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The Role of Race in Mortgage Application Denials

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Abstract

Using the confidential Home Mortgage Disclosure Act (HMDA) data from 2018 to 2020, we estimate differences in denial rates for conventional 30-year mortgage applications for home purchases between racial and ethnic groups. Our work extends the existing literature by controlling for newly available characteristics of the borrower, including credit score and more detailed loan-to-value and debt-to-income ratios associated with an application. In our baseline specification, we estimate that Black applicants are 2.9 percentage points more likely to have their mortgage application denied relative to White applicants, while Asian and Latinx applicants are 2.2 percentage points and 1.5 percentage points, respectively, more likely to be denied. Lone applicants of color face greater disparities than two co-applicants of color, particularly for Black and Latinx applicants. We find that disparities exist for the majority of lenders even after estimating separate models by lender, although the estimated disparities across lenders are quite varied. We find evidence that lender characteristics are associated with the size of disparities: independent mortgage companies and lenders that sell a high proportion of their loans have the lowest denial rates and smallest racial disparities in denial rates. Our results suggest the persistence of racial disparities in mortgage access and can inform policymakers interested in addressing the broader racial wealth and homeownership gap.

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1 Introduction

Homeownership in the U.S. has been seen as an established means to build wealth. People of color, especially Black Americans, have historically been excluded from government policies that lower the costs of borrowing to promote homeownership and were blocked from accessing credit to purchase homes in certain areas through redlining (Rothstein, 2017). In the first quarter of 2021, an estimated 74 percent of White non-Hispanic households owned homes compared to 45 percent of Black households, 49 percent of Hispanic households and 60 percent of Asian households.[1]

In this paper, we explore the role of race and ethnicity in lenders' credit decisions for mortgage applications, which may contribute to perpetuating continued racial gaps in homeownership. Using the confidential Home Mortgage Disclosure Act (HMDA) data from 2018 to 2020 and focusing on conventional conforming 30-year term mortgage applications for home purchases, we estimate disparities in mortgage denial rates between racial and ethnic groups. Our work extends the existing literature by controlling for newly available characteristics of the borrower, including credit score and more detailed loan-to-value ratio (LTV) and debt-to-income ratio (DTI). A primary criticism of previous work is that without accounting for these important inputs in the mortgage approval decision, the estimated racial and ethnic disparities in mortgage denial rates may be overstated. Our paper complements recent work by Bhutta et al. (2021) who also use the new HMDA data to show the importance of these controls and others in accurately estimating denial disparities. We examine the disparities separately for each racial and ethnic group and consider the role of the co-applicant's race and ethnicity in determining mortgage denial rates.

Our baseline results suggest that people of color have higher mortgage application denial rates. We estimate that Black applicants are 2.9 percentage points more likely than White applicants to have their application denied. The difference for Latinx borrowers is 1.5 percentage points, and it is 2.2 percentage points for Asian applicants.[2] These disparities are substantial, when compared to the overall denial rate in our sample of 3.8 percent and a 3.0 percent denial rate among White applicants. The results are qualitatively robust to the inclusion of additional controls and changes in functional form.

[1]U.S. Census Bureau, Quarterly Residential Vacancies and Homeownership, `https://www.census.gov/housing/hvs/files/qtr121/Q121press.pdf`

[2]Throughout the paper, we refer to applicants of Hispanic or Latino origin as Latinx. All other racial groups are of non-Latinx origin.

The remainder of the paper studies heterogeneity in the estimated disparities. We find that single applicants of color have larger disparities than two co-applicants of color. This is particularly true for Black and Latinx applicants. When focusing on the role of the lender, we find that independent mortgage companies have the smallest estimated disparities in mortgage denials between applicants of color and White applicants and the lowest overall denial rates when compared with commercial banks, credit unions, and thrift institutions. Consistent with the lender type results, lenders that sell a higher share of the loans they originate also have lower estimated disparities and denial rates. Next, we estimate lender-specific disparities for the top 50 lenders by volume in our sample and find that the majority of lenders have sizable disparities that compare in magnitude with our baseline results. These within lender results suggest that the estimated disparities cannot be explained by applicants of color being more likely to work with high-denial lenders than White applicants, and that the results are not driven by a few high-disparity lenders.

Finally, we examine differences in disparities by geography. We find that after controlling for the applicant's race and ethnicity, there are not differences in estimated disparities associated with the racial composition of the neighborhood in which the property is located.[3] However, when we look at disparities by neighborhood income levels, we see that racial disparities in denials are lower in higher-income neighborhoods even after accounting for individual applicant characteristics. We also see different patterns by racial group when we estimate state and metropolitan statistical area (MSA) specific disparities. Asian and Black applicants experience higher denial rates relative to White applicants and these disparities exist in states all over the U.S., while Latinx applicants experience higher disparities in denial rates in states in the eastern half of the country. We find that disparities within MSAs vary, although generally disparities between Black and White applicants are largest followed by disparities between Asian and White applicants and Latinx and White applicants.

Our results suggest that disparities in treatment on the basis of race and ethnicity exist even in the most standardized of mortgage products with relatively low risk for lenders: conventional, conforming, 30-year mortgages.[4] Almost 96 percent of the loans in our sample are initially evaluated by an automated underwriting system (AUS) developed by government agencies providing some guidance to lenders in their acceptance decisions. Additionally, the pricing matrices for

[3]Throughout the paper, we refer to census tracts as neighborhoods, and the two terms are used interchangeably.
[4]See Bartlett et al. (2019) for a description of this market and lender incentives.

this type of mortgage are public, making the lender decision relatively more straightforward.

While these applications represent an important subset of all home-purchase mortgage applications, disparities in the mortgage lending market likely also occur in other products and at different stages. The overall rates of mortgage denials in our sample are extremely low, likely in part because these borrowers probably secure a pre-approval prior to submitting a formal application for a loan to buy a specific property. It is possible that racial disparities in pre-approval decisions also disadvantage applicants of color, but those would not be included in our analysis. Additionally, our sample excludes applications made for FHA- (Federal Housing Administration), VA- (Veterans Administration), and USDA- (United States Department of Agriculture) backed loans, which have different application requirements and loan characteristics. Any behavior by lenders or realtors that may guide applicants toward those loans that differs by race and ethnicity would be outside of the scope of our analysis. Similarly, our results do not include any disparities that may exist in assistance during the application process. Finally, our analysis looks at racial disparities at the time of application saying nothing about the role of systemic racism in determining the borrower characteristics such as credit worthiness, income, employment, and wealth that are factored into lenders' credit decisions.

2 Existing Evidence

There is a large literature studying racial disparities in the mortgage lending market. A notable initial study, Munnell et al. (1996), was done by researchers at the Federal Reserve Bank of Boston where they collected additional data from lenders to supplement the existing HMDA data and better control for factors that lenders use in their credit decisions. They find that disparities in loan acceptance rates remain, but the estimated differences are much smaller after additional factors are controlled for in the analysis. More recent work has continued to find disparities in mortgage denial rates between racial groups. Bartlett et al. (2019) find that Black and Latinx applicants are 9.6 percentage points more likely to have their mortgage applications for home purchase denied compared to White applicants between 2009 and 2015 although they do not find disparities among FinTech lenders. Hirasuna and Allen (2012) document higher denial rates between 2004 and 2008 for mortgage applications in the Upper Midwest for non-traditional applicants, which they characterize using the combinations of race, ethnicity, gender, and same sex couple status.[5]

Bhutta et al. (2021) find that disparities, while at a much smaller magnitude, remain after controlling for recently available information in HMDA, including credit score and the AUS recommendations. They estimate that Black applicants are 1.9 percentage points more likely to be denied compared to White applicants, while Asian and Latinx are 1.3 percentage points and 1.0 percentage points more likely, respectively. Their paper focuses on applications that are evaluated using an AUS and includes mortgages for both home purchase and refinance in 2018 and 2019. Frame et al. (2021) show that minority applicants are more likely to have their application denied, but that denial probability varies based on the race of the loan officer. They estimate that minority applicants are 1.9 percentage points more likely to be denied overall but that difference declines by 1.1 percentage points when the loan officer is a minority.

This study builds on previous work by including additional controls that are relevant to the lender's acceptance decision, most notably credit scores, and focusing on the most standardized type of mortgages. Our data come from the most recent HMDA filings from 2018 to 2020, an era when overall denial rates were lower than in previous years. Finally, we focus on applications meeting the basic underwriting standards for 30-year, conventional, Government-Sponsored Enterprise (GSE) backed loans making the population studied different from existing work on subprime mortgages (Bayer et al. (2018)), FHA loans (Bhutta and Hizmo (2021)), and more general mortgage applications (Bhutta et al. (2021)).

3 Data and Empirical Strategy

We use the confidential HMDA data from 2018 to 2020 for our analyses. These data are the only source of information on the race and ethnicity of mortgage applicants and cover an estimated 88 percent of mortgage originations in the U.S.[6] Additionally, beginning in 2018 they include the applicants' credit scores and more detailed loan characteristics. These additional pieces of information allow us to control for more factors in the lender's credit decision, although there remain omitted variables that could affect the lender's decision, including work experience, income stability, and credit history.

We focus on 30-year conventional mortgage applications for home purchases where our model will most closely account for factors that enter the lenders' approval decision. Additionally,

[5] They define "traditional" applications as those from White, non-Hispanic, opposite-sex couples.
[6] see Consumer Financial Protection Bureau (2019) for more information on HMDA coverage

the lender's decision is the most straightforward on these standardized mortgages as the vast majority of these loans are initially evaluated by an AUS and the pricing mechanisms are public. Most of these loans can be sold to GSEs reducing some of the risk to the lender. While studying these types of mortgage applications eases the interpretation of our findings because we are more likely to have controlled for the relevant information that the lender used to determine acceptance of the application, this analysis will not capture disparities in other loan programs like FHA or VA loans, non-conforming and non-30 year mortgage applications for home purchase, or applications for refinancing.[7]

Our sample includes applications for properties in the 50 U.S. states and the District of Columbia that received an approval or denial decision. We include applications for 30-year term loans for single dwelling units used as a primary residence that are within the county-level conforming limit secured by a first lien. We exclude applications for loans for commercial or business purpose and those that are for an open line of credit. To focus on applications that meet GSE standards we exclude applications where a borrower has a credit score below 620, those with an LTV above 97 percent, and those with back-end DTI above 50 percent.[8] Finally, we winsorize the top and bottom 0.1 percent of applicant income to avoid undue influence of outliers.[9] Our final sample covers about 37 percent of all completed applications for home purchases in the HMDA data over the three-year period.[10]

Our main explanatory variables of interest are mutually-exclusive indicators at the application level for the race and ethnicity of the borrowers. First, we construct individual-level race and ethnicity categories for both primary and secondary applicants.[11] We characterize individuals who report that they are Hispanic or Latino as Latinx. Among applicants who are not Hispanic or Latino, we use their reported race to characterize them as American Indian or Alaska Native, Asian, Black, Pacific Islander, White, multi-racial, or missing. In our analysis, non-Hispanic individuals who report more than one race are multi-racial, and missing includes any individuals who do not report their race and ethnicity. We group multi-racial, American Indian or Alaska Native, and Pacific Islanders together as "All other races" in the analysis

[7] A separate literature has documented racial differences in refinancing behavior. See Gerardi et al. (2020), for example.

[8] Throughout the paper we refer to back-end DTI as DTI.

[9] Our results are not qualitatively sensitive to winsorizing income variable.

[10] Our sample represents 49 percent of applications for home purchases that are similar in character to our sample (single dwelling, primary residence, first lien, not open line of credit, not for business or commercial purpose, site built).

[11] "Primary applicant" refers to the first individual listed in the application, and "secondary applicant" refers to the second individual listed as the co-applicant, if applicable.

because we do not have the sample size to reliably estimate separate effects for these groups. We leave it to future work to focus on these groups specifically.

We construct the application-level category by assigning a race-ethnicity category (other than multi-racial) only when the primary and secondary characterizations match. For example, if the primary borrower is Black and the secondary borrower is Asian, then the application would be characterized as multi-racial. If the primary applicant has missing race and ethnicity information, but it is available for the co-applicant, we use the co-applicant's information to characterize the application-level race-ethnicity category.

Our results focus on the effects for Asian, Black, and Latinx applicants, with the reference group being White applicants. We also include indicators for the missing race and the combined multi-racial, American Indian or Alaska Native, and Pacific Islander group, but their estimates are not always reported or interpreted. We test alternative methods of characterizing race and ethnicity, and we also explore differences across all combinations of race and ethnicity for co-applicants.

Our outcome variable is an indicator for whether the mortgage application was denied by the lender. We estimate a linear probability model where denial is a function of borrower characteristics, loan characteristics, and state and time fixed effects.[12] Specifically we include interactions between the year and month of the action date with each state, which control for seasonality and time trends in denial rates that are allowed to differ across states.[13] We estimate the following linear probability model of loan application denial:

$$\begin{aligned}\text{denial}_{ijt} =& \beta_0 + \gamma \text{racial group}_i + \beta_1 \log(\text{income}_i) + \beta_2 \log(\text{loan amount}_i) \\ & + f(\text{credit score}_i, \text{loan-to-value}_i, \text{debt-to-income}_i) + \alpha_{jt} + \epsilon_{ijt}\end{aligned}$$

where β_0 is the intercept, γ is a vector of the estimated effects of racial and ethnic groups, β_1 is the estimated effect of one unit increase in the natural logarithm of applicant's income, β_2 is the estimated effect of one unit increase in the natural logarithm of the requested loan amount, f defines how credit score, DTI, and LTV, are specified, α_{jt} is the fixed effect for state

[12] We also estimate a logit model in the "Robustness" section and the results are comparable.

[13] The data reporting process may also create seasonality because applications are included in the HMDA year when an action was taken and the time between application and action is generally longer for accepted applications. See Avery et al. (2007) for discussion. We also see evidence that denial rates were decreasing throughout the calendar year as well as from 2018 to 2020 overall.

j in month-year t, and ϵ_{ijt} is the error term for observation i in month-year t in state j. We cluster our standard errors at the lender level because that is the unit of analysis where the denial decision is being made.

In our main specification, f is defined as a vector of three-way interactions between discretized bins of credit scores, LTV ratios, and DTI ratios. This specification is motivated by our desire to be flexible in how lenders consider these important characteristics and to allow for the effect of say credit score to vary depending on the DTI or LTV associated with the loan. In practice, lenders can use compensating features of the application to approve it. For example, an application with high DTI might be approved if the LTV is low and the credit score is high. We separate applications into categories based on the lowest credit score on the application being in each of the GSE matrix categories (see Appendix Figure A1). We create bins of LTV ratios according to the same GSE matrix. For DTI ratios, we use bins based on the publicly available HMDA cutoffs with categories of < 20, 20-29, 30-35, and every one percentage point above 35. Our results are not sensitive to the exact bins selected for credit score, LTV, and DTI as shown in a robustness exercise.

4 Summary Statistics

Our final sample includes around 6.1 million mortgage applications. Information on the sample can be found in Table 1. The table shows the counts of applicants in each race-ethnicity category. Using our preferred categorization that incorporates the race and ethnicity of both applicants, our sample is around 66 percent White, 6 percent Asian, 4 percent Black, and 9 percent Latinx. Importantly, 10 percent of applications have missing race and ethnicity information.

The overall denial rate in our sample is 3.8 percent. This low rate likely results from our focus on applications that meet GSE underwriting requirements like a minimum credit score and maximum LTV and DTI cutoffs and the market environment that likely required preapprovals before making an offer and submitting a formal application. These average rates mask large variation across racial and ethnic groups. Black applicants have the highest denial rates at 7.4 percent, followed by Latinx applications with a denial rate of 5.8 percent (Table 2). White applicants have the lowest denial rates at 3.0 percent.

Over 60 percent of applicants have a credit score of 740 or above, which is a relatively high credit score. The median income used in the application is \$87,000 (Table 3).[14] The median

[14] Income used in the application is the gross annual income a lender relies on to make approval decision. For

LTV is 87.4 with almost one third of applicants borrowing 95 percent or more of the home value. The median DTI is 37.0 and the 75th percentile is 43.2 percent. These LTV and DTI ratios are at the higher ends of what is eligible under GSE underwriting standards, but overall acceptance rates are still relatively high perhaps because the applications have other compensating factors and have likely already gone through at least an informal pre-approval process.

Table 2 shows that there are differences in application characteristics by race. Median credit scores are lower among Black and Latinx applicants compared to Asian and White applicants. The median LTV ratio among Black and Latinx applicants exceeds 90 while it is 80 for Asian applicants and 85 for White applicants. The loan amounts requested are highest for Asian borrowers with median at nearly $330,000, which partially reflects the geographic markets where Asian borrowers are concentrated. Median loan amounts for White, Latinx, and Black borrowers are between $220,000 and $240,000.

5 Results

Our baseline results suggest that applicants from racial and ethnic groups other than White applicants are more likely to have their mortgage applications denied even after controlling for loan and borrower characteristics. We find the largest disparities between White applicants and Black applicants, with Black applicants being 2.9 percentage points more likely to have their application denied (Table 4). We find smaller, but still economically important, effects for Latinx and Asian applicants, highlighting the importance of separately identifying the effects across racial groups. Asian applicants are an estimated 2.2 percentage points more likely than White applicants to have their application denied while Latinx applicants are 1.5 percentage points more likely. These disparities are large when compared to the overall sample denial rate of 3.8 percent and the unadjusted denial rate among White applicants of 3.0 percent.

