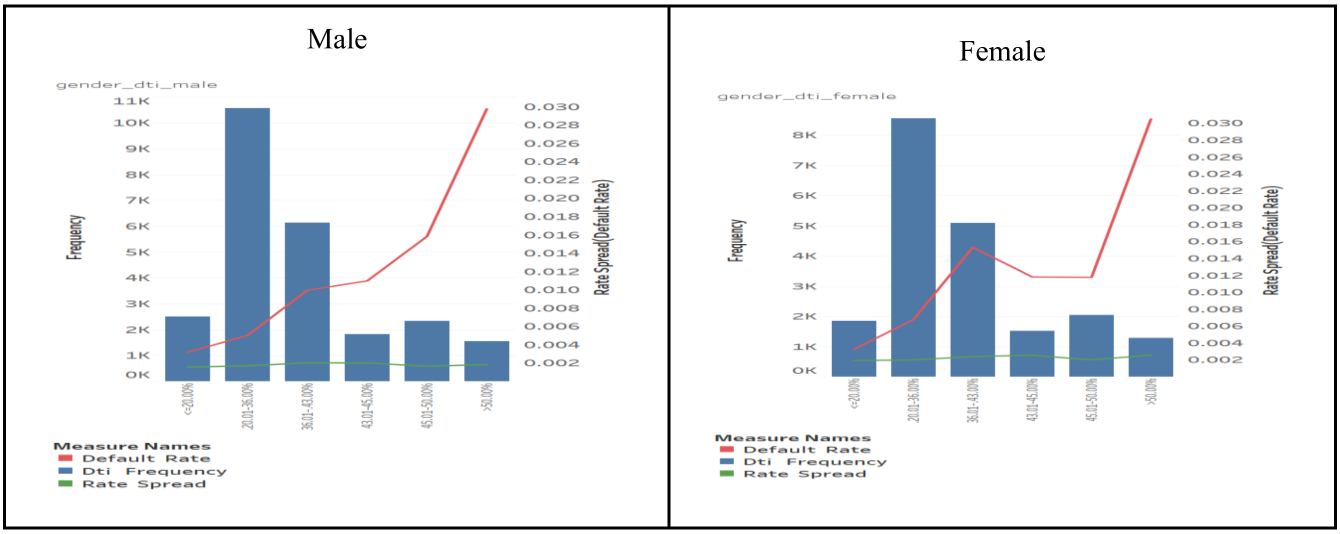
Figure A2: Loan Amount, Rate Spread, and Default Rates

