How Much Does Racial Bias Affect Mortgage Lending? Evidence from Human and Algorithmic Credit Decisions

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Abstract: We assess racial discrimination in mortgage approvals using new data on mortgage applications, including key underwriting fields as well as the algorithmic recommendations from government Automated Underwriting Systems (AUS). Minorities are less likely than whites to receive an approval recommendation from color-blind AUS, partially explaining disparities in lenders' rejections. Controlling additionally for observable risk factors (as lenders often impose tougher standards than AUS) explains most of the disparities. We exploit the AUS data to show there are additional risk factors we do not directly observe, and provide evidence that such unobserved factors explain some of the residual 1-2 percentage point lender approval gaps.

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Introduction

In 2018 and 2019, black mortgage applicants were twice as likely as white applicants to have their application denied by lenders. To what extent are such disparities in mortgage approval decisions due to discrimination by lenders? Basing mortgage lending decisions on race or ethnicity has been illegal since the Fair Housing Act of 1968. However, discrimination could persist due to limited enforcement, potentially contributing to the wide racial and ethnic gaps in homeownership and wealth (Bhutta et al. 2020).

A longstanding challenge in assessing the role of discrimination in mortgage approvals has been the lack of underwriting data on applicants. Such data are needed to account for differences across applicants in risk that might be correlated with race or ethnicity. Not since the seminal work of Munnell et al. (1996) nearly 30 years ago have researchers had access to the most important information lenders use in making credit decisions. In this paper, we draw on new confidential-supervisory data collected since 2018 under the Home Mortgage Disclosure Act (HMDA) to assess the extent of discrimination in mortgage lending decisions. Unlike pre-2018 HMDA data, these data include key underwriting information, such as credit score, debt-payments-to-income ratio (DTI), and combined loan-amount-to-home-value (LTV) ratio, for both approved and rejected mortgage applications, along with detailed demographic information on the applicants. In addition, since lenders today typically feed applicant data through an automated underwriting system (AUS), they are now required to report the algorithmic credit recommendation the AUS provides.

We use the new HMDA data to make several contributions to the literature. First, we document that Black and Hispanic applicants are less likely to receive an algorithmic AUS approval recommendation than white applicants. AUS recommendations reflect minimum government underwriting and eligibility guidelines of Fannie Mae, Freddie Mac, the Federal Housing Administration (FHA), and the Veterans Administration (VA), and are "color blind" in that race and ethnicity (or proxies like neighborhood location) cannot be used in the algorithm. Nevertheless, these recommendations account for about half of the Black-white gap in denial rates.

Second, after controlling for credit score, DTI, and LTV in addition to AUS recommendations, we find denial gaps that are substantially smaller than previous estimates which did not control for any of these risk factors or AUS recommendations. The Black-white denial gap drops to two percentage points, and the Hispanic and Asian gaps relative to white applicants are about one percentage point. The additional explanatory power of observed risk characteristics on top of AUS recommendations reflects lender "overlays," or deviations from AUS recommendations based on lenders' own assessment of applicants' risk factors.[2] All that said, the risk factors observable in HMDA cannot fully explain higher denial rates among minority applicants. We refer to these remaining gaps as "excess denials".

Third, we provide evidence that risk factors that are not observed in the HMDA data explain at least some of the excess denials of minority applicants. We show that there are racial gaps in AUS recommendations conditional on observables (credit score, DTI, LTV, loan amount, etc.). Given that AUS is color-blind, we interpret these residual AUS gaps as reflecting differences in unobserved (to us) risk or eligibility variables. For example, AUS algorithms consider applicants' liquid reserves; they also consider several credit history variables independently of credit score. While controlling for AUS recommendations in our lender denial regressions helps account for unobservables, this simple AUS control is not sufficient if lenders have overlays on these unobservable factors (for example, tougher requirements than AUS for liquid reserves). Indeed, we find that lenders with the highest unexplained rate of denials of their white applicants also have the largest excess denial rates of minorities relative to white applicants. In other words, when lenders exhibit "strictness" on unobservable factors, it tends to have a disproportionate impact on minority applicants.