Our results also show the importance of observed control variables. We add the covariates to our model in steps to illustrate their importance (Figure 1 and Table 4). First, we show the raw differences in denial rates without any covariates. Second, we include variables that have been available to previous researchers (loan amount, income, state, action month-year, LTV and DTI ratios), and finally we include credit score. We find that the inclusion of credit score significantly reduces the estimated racial disparities even when added as the final control.

example, if two co-applicants have a combined income of $100,000 but the lender only relies on $60,000 of their income in making their credit decision, $60,000 will be reported.

The effect of controlling for credit score is much larger for Black and Latinx applicants relative to Asian applicants. In general, control variables decrease the magnitude of our disparity estimates for Black and Latinx applicants relative to White applicants, and they increase or leave it unchanged for Asian applicants.

In order to better understand the role of our covariates in determining denials, we create plots of the estimates of the three-way interaction between LTV, DTI, and credit score. Appendix Figure A2 shows how changes in credit score affect the probability of denial for different values of LTV with DTI fixed at the median sample value of 37 percent. As expected, increases in credit scores yield larger declines in denial probabilities for high-LTV loans as shown by the increasingly steep slope for lines representing high-LTV applications. Interestingly, increasing credit scores above 720 does not appear to have much effect on denial probability across all LTV values. Next we show the effect of credit scores at varying DTI ratios holding LTV constant between 85 to 90 in Appendix Figure A3. We find that an increase in credit score has a larger effect on denial probabilities for applications with lower credit scores and that this effect is relatively constant across all DTI ratios. For high DTI ratios above 45, it is particularly important for the application to have a credit score above 680. Interestingly, the effect of DTI, holding credit score constant, does not appear to be particularly large. Lower credit scores have higher denials at all DTIs but the effect of DTI is particularly stark for DTIs below 20 percent and above 45 percent with a jump in the likelihood of denial. These estimates suggest that credit score is an important measure for predicting denials. It may also proxy for other unobserved variables not included in our model but used by lenders in determining whether to accept an application.

The magnitudes of our estimated disparities are substantial. A recent paper by Bhutta et al. (2021) uses 2018–2019 HMDA data to estimate denial disparities by race and ethnicity for 30-year, fixed-rate mortgages for purchase or refinance. They estimate smaller disparities at around 1.9 percentage points for Black applicants, 1.3 percentage points for Asian applicants, and 1.0 percentage points for Latinx applicants. There are a number of differences between our studies, but a primary contribution of their study is the focus on the role of the AUS recommendations. When we control for the AUS recommendation as they do, our estimates of the disparities fall to 2.0 percentage points for Black applicants, 1.8 percentage points for Asian applicants, and 1.1 percentage point for Latinx applicants. Importantly, a considerable portion of the effect of controlling for AUS is due to changing the sample to only include applications that are run through an AUS. The sample restriction to AUS applications accounts for 0.2 percentage points of the total 0.9 percentage point difference for Black applicants, 0.1 percantage points of the 0.4 percentage point difference for Asian applicants, and 0.2 of a total 0.4 percentage point change for Latinx applicants. Overall, our results after controlling for AUS are similar to those of Bhutta et al. (2021).

Because our time period saw lower overall denial rates and our key control variables are not available before 2018, it is not straightforward to compare our estimates numerically to other previous work. Bartlett et al. (2019) study acceptance rates between 2009 and 2015 with a sample of conventional loans that is relatively similar to ours, and they find that Latinx and Black applicants together were 9.6 percentage points more likely to have their application denied compared to White applicants. The average denial rate for purchase applications in their sample during their time period was 36 percent. We view our results on Black and Latinx disparities as qualitatively comparable.

Overall, the disparities we estimate are modest but meaningful given the context of our study and the many parts of the mortgage process that are outside of the analysis.

5.1 Robustness

5.1.1 Model Specification and Sample

Next, we test the robustness of our estimates to different model specifications and sample restrictions. We find that the results are qualitatively similar across a number of specifications. The impacts of different models on our coefficients of interest are shown in Table 5.

First, we run a version of our baseline model where we only control for loan characteristics that go directly into lenders' credit decisions by excluding the loan amount, income, and state fixed effects from the model specification.[15] The estimated disparities for Black and Latinx applicants are larger under this specification compared to our baseline estimates at 3.2 and 2.1 percentage points, respectively, while the Asian-White disparity is unchanged. If loan amount and income proxy for important unobserved underwriting factors such as wealth and cash reserves, not including them in our model would bias our estimated disparities.

Second, we exclude applications near the cutoffs of GSE underwriting standards to test whether loans that are more likely to be marginal, based on our observed factors, are driving our

[15]While loan amount and income may proxy for the unobserved factors such as wealth or cash reserves, LTV and DTI ratios already capture the relative loan amount and income of the applicant. Additionally, our understanding is that underwriting does not use the state of the application directly in the credit decision.

results. Specifically, we estimate the baseline model with a restricted sample that is limited to applications with LTV at or below 95, DTI at or below 43, and credit scores at or above 660. The estimates change somewhat with the Asian-White disparity going from 2.2 percentage points to 2.1, the Black-White disparity moving from 2.9 to 2.5 percentage points, and the Latinx-White disparity rising from 1.5 to 1.7 percentage points. For Asian and Latinx applicants, it does not appear that our results are driven by mis-specification of the model for applicants near the boundaries of meeting the GSE eligibility matrix, nor does it appear that the disparities are only concentrated among those applicants.[16] The notable decrease in the Black-White disparity is likely driven by a large share of the Black applications being considered "marginal" and therefore excluded from this sample. Nonetheless, the Black-White disparity does not seem to be largely driven by those borderline loan applications, since the disparity after excluding the borderline applications remains qualitatively similar.

Third, we exclude observations where the race or ethnicity is reported by the loan officer rather than the applicant, and we see basically no change in the estimates.[17] Fourth, we control for a quadratic in the applicants' age.[18] Age may proxy for things we cannot see but the lender can use in determining acceptance like credit history, employment history, or wealth.[19] Fifth, we control for the sex of the applicants.[20] We include sex because previous work has suggested that female applicants have higher denial rates compared to male applicants (Hirasuna and Allen, 2012). Controlling for age and sex does affect our estimates slightly for all racial groups, but none of the estimates for Asian, Black, or Latinx disparities change by more than 0.2 percentage points in magnitude. Notably, the estimated effect for the missing category moves from 2.0 to 1.3 percentage points when controlling for sex, which reflects a high degree of correlation between not reporting sex and not reporting race or ethnicity. We further discuss the role of unobserved factors later in the paper.

Sixth, we control for the income and loan amount using a cubic spline rather than taking the

[16] In results not shown, we test whether disparities are different for these applications that we call marginal (those with DTI above 43 or LTV above 95, or credit score under 660. We find that the disparities are slightly larger for Black and Asian marginal applicants relative to White marginal applicants but smaller for marginal Latinx applicants.

[17] Loan officers can report race in HMDA based on visual inspection or surname. The race-ethnicity determination made by a loan officer may be systematically different from self-reported race or ethnicity.

[18] If there are two co-applicants, the minimum age between the two is used.

[19] Interestingly, age may also interact with race. For example Black applicants tend to be older than applicants from other racial or ethnic groups.

[20] Sex is characterized using the reported sex of both applicants into the following categories: lone female, lone male, same sex-female, same sex male, opposite sex co-applicants, other and missing. Other includes applications where one or both applicants report both male and female.

natural log. We try using these more flexible non-linear functional forms to verify that our exact model specification is not driving the results. Again, the estimates change very little. Seventh, we add a co-applicant indicator to control for the number of applicants because two applicants may have more resources or two incomes, which may represent more stable job history or income stability. This control reduces the magnitude of the point estimates by 0.1 to 0.2 percentage points, and we explore the role of the co-applicant more fully later in the paper.

Our eighth and ninth specifications examine more flexible fixed effects modeling for the DTI, credit score, LTV interactions, and the state, time interactions, respectively. When we use very fine bins for DTI, credit score, and LTV, we find basically no effect on our estimates of interest. Interestingly, this result suggests that for our purposes, the DTI categories reported in the public HMDA would be adequate for estimating our model. When we use county rather than state in our geographic by year-by-month fixed effects, we see that the estimated disparities decline to 2.0 percentage points for Asian applicants, 2.6 percentage points for Black applicants, and 1.1 percentage points for Latinx applicants. We think that including the county-by-year-by-month fixed effects may over control for denials because there are many county-by-year-by-month combinations that do not have applications from different racial groups.[21] We also examine disparities by MSAs, which should allow readers to examine whether specific cities have heterogeneous effects and may alleviate some concerns about the state being too large of a geography for our controls.

Our tenth specification combines a number of the previous robustness specifications to simultaneously add controls for age, sex, whether a coapplicant is present, and county-by-year-by-month fixed effects instead of state-by-year-by-month fixed effects. These controls reduce the magnitudes of the estimated racial disparities from 2.9 percentage points to 2.3 percentage points for Black applicants, from 2.2 percentage points to 1.9 percentage points for Asian applicants, and from 1.5 percentage points to 1.0 percentage point for Latinx applicants. Even after simultaneously controlling for a number of loan and borrower characteristics, we still see statistically significant disparities across Asian, Black, and Latinx applicants relative to White applicants.

Finally, we use a logit model to predict our binary outcome rather than a linear probability model to understand whether our results are driven by the linear functional form assumption.

[21] This is another difference in specification between ours and Bhutta et al. (2021), but their sample size is much larger possibly allowing for better estimation of county-month-year fixed effects.

The estimates are qualitatively similar with Asian applicants being 1.9 times more likely to be denied than White applicants, while Black and Latinx applicants are 1.8 and 1.5 times more likely to be denied, respectively (Table 6). The predicted probabilities of denial from the logit and our baseline model are also highly correlated at 0.95.

Overall, our estimates of racial disparities in conventional GSE-backed mortgage application decisions do not appear overly sensitive to our specific sample or modeling specification, and our qualitative findings are very robust.

5.1.2 Race and Ethnicity Definitions

Next, we test whether our results are sensitive to our definition of the race and ethnicity of the application. One contribution of our paper is to examine differences broken out by racial group instead of considering people of color as one category as previous work has done (e.g., Bartlett et al. (2019), Frame et al. (2021)). We tried different definitions to test whether the results differ based on the exact approach used to map the multidimensional information on race and ethnicity in HMDA down to six mutually exclusive categories.

Perhaps surprisingly, the estimates are not particularly sensitive to the different methods we tried. First, we used only the primary applicant's information to characterize the application following our baseline methodology. The estimates are slightly smaller in magnitude using only the primary applicant's information, but they are qualitatively similar (Table 7). Second, we test whether prioritizing race over ethnicity matters. For example, a Latinx-Black applicant would be considered Latinx under our baseline specification, but under this racial-prioritization specification they would be considered Black. We keep Latinx-White applicants separate so that the reference group remains non-Latinx White applicants. The estimated disparities are very similar for Asian and Black applicants. Latinx-White applicants have slightly lower disparities relative to non-Latinx White applicants compared to our baseline disparity estimates that compare all Latinx applicants to non-Latinx White applicants. Finally, we used a stricter method to assign an application to a race or ethnicity category by only making an assignment for applications with no missing race or ethnicity responses for either applicant. This specification does not affect the Asian and Black estimates, but does lower the Latinx estimate by 0.2 percentage points as Latinx applicants are more likely to have missing race information.

5.1.3 Missing Race and Ethnicity

One concern with our analysis is that a non-trivial fraction (around 10 percent) of our sample have missing race and ethnicity. Race may not be reported if the applicant declines to report it and the loan officer does not report based on visual inspection or surname. For example, this may happen if the application was submitted online without race information and transactions were done over the phone. We find that the fraction of applications that have missing race or ethnicity varies by lender, which is consistent with different lenders having different mixtures of online versus in-person applications and different interfaces for filling out demographic information. If the individuals in the missing race category are systematically selected, our results could be biased, although the bias is difficult to determine a priori. For example, say Black applicants who apply online are more likely to be missing than other Black applicants and that the applicants who apply online are stronger applicants. If White applicants do not exhibit similar behavior, the magnitude of our coefficient on Black denials would be biased upward.

When we examine the estimated coefficients for our missing race category, we find that they are about 2.0 percentage points more likely to have their applications denied relative to White applicants and that the estimated effect changes very slightly with the addition of covariates (Table 4). To further investigate the applications with missing race, we predict missing race using a simplified model including application income, DTI, LTV, credit score, loan amount, state, and year-by-month indicators (Table 8). Applicants with higher loan amounts and credit scores and very low DTI and LTV ratios are more likely to have missing race or ethnicity. We see the biggest differences across states where applications in some states are over 10 percentage points more likely to have missing race and ethnicity categories relative to others.[22] These geographic differences are likely partially driven by lender differences where lenders are concentrated in certain states and have higher or lower fractions of missing race and ethnicity data. The results from analyzing the characteristics of those with missing race and ethnicity suggest that this category has on average applicants that are slightly less likely to be denied based on the loan and borrower characteristics.

Although we cannot rule out differential selection by race into the missing category, we use the estimated model and the observed characteristics of the sample to predict the probability of missing race for our sample. Appendix Figure A4 shows the distribution of the predicted probabilities of race and ethnicity being missing by reported racial group. It shows that based

[22] The coefficients are not reported but are available upon request.

on the model, our sample of Asian applicants would be more likely to have missing race than White, Black, or Latinx applicants. Put another way, the characteristics of the missing race-ethnicity sample match more closely to the characteristics in the Asian sample than the other races, although as the figure shows there is a lot of variation within each racial-ethnic category.

Without more information, we cannot determine whether our estimates are biased up or down due to some applicants not being categorized into racial-ethnic categories. Our analysis of the relationship between observed characteristics and missing race or ethnicity suggests that there is not a strong selection into missing status and the estimated coefficient in our baseline model is consistent with the category including a general mixture of racial groups. Further work could investigate reasons for the differences in the share of missing observations across states and by lender.

5.2 Disparities by Detailed Race and Ethnicity Categories

While our baseline model places each application into one racial category for simplicity, in this section we explore differences across all racial-ethnic combinations for co-applicants and for more detailed subgroups within Asian applicants. We also investigate differences in the treatment of lone applicants across races and ethnicities.

To study the disparities for co-applicants of different races or ethnicities, we include indicators for every possible combination of co-applicants' races and ethnicities, including combinations where there is no co-applicant. Our results are shown in Figure 2 and detailed in Table 9 where all estimates are relative to applications from two White applicants.

The first striking result is that one-applicant applications are more likely to be denied than two-applicant ones, and these differences are larger for applicants of color. Lone Black applicants are 2.4 percentage points more likely to be denied relative to two Black applicants after controlling for our observed loan and borrower characteristics. That number for lone Asian applicants is 0.5 percentage points, 1.7 percentage points for Latinx applicants, and 0.8 percentage points for single White applicants relative to two White applicants. Our baseline disparity estimates are at least partially driven by those with no co-applicant, and this is especially so for Black applicants.

It is not clear why we see significantly higher denial rates among two-applicant applications compared to one-applicant applications, holding application income and other factors constant. It's possible that having either two working adults or one working and one not working adult is preferred to only one working individual in terms of income and employment stability. On the other hand, if both applicants are working and the sum of their income is similar to the one applicant, higher turnover at lower paid positions may indicate a higher likelihood of income and employment instability. However, these explanations do not exclusively apply to applicants of color and not lone White applicants who have much more similar denial rates to two White co-applicants. We also cannot rule out differences in other unobserved factors such as liquid wealth between lone and dual applicants.[23]

We lack the precision to tightly estimate a differential effect for some combinations of applicants, but others show suggestive patterns. Perhaps surprisingly our estimates for Black-Latinx co-applicants suggest that their denial rates are not different from White-White applicants (0.5 percentage points with confidence interval that includes zero). Black-White applicants see denial rates that are similar to White-White applicants, and Asian-White and Latinx-White applicants have an estimated 0.8 percentage points and 0.1 percentage points, respectively, higher denial rates. The estimate for Asian-Black co-applicants is 1.1 percentage points but it has a wide confidence interval that almost includes zero.

Finally, taken as a whole these results reject the idea that Asian applicants may be treated similarly to White applicants. Among same race co-applicants, Asians have the highest denial disparities and having a co-applicant of a different race reduces those disparities. Lone-Asian applicants also have large estimated disparities although they are smaller than for lone-Black applicants.

Although there is a large amount of diversity in economic measures within all racial groups, the largest variance has been documented within Asians (Kochhar and Cilluffo, 2018). These differences are at least partially driven by the conditions under which individuals of Asian origin immigrated to the U.S. In particular, some immigrants came as refugees after the end of the Vietnam war while other immigrants came for post-secondary education or high-skill jobs under the H-1B visa program.