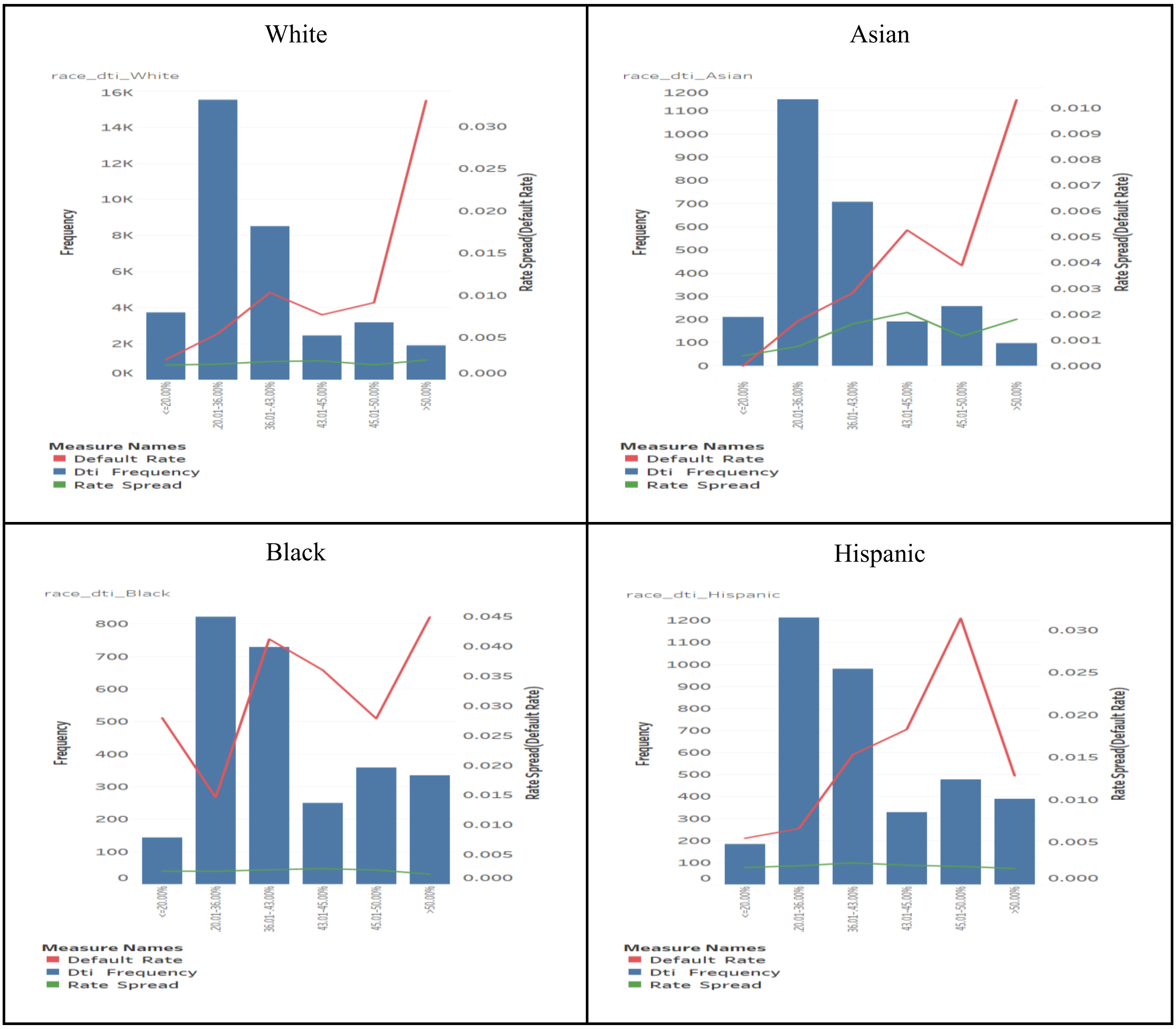




This figure illustrates how loan amounts affect rate spreads and default rates, broken down by gender (Panels A and B) and race/ethnicity (Panels C through F: White, Hispanic, Black, Asian).