Finally, we examine heterogeneity in excess denials across lenders and markets to indirectly assess whether excess denials reflect discrimination. Discrimination may be worse when borrowers have more in-person contact with lenders; in markets where lenders have more market power (and are thus freer to discriminate, unconstrained by market discipline); and in markets where the general population displays a greater degree of racial animus. However, we do not find that Fintech lenders (where in-person contact and subjective assessments are most likely to be minimized) have lower excess denials than traditional lenders, nor do we find that excess denials increase in less competitive markets. We do find larger excess denials in markets where

[2] For example, Fuster, Plosser, and Vickery (2021) show that regulation can affect willingness of lenders to make FHA loans. See also Bhutta, Laufer, and Ringo (2017).

measures of racial animus are higher; however, those same markets also exhibit larger residual racial gaps in AUS denials, which suggests a role for unobserved risk factors in explaining the variation in excess denials across markets.

Overall, our results suggest less scope for discrimination driving racial and ethnic differences in denial rates relative to recent analyses. After flexibly controlling for AUS recommendations and individual observable risk factors, we find racial and ethnic denial gaps of 1-2 percentage points. Moreover, we provide evidence that lender overlays on risk factors not observed in the HMDA data at least partially explain these remaining gaps. Additionally, using heterogeneity in excess denials across lenders and markets we fail to find evidence that these gaps are consistent with discrimination. Thus, we view the 1-2 percentage point magnitudes as upper bounds on the extent of discrimination in the loan approval process.

Recent, widely-cited analyses of denial rates have documented larger racial and ethnic gaps in denial rates, but they are unable to control for important individual underwriting variables. Bartlett et al. (2019) use neighborhood-level proxies for credit scores and estimate denial rate differences of 7-10 percentage points. Glantz and Martinez (2018) find similar or larger denial gaps in a number of city-specific estimates.[3]

Giacoletti, Heimer, and Yu (2021) also argue that discrimination plays a large role in denials of Black applicants. They document that originations surge on the last days of the month, especially for Black borrowers, and contend that this surge reflects less discrimination at month's end as loan officers must hit monthly production quotas. One concern, however, is that the date variable in HMDA refers to loan closing rather than the timing of lender decisions and thus their evidence may reflect borrower demand for closing at the end of the month.[4]

Our estimates are also smaller than those from the seminal work of Munnell et al. (1996). Importantly, Munnell et al. enhanced the HMDA data by collecting detailed applicant data from Boston-area lenders' loan files. That said, their study took place in an era when manual

[3] Park (2021) uses several of the new HMDA fields, including credit score, to estimate loan-level probabilities of default loss in a stressed economy and finds that these modeled loss probabilities do not fully explain racial denial disparities.

[4] Borrowers typically have substantial control over closing dates, and a rule of thumb for borrowers is to close at the end of the month to avoid prepaid interest. Also, many first-time homebuyers are likely to prefer closing at the end the of month to match the end of their rental lease.

underwriting was far more common and therefore may not be informative about the extent of discrimination today.[5]

Finally, in contrast to testing for equality in approval rates as we do in this paper, economists often propose testing for higher marginal profitability of loans to minorities relative to whites. We note that this approach has two significant drawbacks. First, it only detects Becker-style taste-based discrimination, while a lack of equality in approvals could arise from either racial animus or statistical discrimination. Although economists typically focus on the former, in our view it is critical to understand if lender decisions are racially-driven for any reason, even if consistent with profit maximization. Second, loan-level profitability data are generally unavailable. Instead, researchers have used ex-post default data as a proxy (e.g. Berkovec et al. 1998; Pinto and Peter 2021), but the connection between default and profitability is unclear given widespread government guarantees of credit risk and racial differences in prepayment speeds (Gerardi, Willen, and Zhang 2021). Moreover, group differences in *average ex-post* default rates may not be informative about the *expected* default rates of *marginal* applicants (Ladd 1998; Arnold, Dobbie, and Yang 2018).[6]

We believe our results have important policy implications. First, our finding of limited scope for discrimination in the approval process helps guide optimal targeting of marginal policy resources aimed at reducing disparities in mortgage access and homeownership. Our results suggest that disparities in denials largely reflect differences in underlying risk factors, and thus there is a need to better understand the source of these differences and how they might be addressed. For example, gaps in credit scores across groups could potentially be attenuated through education and financial literacy (e.g. Homonoff, O'Brien, and Sussman 2019), or through improvements in the quality of credit history data (e.g. Blattner and Nelson 2021).