In order to more deeply understand our estimate for Asian applicants as a whole, we include each Asian subgroup as its own racial category in our baseline model. The HMDA data include information on specific countries of origin for Chinese, Filipino, Indian, Japanese, Korean, and Vietnamese. We use the same racial definition as in our baseline results: An application from

[23] Although we do not control for age in our baseline regressions, lone applicants are generally older and controlling for age does not explain the differences we identify here.

two individuals of Chinese heritage is considered Chinese while one from a co-applicant of Vietnamese origin and one of Korean origin would fall in the "All other Asians" category. As Figure 3 shows, all Asian subgroups have higher denial rates relative to White applicants, but applicants of Chinese, Indian and Vietnamese origins have the highest estimated disparities in denial rates among the Asian subgroups at 2.8, 2.7 and 2.5 percentage points respectively. Japanese applicants are the Asian subgroup with the smallest denial disparity relative to White applicants with a relatively wide confidence interval that includes zero. Filipino and Korean applicants fall in the middle with estimated disparities of 1.5 and 2.2 percentage points respectively.

The patterns of disparities across Asian subgroups do not support the hypothesis that omitted variables like wealth are driving the results. Asian Indians and Filipinos are the subgroups with the highest levels of income with median incomes above the national median, which based on unobserved economic resources suggests that their disparities relative to White applicants would be underestimated (Budiman and Ruiz, 2021). Although data on wealth at a subgroup level is sparse, Japanese, Chinese and Asian Indians have the largest average income from sources like interest, dividends, and rental income all of which are income flows based on assets Patraporn et al. (2021). Again these suggest that the role of wealth as an unobserved variable should bias these coefficients downward, yet our estimates suggest higher levels of disparities for Chinese and Asian Indians relative to other subgroups.

Asian individuals in the U.S. are much more likely to be immigrants, which may affect their ability to qualify for a mortgage. In 2019, 76 percent of Asian adults were foreign-born compared to 42 percent of Latinx adults, 11 percent of Black adults, and 4 percent of White adults (American Community Survey Public Use Microdata Sample 1-Year Estimates). It is not possible to know the citizenship and immigration history of the applicants in our sample, but requirements regarding income history or credit score history may be more difficult for recent immigrants to meet. Between 2018 and 2020, most of these applications were likely coming after a pre-approval process that should have checked eligibility for a mortgage, but it's possible that Asian applicants were more likely to have complications arising from immigration status or history that could contribute to their higher denial rates.

5.3 Role of Lender

Our baseline estimates suggest relatively large disparities in denial rates between applicants of color and White applicants. In this section, we explore the role of the lender in explaining the results. One potential explanation for our results is that applicants of color are more likely to apply with high-denial rate lenders. Indeed previous work has suggested that certain lenders play an outsized role in driving racial differences in the mortgage market during the run-up to the 2008 financial crisis (Bayer et al. (2018), Wei and Zhao (2021)).

Our analysis starts by testing for differences in estimated racial and ethnic disparities by type of lender and the share of originated loans that are sold to understand whether lenders with certain characteristics are driving our results. Then we focus on the 50 largest lenders to understand the variance in estimated disparities across lenders and to test whether lender-specific specifications reduce these disparities.

In studying different types of lenders, we distinguish between commercial banks, credit unions, independent mortgage companies, and thrift institutions using information on the lender ID.[24] We re-run our baseline model allowing for different disparities by the type of institution. We see that across all institution types all racial groups have the highest denial rates at thrift institutions and the lowest probabilities of denial at independent mortgage companies (see Figure 4). The differences in estimated disparities across types of lender for White applicants vary by about 1.6 percentage points and for Latinx applicants the difference is 3.9 percentage points suggesting that lender type does generally matter for applicants' likelihood of denial.[25]

When we focus on racial and ethnic differences within a type of lender, we see Black applicants have the largest estimated disparities compared to White applicants at credit unions, commercial banks, and thrift institutions at between 3.7 and 3.9 percentage points compared to 2.3 percentage points at independent mortgage companies. For Asian and Latinx applicants, disparities are greatest at thrift institutions and smallest at independent mortgage companies with commercial banks and credit unions in the middle.

Independent mortgage companies received 57 percent of applications in our sample, followed by commercial banks with 30 percent (Appendix Table A1). Credit unions and thrift institutions only made up 8 percent and 5 percent of applications, respectively. Interestingly, when we look at applications by race, we find that independent mortgage companies have the lowest share of White applicants at 63 percent, compared to 69 percent, 70 percent, and 72 percent

[24]Specifically, these classifications come from a file created by Robert B. Avery of the Federal Housing Finance Agency that uses self-identified HMDA filing and matches to the Federal Reserve National Information Center database to generate an indicator of type of institution. See `https://www.ffiec.gov/npw/Help/InstitutionTypes` for the definition of each lender type.

[25]The estimated differences across lender for White applicants are not shown in the figure but are available upon request.

for commercial banks, credit unions, and thrift institutions, respectively. This suggests that disproportionate applications to institutions with higher levels of disparities does not explain the disparities found in our baseline estimates.

Our findings suggest some important differences by lender type with independent mortgage companies showing the lowest level of denials conditional on our observed covariates as well as the smallest racial and ethnic disparities. While we cannot rule out selection in the unobserved characteristics of applicants going to each type of institution or racial differences in applicants being discouraged from applying for a mortgage, two pieces of evidence suggest that this is not the case. First, the underlying loan characteristics of loan applications across the types of institutions look relatively similar and any differences do not provide an obvious explanation (see Appendix Table A2). Second, we see that people of color are actually more likely to apply with independent mortgage companies where disparities are the smallest.

One possible explanation for these results is that independent mortgage companies specialize in mortgage lending and are better able to assist applicants to avoid a denial. Things like training and expertise of the loan officer and a thorough pre-approval process may lower the likelihood of denial particularly for more complex applications. If applicants of color have more complicated or less standard applications, experienced loan officers may be better at helping them navigate the process to receive a loan. A second explanation could be that because independent mortgage companies are more likely to sell loans to a third-party they may be more willing to take on more risky loans.

To test whether lenders that tend to sell loans have different disparities from those that keep the loans on their balance sheets, we calculate the share of originated loans sold that year by lender.[26] We find strong evidence that lenders that sell a higher share of the loans in our sample have both lower denial rates overall *and* smaller racial disparities (Figure 5). For example, a White applicant is 3 percentage points less likely to be denied at a lender in the top quintile of share of loans sold relative to a similar White applicant at a lender in the first and second quintiles.[27] The disparities for Asian applicants relative to White applicants falls from over 3 percentage points to 0.7 percentage points depending on the share of loans the lender sells. For Black applicants the disparity falls from 4.3 percentage points to 1.4 percentage points and for Latinx applicants it falls from 3.2 percentage points to 0.2 percentage points.

[26] HMDA has a calendar year reporting cycle, meaning that we do not know if the loan is sold in following years.

[27] These estimates are not shown in the figure but are available upon request.

Taken together, our results suggest that independent mortgage companies and lenders that sell a high proportion of their originated loans have both the lowest denial rates and the lowest racial and ethnic disparities.

Next, we investigate the size and variance of the racial disparities identified in our baseline model across lenders. Other work on racial disparities in the mortgage market has found that the overall effects can be driven by large disparities among a small group of lenders (Bayer et al., 2018). Additionally, testing for disparities within lenders controls for the extent to which applicants of color disproportionately work with lenders with systematically high or low denial rates for all applicants regardless of race.[28] To do this, we add an interaction between racial-ethnic categories and the specific lender to our baseline model. We include the 50 largest lenders by volume in this analysis because these lenders receive around half of the applications, and they are likely to have many applications from all racial-ethnic groups.[29] This model allows for each lender to have different denial rates overall and then tests whether within lender the denial rate differs by race and ethnicity.

As shown in Figure 6, there is a lot of variation across lenders in the estimated effect of race and ethnicity, but the disparities identified in our baseline results are not driven by a few large lenders. The median estimate suggests that half of lenders have estimated disparities for Black applicants relative to White applicants that are larger than 2.5 percentage points and one-quarter exceed 4.1 percentage points. The estimated effects for Latinx and Asian applicants remain smaller than for Black applicants with the median estimate across lenders being 1.1 percentage point higher than White applicants. We also look at whether lenders with high estimated disparities for one racial group relative to White applicants also have high disparities for other applicants of color. The correlation coefficient of our lender-level disparities is highest between Latinx-White and Black-White applicant disparities at 0.73, followed by disparities for Latinx-White and Asian-White applicants at 0.64, and it is smallest for Asian-White and Black-White applicant disparities at 0.41.

One criticism of using our baseline model to estimate within lender effects is that different lenders may use different models to evaluate applications and combining lenders into one re-

[28]In Appendix Figure A5, we show evidence that the racial composition of applicants does vary across lenders. The denial rates also vary by lender with the 25 percent of lenders having denial rates under 2 percent and 25 percent with denial rates over 6 percent (Appendix Table A3).

[29]Our baseline model specification run using this restricted sample yields point estimates that are similar to the baseline model with the full sample, although the estimated disparities are slightly smaller (2.9 percentage points for Black applicants, 1.8 percentage points for Asian applicants, and 1.3 percentage points for Latinx applicants).

gression could generate biased coefficients. Indeed Bhutta et al. (2021) find evidence that some lenders have stricter underwriting standards than others. To test whether lender differences in evaluating observed loan and borrower characteristics drive our results, we run the model separately for each of the 50 lenders with the greatest number of applications. This model allows each lender to have its own way of evaluating income and credit score, although as previously mentioned these applications are generally evaluated using an AUS. In Figure 7, we show the distribution of the estimated race-ethnicity category coefficients, and the results are very similar to those in Figure 6. The median estimated disparities with the more flexible models are very similar if not slightly larger than the less flexible specification (see Appendix Table A3). The figure suggests that the disparities faced by applicants of color exist across the majority of lenders, although there is a high level of variation in the estimated coefficients. The median estimate across lenders of the coefficient for Black applicants relative to White applicants is 2.3 percentage points, which is comparable to our baseline estimate of 2.9 percentage points using a more restrictive model and all lenders. For Asian applicants, the median within-lender estimate is a 1.1 percentage points higher probability of denial relative to White applicants, which is smaller than our baseline estimate of 2.2 percentage points, possibly suggesting more of a role for sorting across lenders by Asian applicants. The figure shows the results that we estimate in our baseline specification do not appear to solely be a result of different lenders using different models to evaluate the observed application characteristics.[30]

Overall, we find evidence that disparities in mortgage application denials across racial and ethnic groups exist across lenders and cannot be explained by differences in how lenders treat application characteristics. The within lender results show large variation in estimated denial rates by race and ethnicity, suggesting that applicants may benefit from making multiple applications. These results focus only on the acceptance decision and further benefits may occur based on pricing differences across lenders. Pricing discrimination would generally lead to a higher DTI due to higher monthly payments associated with the loan. Because we control for DTI in our model, a denial due to an inflated DTI from pricing discrimination would not contribute to our estimated disparities.

[30]The correlation coefficients between lender-level disparities across racial group pairs are similar when we estimate lender-specific models. The correlation coefficients are 0.54 between Asian-White and Black-White disparities, 0.47 between Black-White and Latinx-White disparities, and 0.63 between Asian-White and Latinx-White disparities.

5.4 Role of Geography

In this section, we explore the differences across geography underlying our baseline estimates by estimating disparities by neighborhood characteristics and by state and metropolitan statistical areas (MSAs). Racial demographics, and housing, labor, and mortgage markets may differ across states and MSAs.

To study whether disparities differ by neighborhood characteristics, we classify the census tract where the application property is located by its median income and share of residents who are of color. Then we estimate different disparities by these tract-level characteristics using our baseline model. We show that disparities generally don't vary by the census tract share of residents of color, with the exception of Black applicants in the tracts with the highest share of residents of color, where Black-White disparities are over 0.5 percentage points larger (see Figure 8).[31] When we look by median income in the census tract, we see that there is no pattern for Asian-White disparities, but that Black and Latinx disparities relative to White applicants are smaller in high income neighborhoods (Figure 9). These results imply that neighborhood racial make-up does not seem to affect disparities after accounting for the race or ethnicity of the applicant but that the income of the neighborhood does seem associated with the disparities. This could reflect that Whites purchasing homes in low-income neighborhoods are more likely to be given the benefit of the doubt than Black or Latinx applicants, or that race and ethnicity matter less for the applicants purchasing homes in high income neighborhoods. While we cannot rule out neighborhood characteristics serving as a proxy for unobserved factors, our results suggest that the relationship between neighborhood composition and income and unobserved factors would have to differ by race.

To understand whether racial disparities differ by state, we include an interaction term in our models between states and our racial-ethnic categories, and we find sizable differences in disparities across states. Figure 10 maps the coefficients for each state for Latinx applicants relative to White applicants. We see higher disparities generally in New England, the mid-Atlantic, and the South and smaller disparities in the Western half of the country. States with higher proportions of applications from Latinx individuals such as New Mexico, Florida, California, Texas, Arizona, and Nevada, generally have relatively low levels of estimated disparities at around or under 1 percentage point higher denial rates compared to similar White applicants

[31]There is some suggestive evidence that Latinx-White disparities are smaller in neighborhoods with higher share of residents of color.

in the same state.[32] Figures 11 and 12 show the same for Asian and Black applicants where the maps generally show disparities exist in most states. In contrast to the Latinx results, states with large shares of Asian applicants like California, Washington, New Jersey, New York, and Virginia do not have lower estimated disparities for Asian applicants; the estimated disparities are between 1.9 and 3.3 percentage points higher relative to White applicants in the same state.[33] We see similar results for states with larger shares of Black applicants like Maryland, Georgia, Washington D.C., Mississippi, and Delaware where estimates of the disparities relative to White applicants range between 2.4 and 3.5 percentage points. Contrary to the positive relationship found between lender-specific racial disparities, state-specific racial disparities do not exhibit a similar relationship. The largest correlation is between Asian-White and Black-White disparities with a coefficient of 0.36. The correlation coefficients are much smaller for Asian-Latinx and Black-Latinx pairs at 0.07 and 0.08, respectively.

Because the relevant geography for mortgage markets might be smaller than the state level, we estimate disparities within the 50 largest MSAs using a similar approach to state-level disparities. We include only applications for properties within the 50 largest MSAs and interact MSA indicators with race-ethnicity indicators. As with our state estimates we see substantial variation across MSAs in these estimated disparities. Black-White disparities in mortgage denials were highest at around 5 percentage points in two of the MSAs with very large cities: New York City and Chicago (Appendix Figure A6). Asian-White disparities were highest for two MSAs in Texas: San Antonio (4.3 percentage points) and Austin (3.9 percentage points) (Appendix Figure A7). Latinx-White disparities were highest in Louisville, KY, Providence, RI, and Buffalo, NY, and consistent with the state level results generally were higher in MSAs located in the eastern half of the U.S. (Appendix Figure A8). When we examine MSAs with the smallest estimated disparities relative to White applicants, we again see it varies by racial group. For Asian applicants, that MSA is Oklahoma City, OK, for Black applicants it is Salt Lake City, UT, and for Latinx applicants it's Los Angeles, CA. Similar to the state-specific disparities, MSA-specific disparities do not appear to have a strong positive relationship between each racial disparity pair suggesting that the geography of disparities is more complex than certain states or MSAs having high disparities for all applicants of color.

Overall, the levels of disparities across most geographies remain highest for Black applicants,

[32]Florida is the exception with an estimated 2.5 percentage point higher denial rate for Latinx applicants.

[33]Hawaii stands out as a state with a large share of Asian applicants, but Asian applicants actually have 0.9 percentage point lower denial rates compared to White applicants in the state.

followed by Asian, and then Latinx applicants, which is consistent with our baseline results.

6 Discussion

Taken together our results suggest that Asian, Black, and Latinx applicants have higher denial rates for mortgage applications for home purchases relative to White applicants even after controlling for loan and borrower characteristics. We show that these disparities are widespread and are not driven by applicants of color concentrating among high-denial lenders. The findings suggest that independent mortgage companies and lenders that sell a higher proportion of their loans have lower denial rates and lower levels of disparities in denial rates. Additionally, there is a wide variation in disparities across lenders with some large lenders exhibiting no differences across racial and ethnic groups.

Our study covers applications for mortgage applications between 2018 and 2020, a period with a strong housing market when sellers would most likely require a pre-approval letter to accept an offer. This pre-approval process is outside the scope of our data and analysis, but it drives the population of applications included in our sample. If applicants had received a pre-approval prior to submitting an application, there are a few reasons why their loan application may still be denied. First, the property may not appraise at the purchase price, which could result in the application having insufficient collateral. A lack of collateral is the most common primary denial reason in our data. Perhaps surprisingly, when we look at the primary denial reasons for denied applications by racial and ethnic groups, almost one in four White applicants were denied due to not having enough collateral, a rate that is higher than all other races and ethnicities (see Appendix Figure A9). This suggests that the denial disparities we estimate are not obviously explained by a lack of collateral.

Mortgage applications may also be denied because of unverifiable information, which could arise if the lender didn't fully verify the applicant's information or check for data errors in the pre-approval application. Bhutta et al. (2021) find that Asian and Latinx applicants are more likely to be denied by a lender after an AUS approval due to an incomplete application. Certain lenders may have different practices regarding how much checking happens after a pre-approval application has been submitted, or different levels in training and experience among their employees working on pre-approvals. While these factors could explain differences in the overall denial rates, there would need to be systematic differences across race and ethnicity populations to explain racial disparities in the likelihood of getting pre-approved but later receiving a denial. It is possible that people of color are more likely to have variable income sources such as contracting income that may be more complicated to assess. For example, Latinx and Black workers are particularly over-represented within temporary agencies (Bureau of Labor Statistics (2018)). It is also possible that lenders treat similar income sources differently based on race and ethnicity due to conscious or unconscious racial bias.