Figure A3: DTI Ratios, Rate Spread, and Default Rates

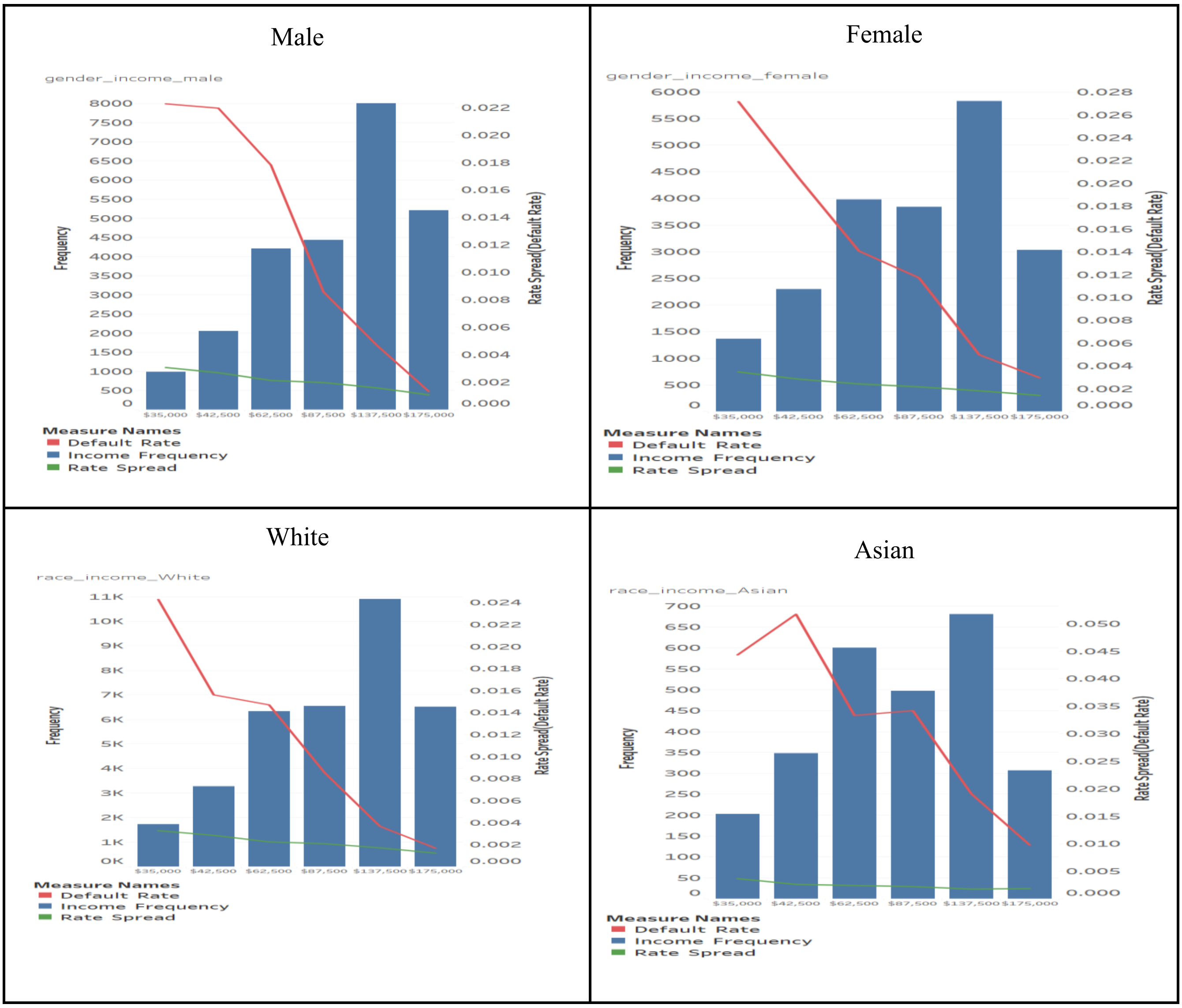


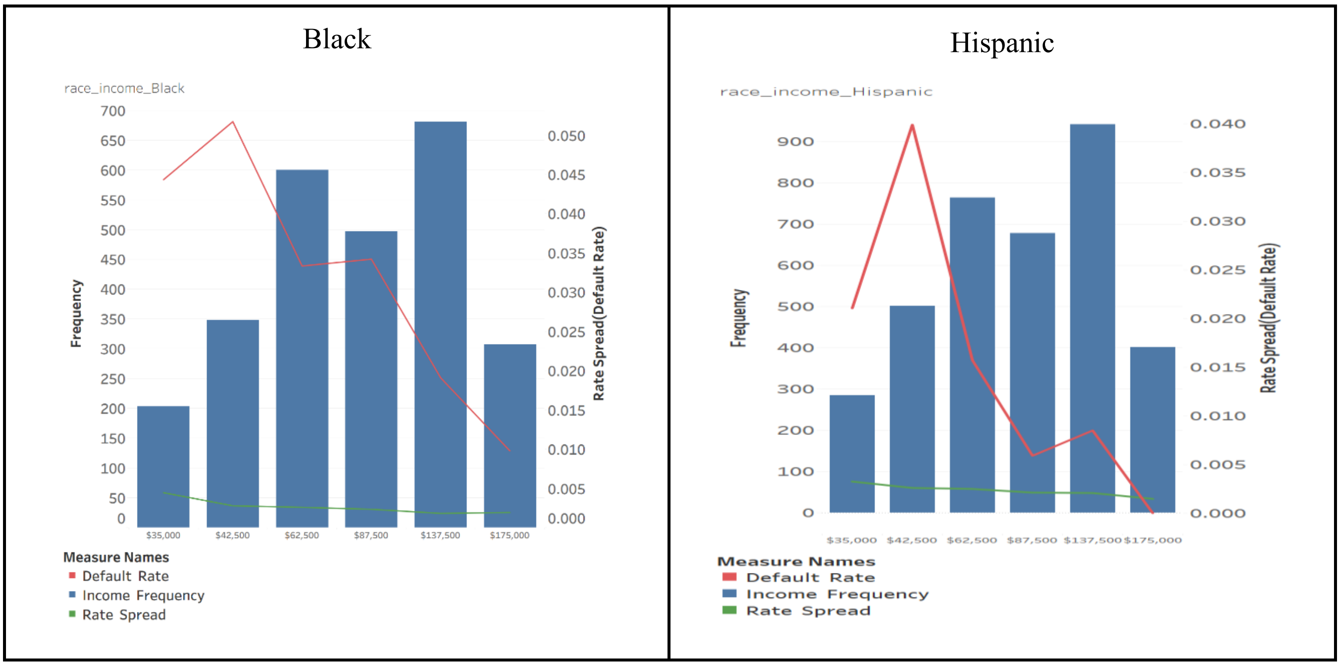


This figure shows the distribution of debt-to-income (DTI) ratios in relation to rate spread and default rates, differentiated by gender (Panels A and B) and race/ethnicity (Panels C through F: White, Hispanic, Black, Asian).

Figure A4: Income Levels, Rate Spread, and Default Rates

This figure analyzes the effect of income levels on rate spreads and default rates, comparing outcomes by gender (Panels A and B) and race/ethnicity (Panels C through F: White, Black, Hispanic, Asian).




Black
race_income_Black
Frequency
Rate Spread(Default Rate)
700
650
600
550
500
450
400
350
300
250
200
150
100
50
0
0.050
0.045
0.040
0.035
0.030
0.025
0.020
0.015
0.010
0.005
0.000
$35,000
$42,500
$62,500
$87,500
$137,500
$175,000
Measure Names
Default Rate
Income Frequency
Rate Spread
Hispanic
race_income_Hispanic
Frequency
Rate Spread(Default Rate)
900
800
700
600
500
400
300
200
100
0
0.040
0.035
0.030
0.025
0.020
0.015
0.010
0.005
0.000
$35,000
$42,500
$62,500
$87,500
$137,500
$175,000
Measure Names
Default Rate
Income Frequency
Rate Spread