Second, our results highlight potential disparate impact issues in lender decisions. We show that lenders often impose stricter standards than AUS recommendations; while these stricter

[5] Other evidence based on detailed lender data from the 1990's also indicates discrimination in application approvals (Courchane et al. 2000).
[6] Recent studies have documented that minority borrowers tend to have higher default rates conditional on observables (Bayer, Ferreira, and Ross 2016; Bhutta and Canner 2013)

standards may be applied in a race-neutral fashion, they can have a disparate impact and may not be entirely justified when government takes most of the credit risk.

Third, public awareness that lenders deny applicants based on objective credit risk factors and not on race or ethnicity could improve trust in the system and encourage more minority borrowers to apply in the first place. As Charles and Hurst (2002) show, an important reason for the homeownership gap is that many minority families may not even attempt to get a mortgage in the first place – assuming they will likely be rejected.

That said, an important caveat to our study is that we only study discrimination in approval decisions conditional on formally applying. Minority borrowers may be more likely to be discouraged and informally rejected by lenders before even submitting a formal application (e.g. Hanson et al. 2016). Such unobserved denials may also contribute to perceptions of a lack of fairness. We also recognize that there are other margins along which discrimination may occur which we do not study here. Lenders may provide minority applicants with poor service, which could contribute to some of the racial and ethnic differences we find in verification and completeness of applications (Ross et al. 2008). Also, discrimination in pricing has been the subject of several recent papers (Bhutta and Hizmo 2020; Bartlett et al. 2019; Willen and Zhang 2020). These papers find modest to no differences in pricing.

1. Background

Most mortgage originations are made through one of three government-related programs: (1) "conventional conforming" loans sold to Fannie Mae and Freddie Mac (government-sponsored enterprises, or GSEs); (2) loans insured by the Federal Housing Administration (FHA), which is the main program for borrowers with small down payments and lower credit scores; and (3) loans guaranteed by the Veteran's Administration (VA) for military families. Each program has specific eligibility criteria (e.g. maximum loan size) and underwriting standards. Outside of these programs, roughly 20 percent of mortgages are held in the portfolios of banks, credit unions and other financial institutions, including most "jumbo" loans – that is, conventional loans beyond the loan size limits of the GSEs.

In the typical first stage of the mortgage application process, prospective mortgage borrowers contact a lender or a mortgage broker (someone who works with multiple lenders) to inquire about getting a mortgage. Inquiries over the internet have become more common in recent years, along with application processes that are fully online (Buchak et al. 2018; Fuster et al. 2019). Loan officers (or online algorithms) will gauge the needs and resources of the borrower and recommend a particular loan program, and can then quickly conduct a prequalification screen based on a check of their credit score and the stated income and assets of the borrower. At this stage, potential applicants who have a low credit score or who appear to lack income or down payment funds may be dissuaded from moving forward. Racial or ethnic bias that impedes minorities from moving beyond this first stage will not be captured in our study.[7]

The second stage is to submit a formal application, along with documentation of income and assets (e.g. pay stubs, tax returns, account statements, etc.). Loan officers help ensure borrowers provide the right documentation and fill out the application correctly. However, loan officers do not make final credit decisions. Application information is entered into an automated underwriting system (AUS), and the associated documents are sent to a separate underwriting department, which will make the ultimate determination of whether the loan will be approved.

An AUS uses the application information to provide a recommendation for whether the loan may be approved. The AUS scores loans for credit risk based on statistical default models, and also ensures that loans meet certain eligibility requirements depending on the specific loan program. These models must follow fair lending regulations, and therefore cannot take into account race or ethnicity, or proxies such as neighborhood location or ZIP code. The most commonly used AUS is Desktop Underwriter (DU), created by Fannie Mae.[8] DU assesses the application information and provides an up or down decision along the two dimensions of risk and eligibility: "approve" or "refer" and "eligible" or "ineligible", respectively. For example, if a conventional conforming loan application targeted for sale to Fannie Mae receives an "approve/ineligible" decision, this implies that while it presents low enough credit risk for Fannie Mae to purchase it, it nonetheless falls outside at least one eligibility requirement, such as

[7] See Hanson et al. (2016) and Ross et al. (2008) for evidence of differential treatment in pre-application stages.