Credit history, debt-to-income ratio and insufficient cash are a few more common reasons a mortgage application was denied in our sample. Although a pre-approval gives an interested homebuyer an approximate purchase price, there are a number of reasons that could lead buyers to exceed their approved monthly payment or required cash at closing, which could lead to a denial. Buyers may make a higher offer than expected or other costs like closing costs; Homeowners Association (HOA) fees or taxes could increase the expected payment, which in turn could increase their DTI ratio or require more cash upfront than expected. In fact, credit history is the most commonly cited denial reason for Black applicants (see Appendix Figure A9). Black applicants are also denied due to high debt-to-income ratios at a higher rate than all other races and ethnicities. Insufficient cash is more frequently cited for Asian applicants, but the differences are minimal across racial and ethnic groups. While credit history may be partially encompassed in the overall credit score, these unobserved factors may explain some of the disparities we estimate. Bhutta et al. (2021) find that AUS denials are higher for Black applicants even after controlling for HMDA observed factors, suggesting that additional factors fed into AUS that are unobserved in HMDA differ by race. They also find evidence that some lenders use stricter requirements to assess loan applications, and these requirements may disproportionately hurt applicants of color possibly due to their interaction with factors that are not observed in HMDA.

Additionally, it's well-documented that wealth in the U.S. is unequally distributed across racial and ethnic groups (Thompson and Suarez, 2015). Applicant's and their family's wealth, beyond the income, DTI, and LTV measured in our analysis, may play an important role in determining whether a loan is approved or denied because it may affect the perceived risk of the loan. Two applicants may have the same observed characteristics in our sample, but the one with higher cash reserves would be more likely to receive a loan. Although these should be factored in during the pre-approval process, it's possible that prior to denial White applicants are more likely than Black, Asian, or Latinx applicants to bring new positive information, such as gifts from a family member, to their application to avoid a denial.

Finally, we cannot rule out explicit racial bias in how applications are perceived by individual loan officers or underwriters and lenders more generally. Racial differences in the level of assistance provided to move the application from a denial to an approval may also contribute to the disparities we identify. Consistent with the importance of the loan officer in the approval decision, Frame et al. (2021) find evidence that when minority borrowers work with a minority loan officer rather than a White loan officer at the same branch, it has a large positive effect on the probability of the loan being approved.

Our finding that applicants of color are more likely to have their mortgage application denied even after controlling for important loan and borrower characteristics that affect the risk of the loan is economically meaningful. Although these applicants may later apply with a different lender or for a different product and be accepted, the time frame between making an offer and securing financing on a home purchase may be such that the applicant loses the home. Applicants who are denied for a GSE-backed conventional loan may also be accepted for other loan products with less strict lending standards like FHA-backed loans, but depending on the borrower's situation these loans may be more expensive. Finally, an application that results in a denial may lower the applicants' credit score for their next financing application if they fail to apply for and secure financing for a home within 45 days of the original application.

More broadly our results point to the possibility of disparities in other parts of the mortgage process or in other products, as we have focused on a group of applicants that are highly likely to meet underwriting standards for loans that could be sold to GSEs. There are other aspects of the mortgage process where different treatment by race and ethnicity may result in negative economic consequences for people of color. If applicants of color are offered higher-priced mortgages after acceptance (Lin and Liu (2015), Bartlett et al. (2019)) or are less likely to refinance to lower their monthly payments (Gerardi et al. (2020)), they may end up paying significantly more than White applicants for the same home.[34]

[34]One recent study by Bhutta and Hizmo (2021) suggests that higher interest rates among FHA borrowers of color result from differences in discount points, which could point to differences in borrower choices rather than mortgages offered by the lender.

7 Conclusion

Our findings suggest that even within relatively standard application types backed by GSEs, we see meaningful differences in denial rates across racial groups. We find that Black applicants are 2.9 percentage points more likely to have their mortgage application denied relative to similar White borrowers, while Asian applicants are 2.2 percentage points more likely to be denied and Latinx applicants are 1.5 percentage points more likely. Compared to two-coapplicants, lone applicants see higher denial rates, especially among Black and Latinx applicants. When taking the type of lender into account, we find that independent mortgage companies tend to have lower overall denial rates as well as lower racial disparities in denial rates. Lenders that sell a higher share of their originated loans also have lower estimated disparities. Disparities exist within lenders even after estimating separate models for each lender, although the disparities across the top 50 lenders are quite varied. When we look at the role of neighborhood characteristics, we find that the disparities do not appear to vary by the racial composition of the neighborhood where the property is located, but we do find lower racial disparities in higher-income neighborhoods even after controlling for the application-level characteristics. When we look at disparities by state, we find variation in the levels but again higher denial rates for Black and Asian applicants that are widespread across states. Latinx applicants have denial rates more similar to Whites in the western half of the country, while experiencing higher denial rates among most eastern states.

Although they may appear small in magnitude, the results are important for a number of reasons. First, they represent a large percentage increase in the probability of denial, as less than 4 percent of the applications in our sample are denied. Second, they represent disparities in a standard, relatively safe loan product that comprises a large share of the mortgage purchase market. Third, these estimates control for covariates that themselves could be the result of racial discrimination, like loan-to-value ratios, income, and credit scores.[35] Finally, we are focused on one stage of the mortgage application process. Additional racial disparities may exist prior to this step, in determining who applies for a mortgage, or after this step, in the pricing decisions, which may further exacerbate racial differences in equitable access to credit.

[35] See Lang and Spitzer (2020) for discussion of discrimination as a system.

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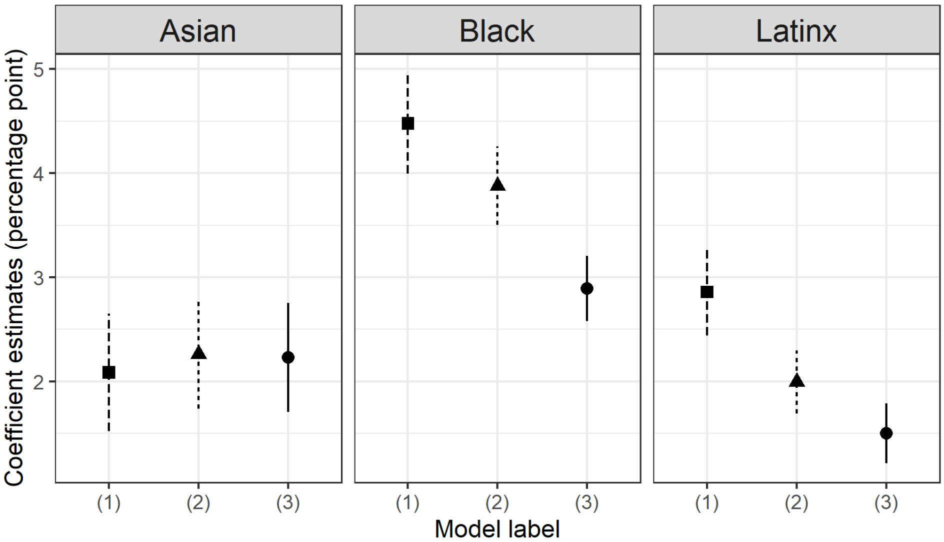
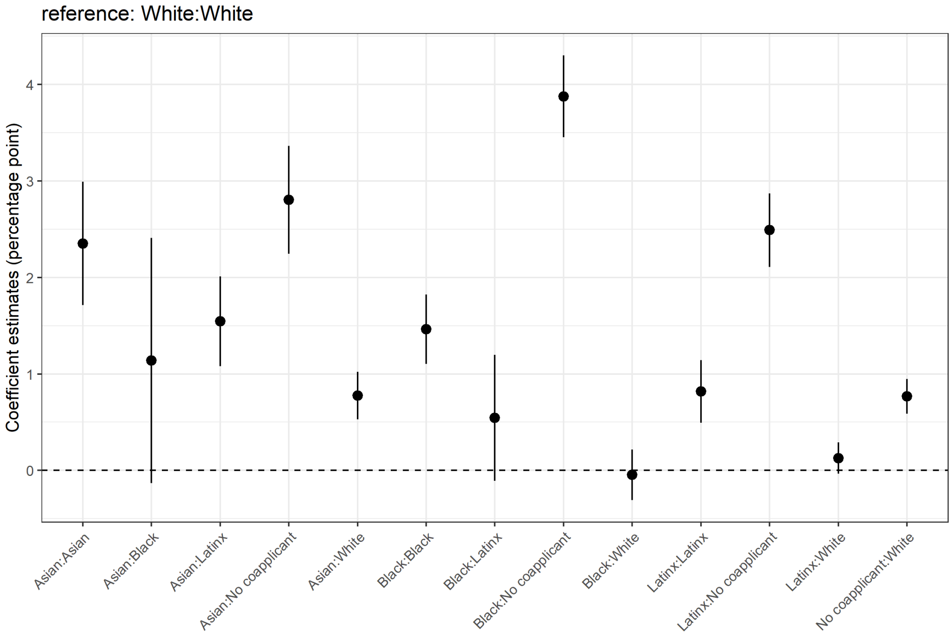
8 Figures

Figure 1: Baseline estimated disparities in mortgage denials



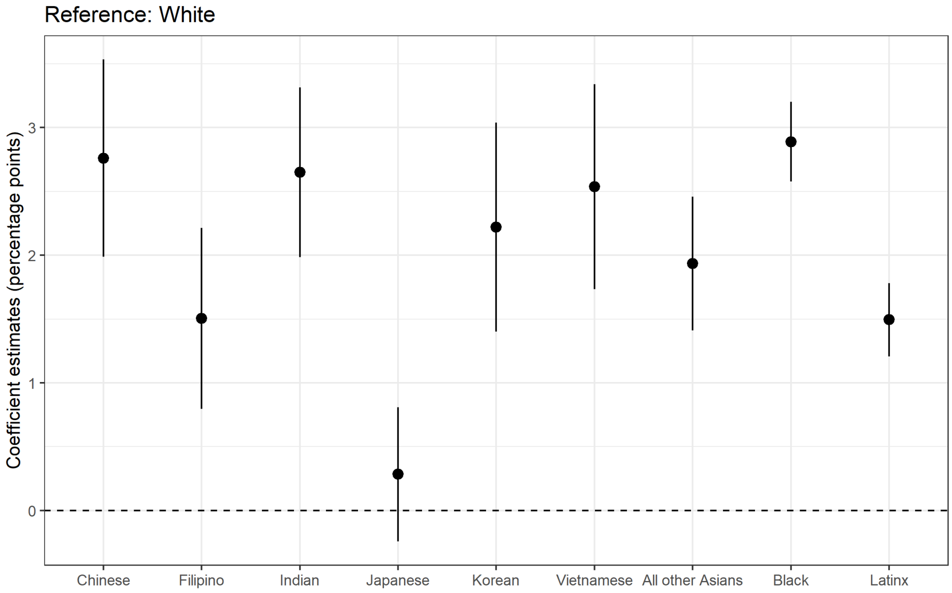
Plot shows coefficients on race and ethnicity indicators from regressions predicting mortgage purchase application denials where White applicants are the reference group. Standard errors are clustered at the lender level. Model (1) only includes racial and ethnic categories as predictors. In model (2), we add state, year, and month three-way interactions, log of loan amount, log of income and the LTV and DTI two-way interaction fixed effects. And finally, we expand the LTV and DTI two-way interaction to three-way interaction fixed effects with credit score in model (3). Analysis uses HMDA 2018 to 2020 data and sample includes conventional home-purchase applications for 30-year term loans, within the county-level conforming limit for single dwelling units used as a primary residence. Applications must have credit scores above 620, loan-to-value ratios between 0 and 97 percent, and debt-to-income ratios below 50 percent. Applications are considered Latinx if both applicants report being Hispanic or Latino/a. All other applicants are characterized using both applicants' reported race as Asian, Black, White, multi-racial or other race, and missing.

Figure 2: Estimated denial disparities for detailed co-applicant race-ethnicity combinations



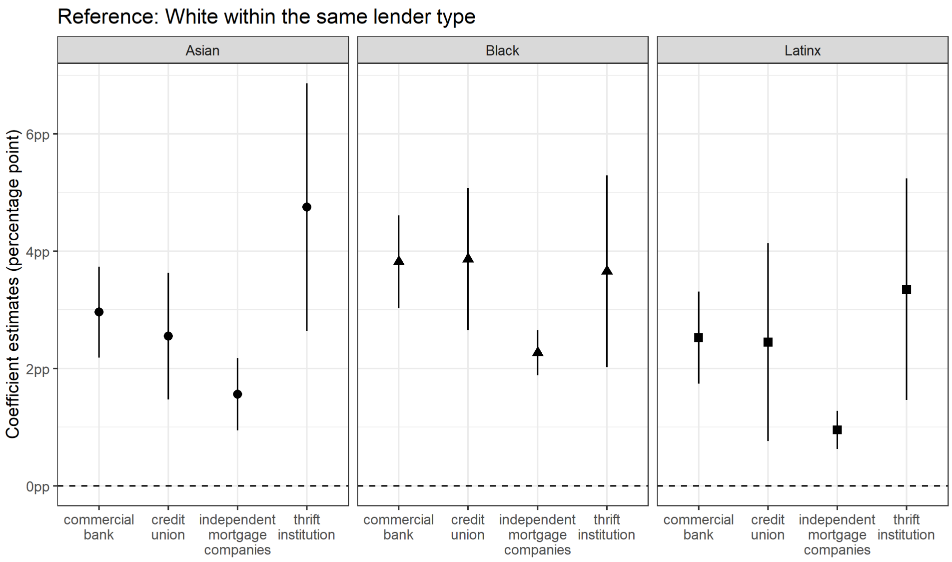
Plot shows coefficients on race and ethnicity combinations across all co-applicants from regressions predicting mortgage purchase application denials where White-White applicants are the reference group. Standard errors are clustered at the lender level. Analysis uses HMDA 2018 to 2020 data and sample includes conventional home-purchase applications for 30-year term loans, within the county-level conforming limit for single dwelling units used as a primary residence. Applications must have credit scores above 620, loan-to-value ratios between 0 and 97 percent, and debt-to-income ratios below 50 percent. Applications are considered Latinx if both applicants report being Hispanic or Latino/a. All other applicants are characterized using both applicants' reported race as Asian, Black, White, multi-racial or other race, and missing.

Figure 3: Estimated denial disparities for Asian subgroups



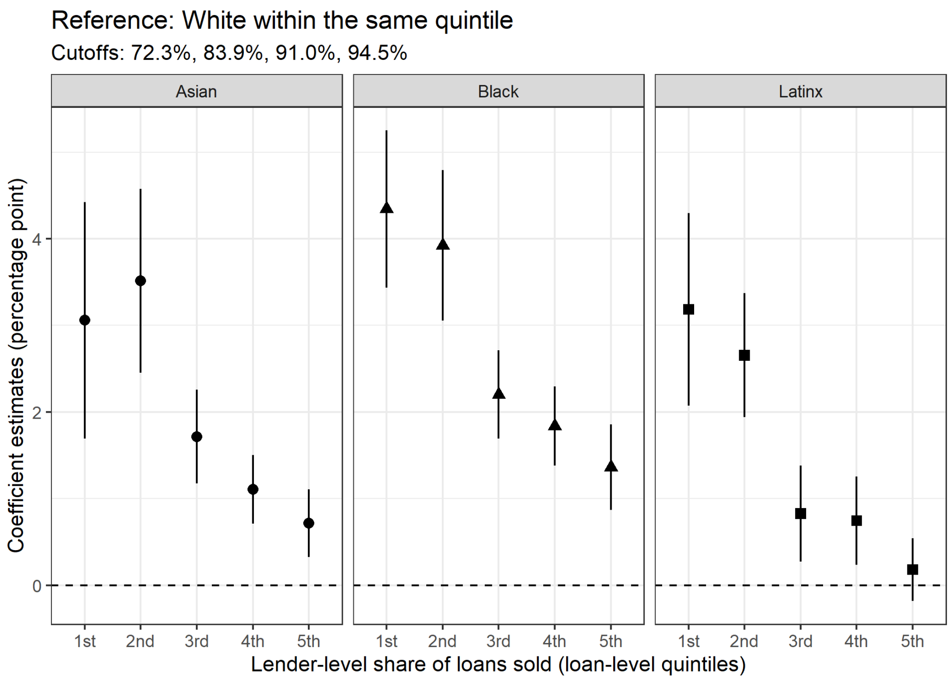
Plot shows coefficients on race and ethnicity combinations separating out by Asian subgroups from regressions predicting mortgage purchase application denials where White applicants are the reference group. Standard errors are clustered at the lender level. Analysis uses HMDA 2018 to 2020 data and sample includes conventional home-purchase applications for 30-year term loans, within the county-level conforming limit for single dwelling units used as a primary residence. Applications must have credit scores above 620, loan-to-value ratios between 0 and 97 percent, and debt-to-income ratios below 50 percent. Applications are considered Latinx if both applicants report being Hispanic or Latino/a. All other applicants are characterized using both applicants' reported race as Asian, Black, White, multi-racial or other race, and missing.

Figure 4: Estimated denial disparities by lender type



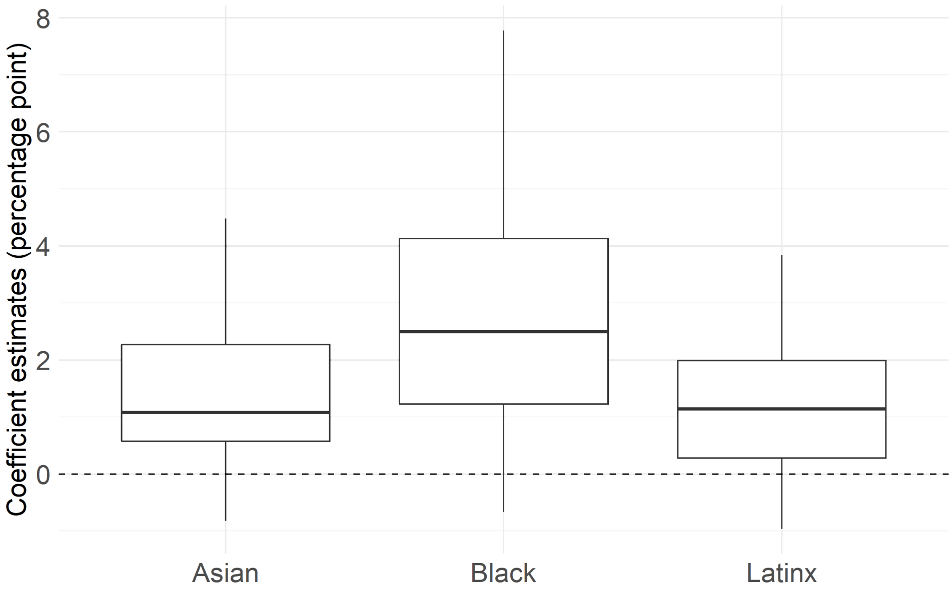
Plot shows coefficients on race and ethnicity indicators interacted with lender type from regressions predicting mortgage purchase application denials where White applicants at commercial banks are the reference group. Standard errors are clustered at the lender level. Analysis uses HMDA 2018 to 2020 data and sample includes conventional home-purchase applications for 30-year term loans, within the county-level conforming limit for single dwelling units used as a primary residence. Applications must have credit scores above 620, loan-to-value ratios between 0 and 97 percent, and debt-to-income ratios below 50 percent. Applications are considered Latinx if both applicants report being Hispanic or Latino/a. All other applicants are characterized using both applicants' reported race as Asian, Black, White, multi-racial or other race, and missing.

Figure 5: Estimated denial disparities by lender's share of sold loans



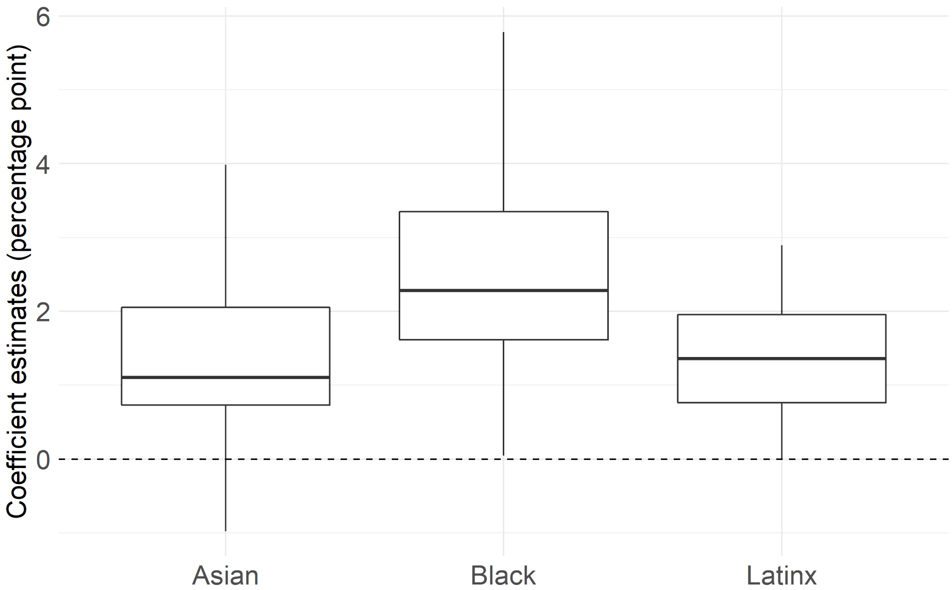
Plot shows estimates of race and ethnicity indicators interacted with lender's share of originated loans sold in the same calendar year from regressions predicting mortgage purchase application denials. Estimates are relative to White applicants at lenders with the same share of loans sold. Standard errors are clustered at the lender level. Analysis uses HMDA 2018 to 2020 data and sample includes conventional home-purchase applications for 30-year term loans, within the county-level conforming limit for single dwelling units used as a primary residence. Applications must have credit scores above 620, loan-to-value ratios between 0 and 97 percent, and debt-to-income ratios below 50 percent. Applications are considered Latinx if both applicants report being Hispanic or Latino/a. All other applicants are characterized using both applicants' reported race as Asian, Black, White, multi-racial or other race, and missing.

Figure 6: Distributions of estimated within lender denial disparities; Top 50 lenders



Plot shows the distribution across the top 50 lenders by volume of coefficients on race and ethnicity indicators interacted with lender fixed effects from a regression predicting mortgage purchase application denials where White applicants at the same lender are the reference group. Analysis uses HMDA 2018 to 2020 data and sample includes conventional home-purchase applications for 30-year term loans, within the county-level conforming limit for single dwelling units used as a primary residence. Applications must have credit scores above 620, loan-to-value ratios between 0 and 97 percent, and debt-to-income ratios below 50 percent. Applications are considered Latinx if both applicants report being Hispanic or Latino/a. All other applicants are characterized using both applicants' reported race as Asian, Black, White, multi-racial or other race, and missing.

Figure 7: Distribution of estimated within lender denial disparities from lender-specific models; Top 50 lenders



Plot shows the distribution across the top 50 lenders by volume of coefficients on race and ethnicity indicators from regressions run separately by lender predicting mortgage purchase application denials where White applicants at the same lender are the reference group. Analysis uses HMDA 2018 to 2020 data and sample includes conventional home-purchase applications for 30-year term loans, within the county-level conforming limit for single dwelling units used as a primary residence. Applications must have credit scores above 620, loan-to-value ratios between 0 and 97 percent, and debt-to-income ratios below 50 percent. Applications are considered Latinx if both applicants report being Hispanic or Latino/a. All other applicants are characterized using both applicants' reported race as Asian, Black, White, multi-racial or other race, and missing.

Figure 8: Estimated denial disparities by neighborhood share of people of color

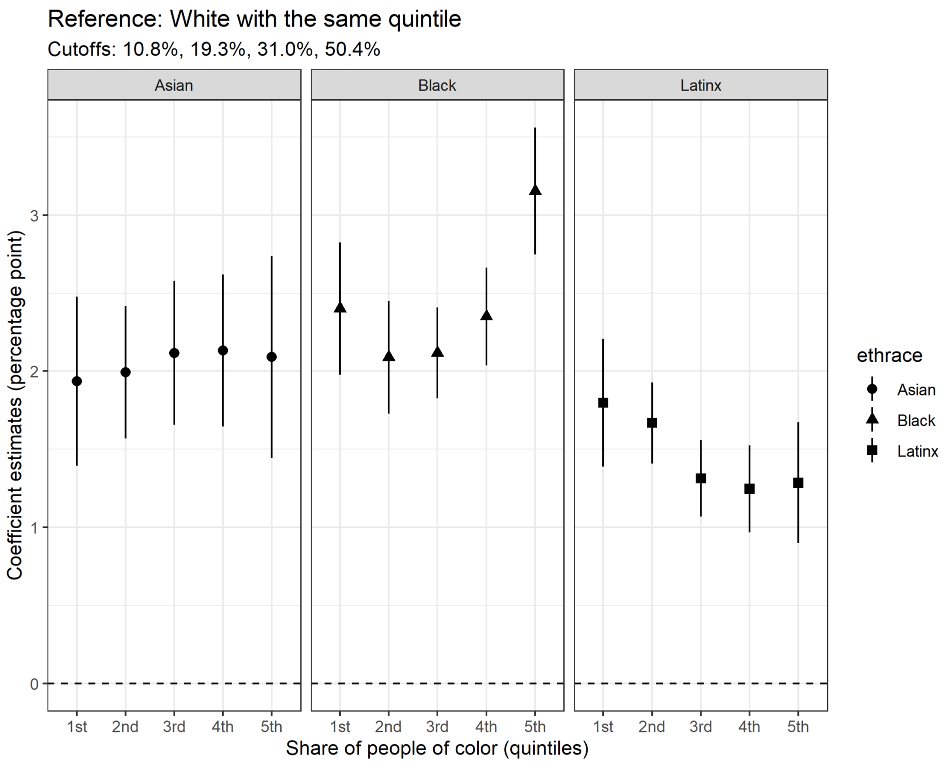


Figure shows the estimated coefficients for mortgage purchase denials for applicants of color relative to White applicants in similar composition census tracts from a model including interaction terms between census tract quintile of share of people of color and race/ethnicity indicators. Standard errors are clustered at the lender level. Analysis uses HMDA 2018 to 2020 data and sample includes conventional home-purchase applications for 30-year term loans, within the county-level conforming limit for single dwelling units used as a primary residence. Applications must have credit scores above 620, loan-to-value ratios between 0 and 97 percent, and debt-to-income ratios below 50 percent. Applications are considered Latinx if both applicants report being Hispanic or Latino/a. All other applicants are characterized using both applicants' reported race as Asian, Black, White, multi-racial or other race, and missing.

Figure 9: Estimated denial disparities by neighborhood income

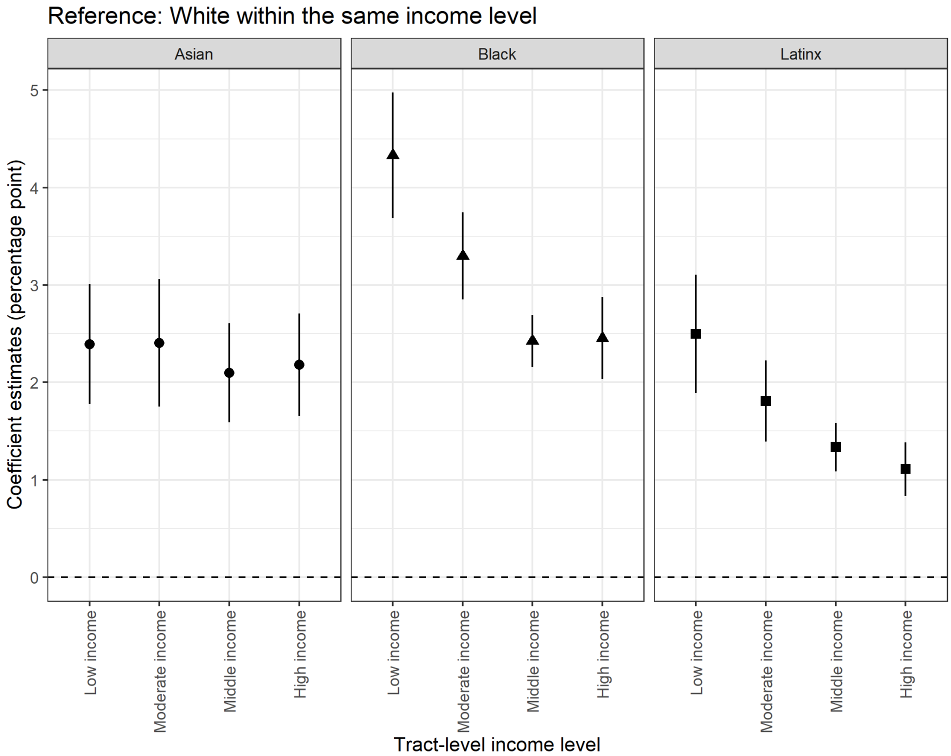


Figure shows the estimated coefficients for mortgage purchase denials for applicants of color relative to White applicants in similar income census tracts from a model including interaction terms between census tract's income levels and race/ethnicity indicators. Low Income tracts are tracts where the median household income is at or below 50 percent of the area median income (AMI), Moderate Income tracts are larger than 50 percent and at or less than 80 percent of AMI, Middle Income tracts are larger than 80 percent and at or below 120 percent of AMI, and High Income tracts have median household income above 120 percent of AMI. Standard errors are clustered at the lender level. Analysis uses HMDA 2018 to 2020 data and sample includes conventional home-purchase applications for 30-year term loans, within the county-level conforming limit for single dwelling units used as a primary residence. Applications must have credit scores above 620, loan-to-value ratios between 0 and 97 percent, and debt-to-income ratios below 50 percent. Applications are considered Latinx if both applicants report being Hispanic or Latino/a. All other applicants are characterized using both applicants' reported race as Asian, Black, White, multi-racial or other race, and missing.

Figure 10: Estimated Latinx-White denial disparities by state

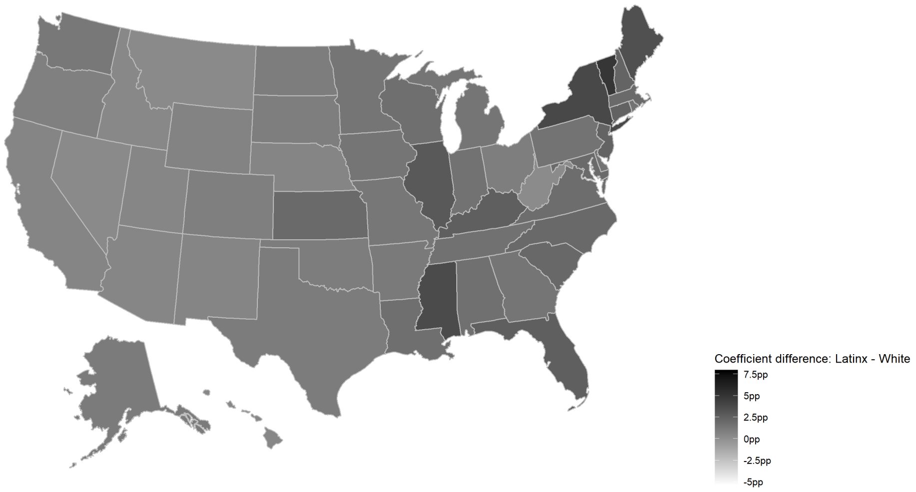


Figure shows the estimated disparities for mortgage purchase denials for Latinx applicants relative to White applicants in the same state from a model including interaction terms between states and race/ethnicity indicators. Standard errors are clustered at the lender level. Analysis uses HMDA 2018 to 2020 data and sample includes conventional home-purchase applications for 30-year term loans, within the county-level conforming limit for single dwelling units used as a primary residence. Applications must have credit scores above 620, loan-to-value ratios between 0 and 97 percent, and debt-to-income ratios below 50 percent. Applications are considered Latinx if both applicants report being Hispanic or Latino/a. All other applicants are characterized using both applicants' reported race as Asian, Black, White, multi-racial or other race, and missing.

Figure 11: Estimated Asian-White denial disparities by state

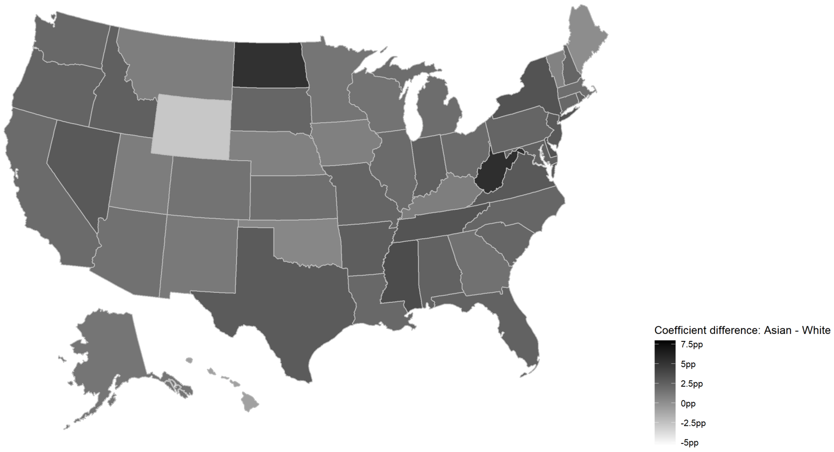


Figure shows the estimated disparities for mortgage purchase denials for Asian applicants relative to White applicants in the same state from a model including interaction terms between states and race/ethnicity indicators. Standard errors are clustered at the lender level. Analysis uses HMDA 2018 to 2020 data and sample includes conventional home-purchase applications for 30-year term loans, within the county-level conforming limit for single dwelling units used as a primary residence. Applications must have credit scores above 620, loan-to-value ratios between 0 and 97 percent, and debt-to-income ratios below 50 percent. Applications are considered Latinx if both applicants report being Hispanic or Latino/a. All other applicants are characterized using both applicants' reported race as Asian, Black, White, multi-racial or other race, and missing.

Figure 12: Estimated Black-White denial disparities by state

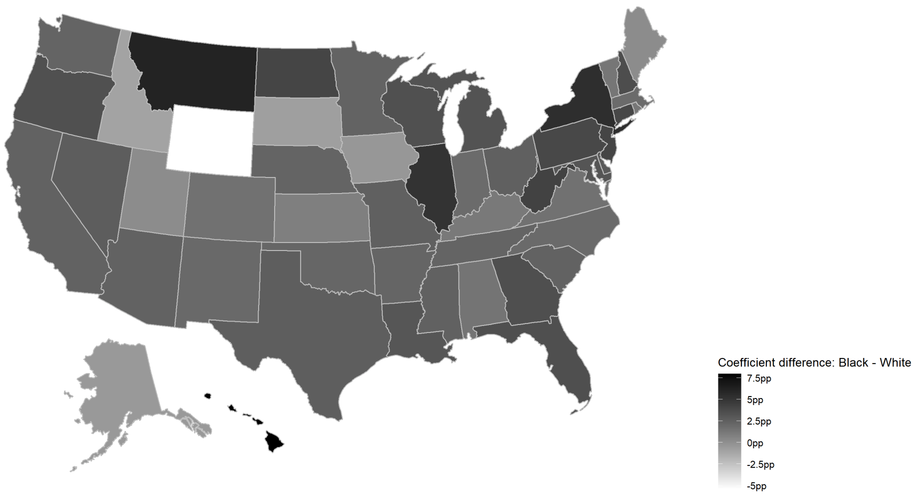


Figure shows the estimated disparities for mortgage purchase denials for Black applicants relative to White applicants in the same state from a model including interaction terms between states and race/ethnicity indicators. Standard errors are clustered at the lender level. Analysis uses HMDA 2018 to 2020 data and sample includes conventional home-purchase applications for 30-year term loans, within the county-level conforming limit for single dwelling units used as a primary residence. Applications must have credit scores above 620, loan-to-value ratios between 0 and 97 percent, and debt-to-income ratios below 50 percent. Applications are considered Latinx if both applicants report being Hispanic or Latino/a. All other applicants are characterized using both applicants' reported race as Asian, Black, White, multi-racial or other race, and missing.

Table 1: Summary statistics for categorical variables

		Count	Percent
Application denied	No	5,873,603	96.2
	Yes	231,058	3.8
Race/ethnicity both applicants	Asian	383,967	6.3
	Black	248,141	4.1
	Latinx	555,095	9.1
	White	3,997,681	65.5
	All other races	286,541	4.7
	Missing	633,236	10.4
Race/ethnicity based on visual observation	No	5,950,718	97.5
	Yes	153,943	2.5
Has coapplicant	No	3,431,362	56.2
	Yes	2,673,299	43.8
Sex	Lone female	1,375,888	22.5
	Lone male	1,859,882	30.5
	Same sex - female	82,892	1.4
	Same sex - male	89,769	1.5
	Opposite sex	2,306,391	37.8
	Other	3,500	0.1
	Missing	386,339	6.3
Credit score bin	[620,640)	86,073	1.4
	[640,660)	159,982	2.6
	[660,680)	248,489	4.1
	[680,700)	463,801	7.6
	[700,720)	631,435	10.3
	[720,740)	759,054	12.4
	[740,800)	3,046,914	49.9
	[800,850]	708,913	11.6
Age bin	[18,25)	364,967	6
	[25,35)	2,247,991	36.8
	[35,45)	1,523,944	25.0
	[45,55)	924,174	15.1
	[55,65)	654,933	10.7
	65+	388,003	6.4

Table shows summary statistics for our sample from 2018–2020 HMDA data. "Other" sex includes applications where at least one applicant selects both male and female as their reported sex. Age and credit score bins are based on the smallest value between co-applicants, if any. Sample includes conventional home-purchase applications for 30-year term loans, within the county-level conforming limit for single dwelling units used as a primary residence. Applications must have credit scores above 620, loan-to-value ratios between 0 and 97 percent, and debt-to-income ratios below 50 percent. Applications are considered Latinx if both applicants report being Hispanic or Latino/a. All other applicants are characterized using both applicants' reported race as Asian, Black, White, multi-racial or other race, and missing.

Table 2: Summary statistics by race/ethnicity

	Asian	Black	Latinx	White	All other races	Missing
Count	383,967	248,141	555,095	3,997,681	286,541	633,236
Denial rate (%)	5.1	7.4	5.8	3.0	3.5	5.1
Credit score						
median	759.0	728.0	736.0	759.0	748.0	759.0
mean (sd)	753.0 (40.1)	727.3 (47.7)	733.7 (45.0)	751.3 (44.1)	742.1 (44.6)	750.8 (44.0)
Loan amount						
median	330,000	224,900	231,300	237,553	294,500	271,225
mean (sd)	346,678 (151,063)	244,831 (121,758)	253,845 (122,087)	257,820 (125,250)	312,843 (138,552)	291,831 (138,234)
Applicant's income						
median	98,000	75,000	71,000	86,000	108,000	94,000
mean (sd)	111,996 (431,557)	89,688 (92,129)	84,828 (76,565)	104,262 (780,577)	125,963 (1,684,989)	111,320 (446,833)
Year						
2018	127,875	76,172	166,207	1,277,669	85,591	188,731
2019	126,836	80,396	182,304	1,302,925	92,707	213,959
2020	129,256	91,573	206,584	1,417,087	108,243	230,546
Loan-to-value ratio						
median	80.0	95.0	93.4	85.0	89.4	85.0
mean (sd)	80.4 (13.8)	89.2 (11.0)	87.2 (12.5)	83.1 (14.4)	84.4 (13.3)	83.1 (14.3)
Debt-to-income ratio						
median	38.6	39.5	40.2	36.2	36.3	37.0
mean (sd)	37.0 (9.1)	37.8 (8.4)	38.5 (8.3)	35.1 (9.3)	35.2 (9.2)	35.7 (9.4)

Table shows summary statistics for our sample from 2018–2020 HMDA data. Sample includes conventional home-purchase applications for 30-year term loans, within the county-level conforming limit for single dwelling units used as a primary residence. Applications must have credit scores above 620, loan-to-value ratios between 0 and 97 percent, and debt-to-income ratios below 50 percent. Applications are considered Latinx if both applicants report being Hispanic or Latino/a. All other applicants are characterized using both applicants' reported race as Asian, Black, White, multi-racial or other race, and missing.

Table 3: Summary statistics for numeric variables

	25th percentile	Median	75th percentile	Mean	Number Missing
Credit score	717	756	785	748	0
Loan amount	170,000	247,200	348,000	268,630	0
Applicant's income	58,000	87,000	127,000	104,140	0
Loan-to-value ratio	80.0	87.4	95.0	83.6	0
Debt-to-income ratio	29.3	37.0	43.2	35.7	0
Age	30.0	37.0	49.0	40.3	649

Table shows summary statistics for our sample from 2018–2020 HMDA data. Age and credit score bins are based on the smallest value between co-applicants, if any. Sample includes conventional home-purchase applications for 30-year term loans, within the county-level conforming limit for single dwelling units used as a primary residence. Applications must have credit scores above 620, loan-to-value ratios between 0 and 97 percent, and debt-to-income ratios below 50 percent.

Table 4: Model estimates predicting denial

	(1)	(2)	(3)
Race/ethnicity			
Asian	0.0208	0.0226	0.0223
	(0.0029)	(0.0027)	(0.0027)
Black	0.0448	0.0388	0.0289
	(0.0025)	(0.0019)	(0.0016)
Latinx	0.0286	0.0200	0.0150
	(0.0021)	(0.0015)	(0.0015)
All other races	0.0049	0.0065	0.0022
	(0.0010)	(0.0009)	(0.0008)
Missing	0.0211	0.0210	0.0202
	(0.0047)	(0.0044)	(0.0044)
Log loan amount		-0.0137	-0.0072
		(0.0025)	(0.0027)
Log income		-0.0060	-0.0076
		(0.0031)	(0.0033)
state/year/month FEs		X	X
LTV/DTI FEs		X	
LTV/DTI/credit score FEs			X
AUC	0.5821	0.6471	0.6871

Analysis uses 2018–2020 HMDA data and sample includes conventional home-purchase applications for 30-year term loans, within the county-level conforming limit for single dwelling units used as a primary residence. Applications must have credit scores above 620, loan-to-value ratios between 0 and 97 percent, and debt-to-income ratios below 50 percent.

Applications are considered Latinx if both applicants report being Hispanic or Latino/a. All other applicants are characterized using both applicants' reported race as Asian, Black, White, multi-racial or other race, and missing.

Model (1) only includes racial and ethnic categories as predictors. In model (2), we add state, year, and month three-way interactions, log of loan amount, log of income and the LTV and DTI two-way interaction fixed effects. And finally, we expand the LTV and DTI two-way interaction to three-way interaction fixed effects with credit score in model (3). Standard errors are clustered at the lender level.

Table 5: Robustness model estimates predicting denial

	baseline	(R1)	(R2)	(R3)	(R4)	(R5)	(R6)	(R7)	(R8)	(R9)	(R10)
Race/ethnicity											
Asian	0.0223	0.0224	0.0205	0.0224	0.0230	0.0206	0.0224	0.0210	0.0224	0.0198	0.0189
	(0.0027)	(0.0028)	(0.0024)	(0.0027)	(0.0027)	(0.0026)	(0.0025)	(0.0026)	(0.0026)	(0.0025)	(0.0024)
Black	0.0289	0.0316	0.0250	0.0292	0.0268	0.0277	0.0289	0.0271	0.0286	0.0264	0.0234
	(0.0016)	(0.0019)	(0.0014)	(0.0016)	(0.0016)	(0.0016)	(0.0016)	(0.0015)	(0.0016)	(0.0014)	(0.0014)
Latinx	0.0150	0.0209	0.0169	0.0147	0.0148	0.0138	0.0162	0.0142	0.0151	0.0112	0.0100
	(0.0015)	(0.0019)	(0.0015)	(0.0014)	(0.0014)	(0.0014)	(0.0014)	(0.0014)	(0.0014)	(0.0013)	(0.0013)
All other races	0.0022	0.0016	0.0022	0.0022	0.0032	0.0054	0.0013	0.0054	0.0022	0.0013	0.0048
	(0.0008)	(0.0010)	(0.0009)	(0.0008)	(0.0009)	(0.0008)	(0.0009)	(0.0008)	(0.0007)	(0.0008)	(0.0008)
Missing	0.0202	0.0207	0.0177	0.0200	0.0198	0.0131	0.0198	0.0198	0.0201	0.0189	0.0110
	(0.0044)	(0.0045)	(0.0037)	(0.0043)	(0.0043)	(0.0018)	(0.0044)	(0.0044)	(0.0044)	(0.0042)	(0.0016)
Log loan amount	-0.0072		-0.0037	-0.0072	-0.0075	-0.0060		-0.0055	-0.0098	-0.0102	-0.0095
	(0.0027)		(0.0030)	(0.0027)	(0.0027)	(0.0025)		(0.0025)	(0.0022)	(0.0029)	(0.0027)
Log income	-0.0076		-0.0090	-0.0076	-0.0080	-0.0069		-0.0068	-0.0048	-0.0075	-0.0074
	(0.0033)		(0.0039)	(0.0033)	(0.0034)	(0.0032)		(0.0032)	(0.0022)	(0.0033)	(0.0034)
Covariates added as robustness checks											
Age and age squared					X						X
Sex						X					X
Loan amount cubic splines							X				
Income cubic splines							X				
Has Coapplicant								X			X
Fixed effects											
year/month		X									
state/year/month	X		X	X	X	X	X	X	X		
county/year/month										X	X
LTV/DTI/credit score	X	X	X	X	X	X	X	X		X	X
Detailed LTV/DTI/credit score									X		
AUC	0.6871	0.6706	0.6631	0.6871	0.6905	0.6905	0.6929	0.6891	0.6943	0.7398	0.7443

Analysis uses 2018–2020 HMDA data and sample includes conventional home-purchase applications for 30-year term loans, within the county-level conforming limit for single dwelling units used as a primary residence. Applications must have credit scores above 620, loan-to-value ratios between 0 and 97 percent, and debt-to-income ratios below 50 percent.

Applications are considered Latinx if both applicants report being Hispanic or Latino/a. All other applicants are characterized using both applicants' reported race as Asian, Black, White, multi-racial or other race, and missing.

Baseline specification is described in notes for Table 4.

There are ten robustness specifications: R1 represents a lender data only specification where loan amount, income, and state effects are excluded, R2 removes applications near underwriting cutoffs for LTV, DTI, and credit scores R3 removes applications where the race or ethnicity was based on visual inspection, R4 includes age controls, R5 includes sex controls, R6 includes cubic spline controls for the loan amount and income, R7 includes a co-applicant indicator, R8 includes much more detailed LTV/DTI/credit score bins, R9 replaces the state/year/month fixed effects with county/year/month fixed effects, R10 includes all of our more detailed controls from any previous robustness checks simultaneously although it uses our LTV/DTI/Credit score (not the more detailed ones). Standard errors are clustered at the lender level.

Table 6: Logit model odds ratios predicting denial

	Odds ratio	Standard error
Race/ethnicity		
Asian	1.8545	0.0944
Black	1.8170	0.0476
Latinx	1.4507	0.0472
All other races	1.0856	0.0264
Missing	1.7161	0.1176
Log loan amount	0.7741	0.0247
Log income	0.8868	0.0283
AUC	0.6896	

Reported results are odds ratios from a logit specification using our baseline model covariates and sample. State/year/month and LTV/DTI credit score fixed effects are included in the model but not shown here. Standard errors are clustered at the lender level.

Analysis uses HMDA 2018–2020 data and sample includes conventional home-purchase applications for 30-year term loans, within the county-level conforming limit for single dwelling units used as a primary residence. Applications must have credit scores above 620, loan-to-value ratios between 0 and 97 percent, and debt-to-income ratios below 50 percent.

Applications are considered Latinx if both applicants report being Hispanic or Latino/a. All other applicants are characterized using both applicants' reported race as Asian, Black, White, multi-racial or other race, and missing.

Table 7: Comparing race and ethnicity categorizations

	Baseline	(1)	(2)	(3)
Asian	0.0223	0.0214	0.0223	0.0225
	(0.0027)	(0.0025)	(0.0026)	(0.0027)
Black	0.0289	0.0271	0.0291	0.0287
	(0.0016)	(0.0016)	(0.0016)	(0.0016)
Latinx	0.0150	0.0133		0.0133
	(0.0015)	(0.0013)		(0.0016)
All other races	0.0022	0.0087	0.0027	0.0022
	(0.0008)	(0.0020)	(0.0009)	(0.0008)
Missing	0.0202	0.0198	0.0209	0.0184
	(0.0044)	(0.0044)	(0.0042)	(0.0038)
Latinx-White			0.0123	
			(0.0016)	

Analysis uses 2018–2020 HMDA data and sample includes conventional home-purchase applications for 30-year term loans, within the county-level conforming limit for single dwelling units used as a primary residence. Applications must have credit scores above 620, loan-to-value ratios between 0 and 97 percent, and debt-to-income ratios below 50 percent.

Applications are considered Latinx if both applicants report being Hispanic or Latino/a. All other applicants are characterized using both applicants' reported race as Asian, Black, White, multi-racial or other race, and missing.

Baseline specification is described in notes for Table 4.

Column (1) defines race and ethnicity using only information from the primary applicant.

Column (2) defines applicants according to their race first where Latinx only includes Latinx-White applications. The reference group is still non-Hispanic White applicants.

Column (3) only assigns race and ethnicity to applications where neither applicant has any missing race or ethnicity responses. All Standard errors are clustered at the lender level.

Table 8: Model predicting missing race or ethnicity

	Estimate	Standard error
Log loan amount	0.0193	0.0026
Log income	0.0006	0.0018
Credit score		
[640,660)	-0.0017	0.0016
[660,680)	-0.0008	0.0015
[680,700)	0.0017	0.0021
[700,720)	0.0011	0.0020
[720,740)	0.0000	0.0021
[740,800)	0.0048	0.0021
[800,851)	0.0091	0.0020
Loan-to-value ratio		
(60,70]	-0.0081	0.0012
(70,75]	-0.0058	0.0014
(75,80]	-0.0060	0.0013
(80,85]	-0.0031	0.0045
(85,90]	-0.0081	0.0025
(90,95]	-0.0074	0.0033
(95,97]	-0.0054	0.0040
Debt-to-income ratio		
20-29	-0.0098	0.0011
30-35	-0.0126	0.0014
36	-0.0154	0.0015
37	-0.0146	0.0016
38	-0.0145	0.0016
39	-0.0148	0.0017
40	-0.0140	0.0017
41	-0.0151	0.0017
42	-0.0145	0.0018
43	-0.0154	0.0019
44	-0.0157	0.0019
45	-0.0121	0.0026
46	-0.0129	0.0030
47	-0.0120	0.0027
48	-0.0118	0.0034
49	-0.0123	0.0037
50	-0.0118	0.0048
AUC	0.5847	

Analysis uses HMDA 2018–2020 data and sample includes conventional home-purchase applications for 30-year term loans, within the county-level conforming limit for single dwelling units used as a primary residence. Applications must have credit scores above 620, loan-to-value ratios between 0 and 97 percent, and debt-to-income ratios below 50 percent.

The linear model predicts missing race and ethnicity using the covariates (excluding racial indicators) from our baseline regression. Models include LTV, DTI, and credit score bin indicators, and state level fixed effects, year/month fixed effects. Standard errors are clustered at the lender level.

Table 9: Denials by all race-ethnicity pairs

	All other races	Asian	Black	Latinx	Missing	No coapplicant	White
All other races	0.0058	0.0110	0.0113	-0.0012	0.0065	0.0197	0.0033
	(0.0055)	(0.0039)	(0.0064)	(0.0034)	(0.0049)	(0.0023)	(0.0010)
Asian		0.0235	0.0114	0.0155	0.0202	0.0280	0.0078
		(0.0033)	(0.0065)	(0.0024)	(0.0126)	(0.0029)	(0.0013)
Black			0.0146	0.0054	0.0336	0.0388	-0.0005
			(0.0018)	(0.0033)	(0.0075)	(0.0022)	(0.0013)
Latinx				0.0082	0.0218	0.0249	0.0013
				(0.0017)	(0.0077)	(0.0019)	(0.0008)
Missing					0.0150	0.0313	0.0143
					(0.0037)	(0.0055)	(0.0073)
No coapplicant							0.0077
							(0.0009)

Table reports coefficients on race and ethnicity combinations across all co-applicants from regressions predicting mortgage purchase application denials where White-White applicants are the reference group. Standard errors are clustered at the lender level. Analysis uses HMDA 2018 to 2020 data and sample includes conventional home-purchase applications for 30-year term loans, within the county-level conforming limit for single dwelling units used as a primary residence. Applications must have credit scores above 620, loan-to-value ratios between 0 and 97 percent, and debt-to-income ratios below 50 percent. Applicants are considered Latinx if the individual reports being Hispanic or Latino/a. All other applicants are characterized using their reported race as Asian, Black, White, multi-racial or other race, and missing.

9 Appendix

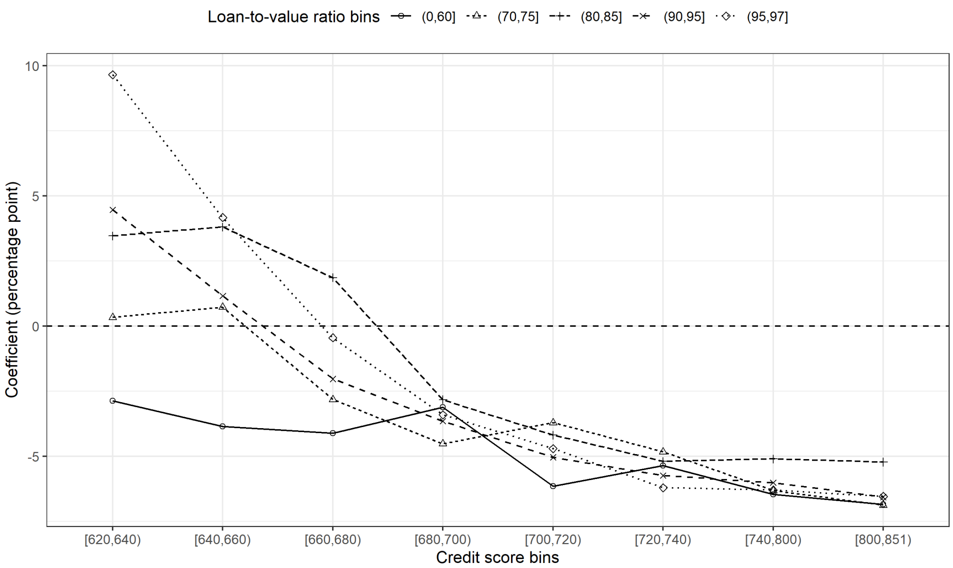
Figure A1: Fannie Mae underwriting table

Table 1: All Eligible Mortgages – LLPA by Credit Score/LTV Ratio

Representative Credit Score	LTV Range Applicable for all mortgages with terms greater than 15 years									
	≤ 60.00%	60.01 – 70.00%	70.01 – 75.00%	75.01 – 80.00%	80.01 – 85.00%	85.01 – 90.00%	90.01 – 95.00%	95.01 – 97.00%	>97.00%	SFC
≥ 740	0.000%	0.250%	0.250%	0.500%	0.250%	0.250%	0.250%	0.750%	0.750%	N/A
720 – 739	0.000%	0.250%	0.500%	0.750%	0.500%	0.500%	0.500%	1.000%	1.000%	N/A
700 – 719	0.000%	0.500%	1.000%	1.250%	1.000%	1.000%	1.000%	1.500%	1.500%	N/A
680 – 699	0.000%	0.500%	1.250%	1.750%	1.500%	1.250%	1.250%	1.500%	1.500%	N/A
660 – 679	0.000%	1.000%	2.250%	2.750%	2.750%	2.250%	2.250%	2.250%	2.250%	N/A
640 – 659	0.500%	1.250%	2.750%	3.000%	3.250%	2.750%	2.750%	2.750%	2.750%	N/A
620 – 639	0.500%	1.500%	3.000%	3.000%	3.250%	3.250%	3.250%	3.500%	3.500%	N/A
< 620[1]	0.500%	1.500%	3.000%	3.000%	3.250%	3.250%	3.250%	3.750%	3.750%	N/A

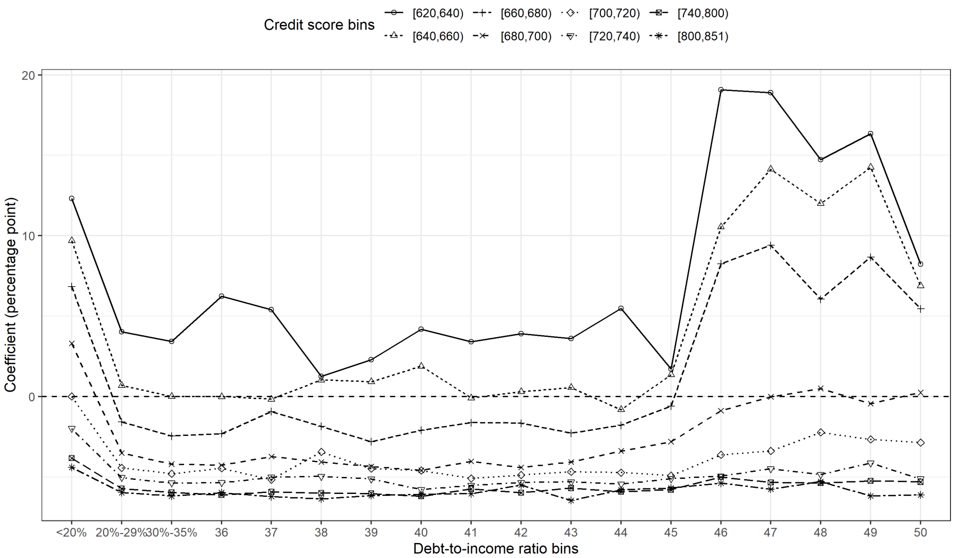
Figure shows the 2021 loan-level price adjustment matrix for single family homes for all eligible mortgages from Fannie Mae `https://singlefamily.fanniemae.com/media/9391/display`.

Figure A2: Credit score and LTV Ratio holding DTI fixed at 37 percent



Plot shows the estimates from our baseline regression model predicting mortgage purchase application denials for LTV and credit score combinations holding DTI fixed at 37 percent. Levels reflect differences compared to the grand mean of the sample. Analysis uses HMDA 2018 to 2020 data and sample includes conventional home-purchase applications for 30-year term loans, within the county-level conforming limit for single dwelling units used as a primary residence. Applications must have credit scores above 620, loan-to-value ratios between 0 and 97 percent, and debt-to-income ratios below 50 percent

Figure A3: Credit score and DTI ratio holding LTV fixed at 85 to 90 percent



Plot shows the estimates from our baseline regression model predicting mortgage purchase application denials for DTI and credit score combinations holding LTV fixed at 85 to 90 percent. Levels reflect differences compared to the grand mean of the sample. Analysis uses HMDA 2018 to 2020 data and sample includes conventional home-purchase applications for 30-year term loans, within the county-level conforming limit for single dwelling units used as a primary residence. Applications must have credit scores above 620, loan-to-value ratios between 0 and 97 percent, and debt-to-income ratios below 50 percent.

Figure A4: Predicted probability of missing race by reported race

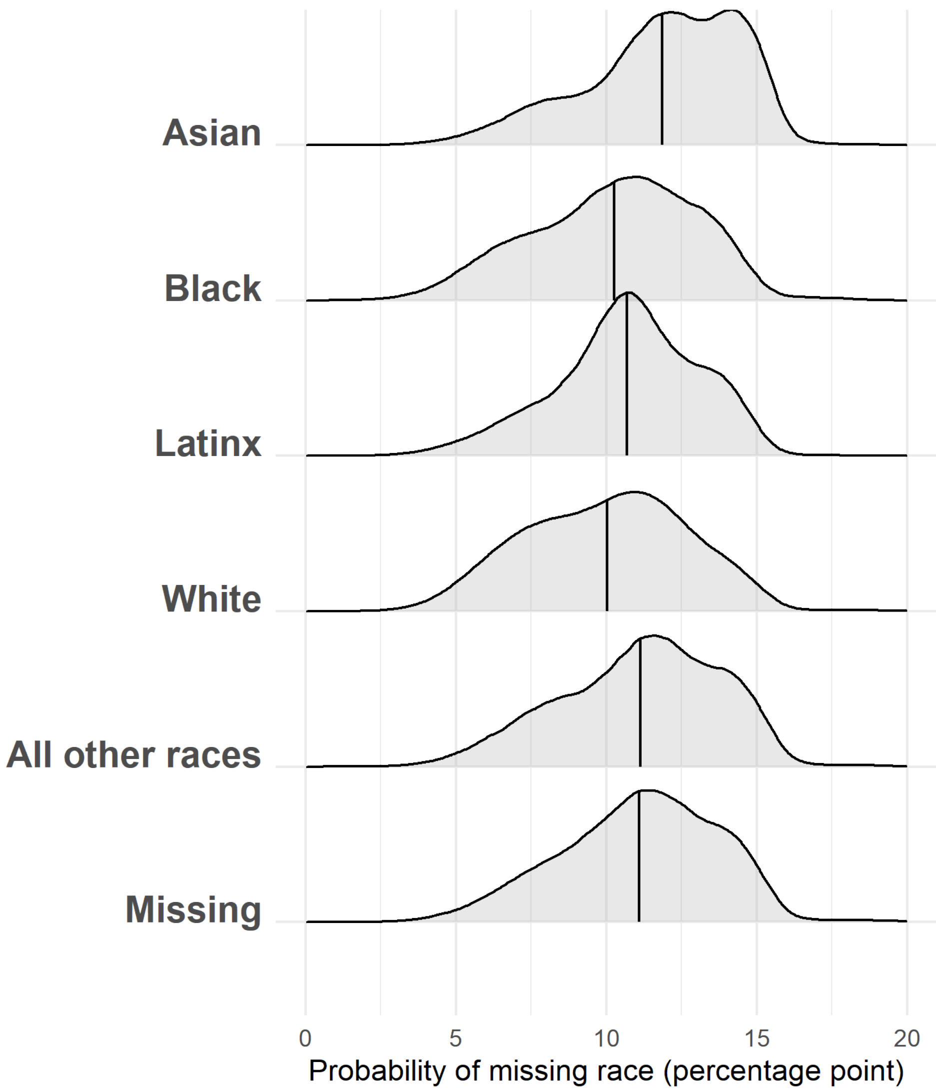
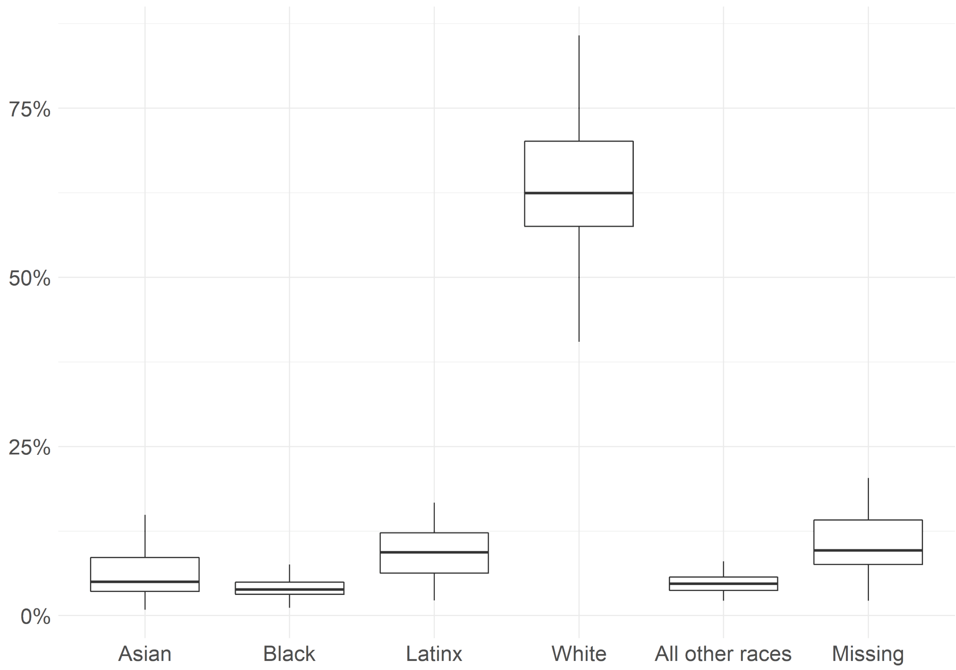


Figure shows the distribution of predicted probabilities of having missing race-ethnicity by reported race-ethnicity using a model that predicts missing race-ethnicity using covariates. The model estimates from that exercise are shown and described in Table 8. Race and ethnicity categories are defined using information from both applicants. Analysis uses HMDA 2018 to 2020 data and sample includes conventional home-purchase applications for 30-year term loans, within the county-level conforming limit for single dwelling units used as a primary residence. Applications must have credit scores above 620, loan-to-value ratios between 0 and 97 percent, and debt-to-income ratios below 50 percent. Applicants are considered Latinx if the individual reports being Hispanic or Latino/a. All other applicants are characterized using their reported race as Asian, Black, White, multi-racial or other race, and missing.

Figure A5: Race and ethnicity of applicants top 50 lenders



Plot shows the distribution across the top 50 lenders by volume of applicants' race and ethnicity. Race and ethnicity categories are defined using information from both applicants. Analysis uses HMDA 2018 to 2020 data and sample includes conventional home-purchase applications for 30-year term loans, within the county-level conforming limit for single dwelling units used as a primary residence. Applications must have credit scores above 620, loan-to-value ratios between 0 and 97 percent, and debt-to-income ratios below 50 percent. Applications are considered Latinx if both applicants report being Hispanic or Latino/a. All other applicants are characterized using both applicants' reported race as Asian, Black, White, multi-racial or other race, and missing.

Figure A6: Black disparities by MSA

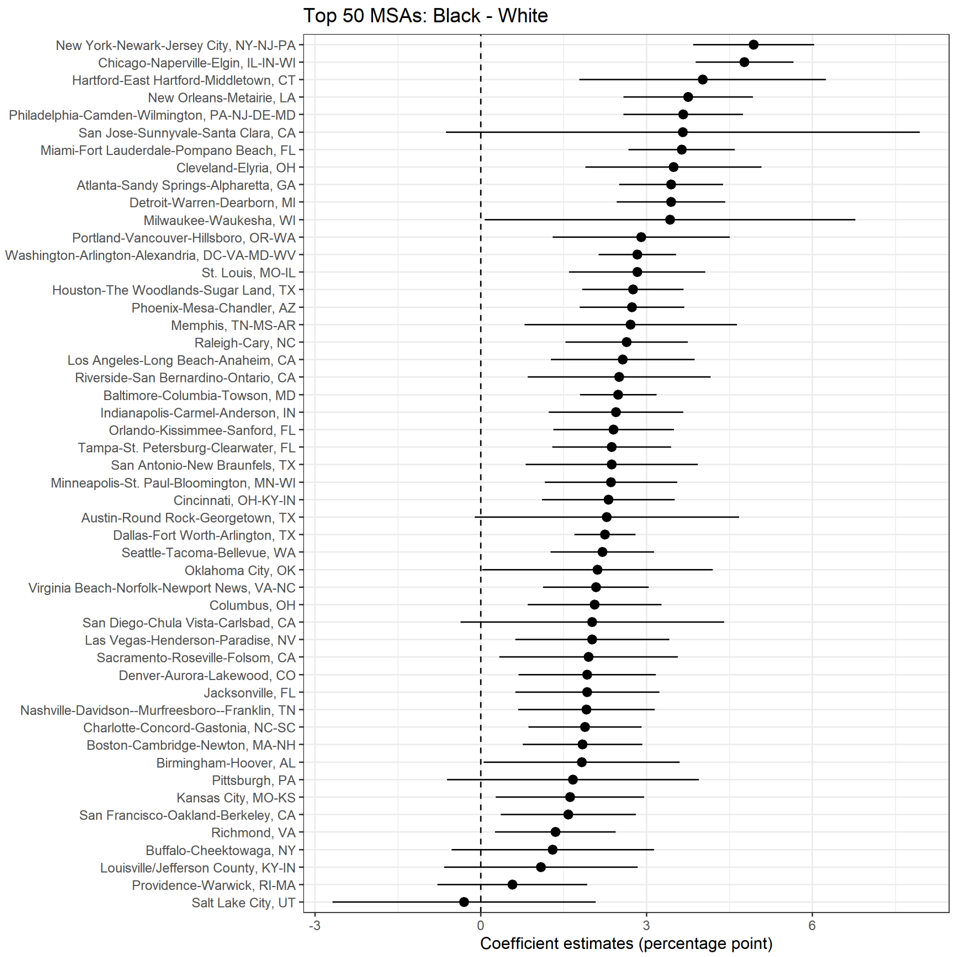


Figure shows the estimated coefficients for mortgage purchase denials for Black applicants relative to White applicants in the same MSA from a model including interaction terms between MSAs and race/ethnicity indicators run using properties in the largest 50 MSAs. Standard errors are clustered at the lender level. Race and ethnicity categories are defined using information from both applicants. Analysis uses HMDA 2018 to 2020 data and sample includes conventional home-purchase applications for 30-year term loans, within the county-level conforming limit for single dwelling units used as a primary residence. Applications must have credit scores above 620, loan-to-value ratios between 0 and 97 percent, and debt-to-income ratios below 50 percent. Applications are considered Latinx if both applicants report being Hispanic or Latino/a. All other applicants are characterized using both applicants' reported race as Asian, Black, White, multi-racial or other race, and missing.

Figure A7: Asian disparities by MSA

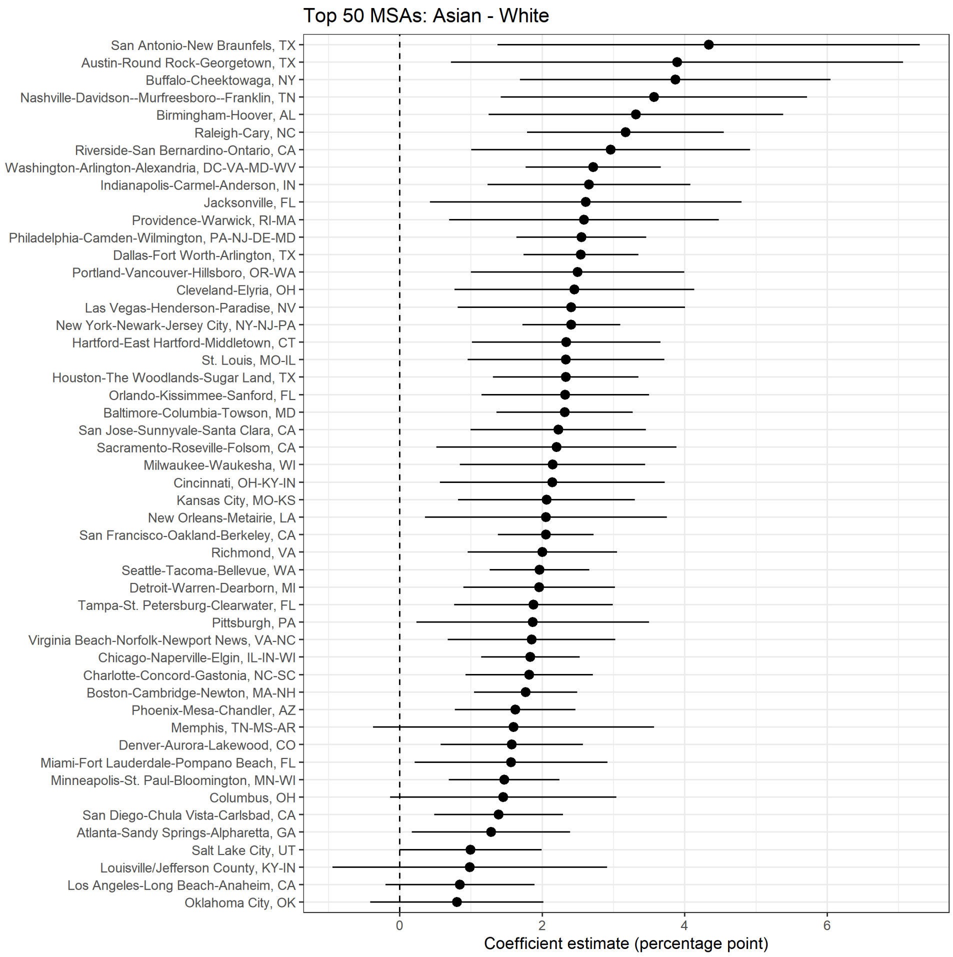


Figure shows the estimated coefficients for mortgage purchase denials for Asian applicants relative to White applicants in the same MSA from a model including interaction terms between MSAs and race/ethnicity indicators run using properties in the largest 50 MSAs. Standard errors are clustered at the lender level. Race and ethnicity categories are defined using information from both applicants. Analysis uses HMDA 2018 to 2020 data and sample includes conventional home-purchase applications for 30-year term loans, within the county-level conforming limit for single dwelling units used as a primary residence. Applications must have credit scores above 620, loan-to-value ratios between 0 and 97 percent, and debt-to-income ratios below 50 percent. Applications are considered Latinx if both applicants report being Hispanic or Latino/a. All other applicants are characterized using both applicants' reported race as Asian, Black, White, multi-racial or other race, and missing.

Figure A8: Latinx disparities by MSA

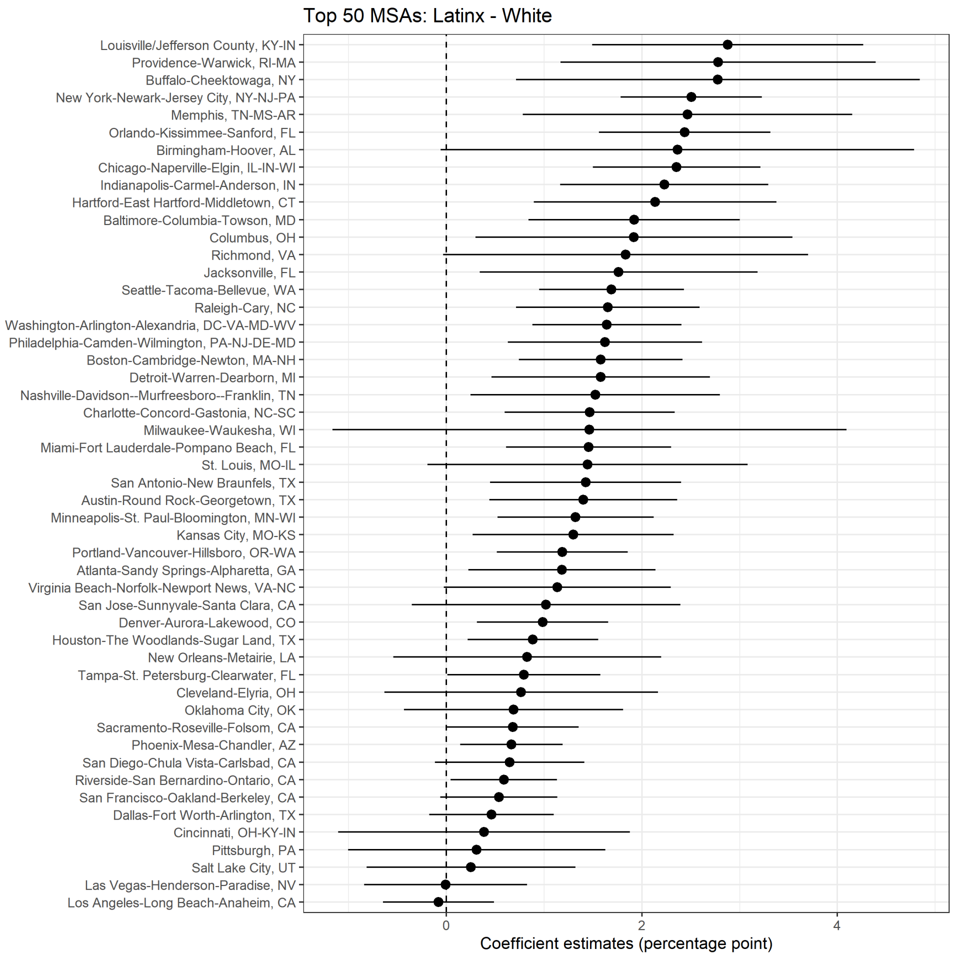
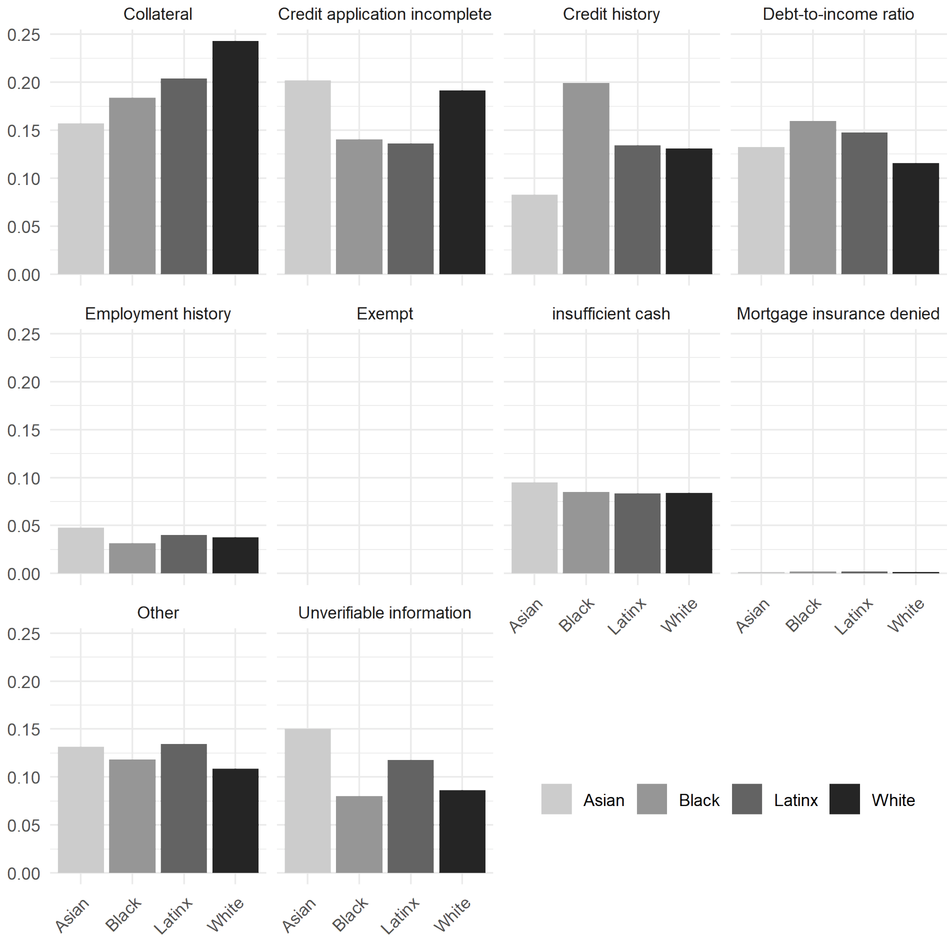


Figure shows the estimated coefficients for mortgage purchase denials for Latinx applicants relative to White applicants in the same MSA from a model including interaction terms between MSAs and race/ethnicity indicators. Standard errors are clustered at the lender level. Race and ethnicity categories are defined using information from both applicants. Analysis uses HMDA 2018 to 2020 data and sample includes conventional home-purchase applications for 30-year term loans, within the county-level conforming limit for single dwelling units used as a primary residence. Applications must have credit scores above 620, loan-to-value ratios between 0 and 97 percent, and debt-to-income ratios below 50 percent. Applications are considered Latinx if both applicants report being Hispanic or Latino/a. All other applicants are characterized using both applicants' reported race as Asian, Black, White, multi-racial or other race, and missing.

Figure A9: Distribution of denial reasons by racial group



Plot shows the share of primary denial reasons reported by lenders by race and ethnicity. The sample includes denied home-purchase applications between 2018 and 2020 submitted for conventional 30-year term loans, within county-level conforming limit for single dwelling units used as a primary residence. Applications must have credit scores above 620, loan-to-value ratios between 0 and 97 percent, and debt-to-income ratios below 50 percent. Applications are considered Latinx if both applicants report being Hispanic or Latino/a. All other applicants are characterized using both applicants' reported race as Asian, Black, White, multi-racial or other race, and missing. Multi-racial, other race or missing are not included in this plot.

Table A1: Application Counts by Race and Lender Type

Lender Type	Total	White	Asian	Black	Latinx
	Count (Share across lender type)	Count (Share within lender type)			
Commercial Bank	1,818,362	1,250,937	120,614	71,982	128,802
	(29.8%)	(68.8%)	(6.6%)	(4.0%)	(7.1%)
Credit Union	480,458	334,937	17,826	19,265	36,384
	(7.9%)	(69.7%)	(3.7%)	(4.0%)	(7.6%)
Independent Mortgage Companies	3,496,303	2,189,758	227,283	146,572	370,606
	(57.3%)	(62.6%)	(6.5%)	(4.2%)	(10.6%)
Thrift Institution	309,538	222,049	18,244	10,322	19,303
	(5.1%)	(71.7%)	(5.9%)	(3.3%)	(6.2%)

Table shows the number and share of applications in our sample from each type of lender by our constructed race and ethnicity categories. Analysis uses HMDA 2018 to 2020 data and sample includes conventional home-purchase applications for 30-year term loans, within the county-level conforming limit for single dwelling units used as a primary residence. Applications must have credit scores above 620, loan-to-value ratios between 0 and 97 percent, and debt-to-income ratios below 50 percent. Applicants are considered Latinx if the individual reports being Hispanic or Latino/a. All other applicants are characterized using their reported race as Asian, Black, White, multi-racial or other race, and missing.

Table A2: Loan Characteristics by Lender Type

	Commercial Bank	Credit Union	Independent Mortgage Companies	Thrift Institution
	Mean			
Properties in urban area	62.3%	60.6%	66.7%	64.9%
	25th Percentile			
Debt-to-income ratio	28.3	27.2	30.3	28.2
Credit score	720.0	713.0	716.0	720.0
Loan amount	$156,300	$143,450	$182,750	$163,400
Applicant's income	$57,000	$55,000	$59,000	$60,000
Loan-to-value ratio	80.0	80.0	80.0	80.0
	Median			
Debt-to-income ratio	36.0	34.7	38.0	35.8
Credit score	759.0	754.0	754.0	758.0
Loan amount	$233,100	$209,000	$260,000	$239,200
Applicant's income	$87,000	$82,000	$87,000	$90,000
Loan-to-value ratio	83.9	88.9	89.9	84.8
	75th Percentile			
Debt-to-income ratio	42.3	41.3	43.9	42.4
Credit score	787.0	786.0	784.0	787.0
Loan amount	$337,500	$298,400	$359,550	$337,500
Applicant's income	$130,000	$119,000	$126,000	$131,000
Loan-to-value ratio	95.0	95.0	95.0	95.0

Table shows the loan characteristics by lender type. Urban area is defined as census tracts where 50 percent or more of their total area overlaps with census-defined urban areas. Analysis uses HMDA 2018 to 2020 data and sample includes conventional home-purchase applications for 30-year term loans, within the county-level conforming limit for single dwelling units used as a primary residence. Applications must have credit scores above 620, loan-to-value ratios between 0 and 97 percent, and debt-to-income ratios below 50 percent. Applicants are considered Latinx if the individual reports being Hispanic or Latino/a. All other applicants are characterized using their reported race as Asian, Black, White, multi-racial or other race, and missing.

Table A3: Underlying Numbers for Top 50 Lender Analyses

Top 50 lenders - denial rates by lender						
25th percentile	0.0180					
Median	0.0317					
75th percentile	0.0618					
	Asian	Black	Latinx	White	Other races	Missing
Top 50 lenders - racial composition by lender						
25th percentile	0.0357	0.0315	0.0628	0.5751	0.0371	0.0754
Median	0.0501	0.0383	0.0935	0.6246	0.0469	0.0965
75th percentile	0.0858	0.0493	0.1223	0.7010	0.0571	0.1414
Top 50 lenders - model coefficients (one model for all 50 lenders)						
25th percentile	0.0058	0.0122	0.0028		0.0004	0.0038
Median	0.0108	0.0250	0.0114		0.0031	0.0101
75th percentile	0.0227	0.0413	0.0199		0.0071	0.0161
Top 50 lenders - models coefficients (separate model by lender)						
25th percentile	0.0073	0.0162	0.0076		-0.0003	0.0048
Median	0.0110	0.0228	0.0136		0.0020	0.0085
75th percentile	0.0206	0.0335	0.0196		0.0050	0.0148

Analysis uses HMDA 2018–2020 data from top 50 lenders by volume and sample includes conventional home-purchase applications for 30-year term loans, within the county-level conforming limit for single dwelling units used as a primary residence. Applications must have credit scores above 620, loan-to-value ratios between 0 and 97 percent, and debt-to-income ratios below 50 percent. Applications are considered Latinx if the individual reports being Hispanic or Latino/a. All other applicants are characterized using their reported race as Asian, Black, White, multi-racial or other race, and missing.

Top panel shows the distribution of the racial composition of applications across lenders.

Second panel shows the distributions of coefficients on race and ethnicity indicators from regressions including only the top 50 lenders and including an interaction term for each lender and race/ethnicity category where White applicants are the reference group.

Third panel shows the distribution of coefficients on race and ethnicity indicators from regressions run separately by lender predicting mortgage purchase application denial where White applicants are the reference group. Race and ethnicity categories are defined using information from both applicants.