[8] Freddie Mac also has an AUS, called Loan Product Advisor (LPA). FHA provides a credit risk scorecard (TOTAL) that can be used by DU and LPA to assess the credit risk of an FHA applicant. DU and LPA can also be used to assess credit risk and eligibility for VA loan applications. In Appendix Table A.1, we report the fraction of applications that were processed by each AUS, broken out by loan program.

exceeding a DTI cap of 50 percent. In such a case, the borrower may need to take out a smaller loan or pay off some other debts in order to ultimately qualify.

AUS only provides a recommendation to underwriters. The final determination on a loan applicant is made by an underwriter. This determination reflects several inputs, including AUS results, any additional lender requirements not in the AUS (referred to as "overlays"), and successful verification of all applicant information (income, assets, employment history, etc.). Loans that pass AUS could still be rejected because, for example, income could not be fully verified or because the property appraisal ended up being lower than expected. Alternatively, loans that do not pass AUS could still be approved; for example the underwriter might be willing to overlook a blemish in one's credit history if the applicant can provide an adequate explanation.

2. Data

We use the HMDA data, which cover nearly the universe of mortgage lending in the U.S. and include data on mortgage applications that were denied or not originated for other reasons.[9] The data have long included important applicant socioeconomic characteristics including race and ethnicity, gender, and borrower income, along with basic loan information such as loan amount, census tract of the securing property, loan purpose (i.e. home purchase, refinance or home improvement), and whether the loan carried government insurance.

However, until only recently, they lacked the most important underwriting variables that lenders use in determining whether to approve a loan. Beginning in 2018, the HMDA data fields were expanded to include borrower credit score, DTI ratio, and combined LTV ratio. In addition, if the lender used an AUS to assist in the credit decision (as described in Section 1) they must report the output of the AUS as well as the specific model used.

We use the full, confidential version of the expanded HMDA data from 2018 and 2019. There were nearly 15 million first-lien home purchase and refinance mortgage applications for owner-occupied single-family properties, excluding observations where no credit decision was made because the application was either withdrawn or not completed by the borrower. We restrict our

[9] For details on the HMDA data including coverage, see Bhutta, Laufer and Ringo (2017).

attention to applications for typical fixed rate, 30-year loans, and drop any applications with missing or invalid credit scores.[10] Finally, for our main analysis we focus on the nearly 90 percent of these applications that went through one of the three main AUS (DU, LPA and TOTAL), leaving us with a dataset of nearly 9 million applications.

3. Estimating "Excess Denials" of Minority Applicants

In this section we assess how much more likely minority mortgage applicants are to be rejected than otherwise similar white applicants. Our empirical analysis first compares lender denial decisions with the algorithmic recommendations from AUS. Then we evaluate how much of the denial gaps can be explained by observable risk factors.

Comparing Lender Decisions to Algorithmic Decisions

We start by fixing some ideas as to how AUS recommendations, lender decisions and borrower characteristics relate to each-other. The binary outcome of an AUS denial recommendation can be written as:

$$D_{AUS} = g(X, u) \tag{1}$$

Where $g(\cdot)$ is a deterministic function of risk characteristics, *X*, which are observable in the HMDA data, and other risk characteristics, *u*, which are not observed in the HMDA data. D_{AUS} takes a value of 1 if the application receives an AUS denial, and zero otherwise.

Lender *i*'s binary denial decisions can similarly be written as:

$$D^{i}{}_{Lender} = h_i(X^*, u, w, r) + e \tag{2}$$

Lenders also base their decisions on *X* and *u*, but lender *i*'s decision function $h_i(\cdot)$ may differ from the AUS function $g(\cdot)$ in its treatment of these inputs. Furthermore, the values of *X* may be revised during verification after initial underwriting, so equation 2 takes a potentially modified version of *X*, *X**. Lenders may also take into account risk factors not considered by AUS, *w*, or

[10] Small lenders – those who originated fewer than 500 closed-end mortgage loans in each of the prior two years – are exempt from reporting the new fields, such as credit score.

they may base decisions on race or ethnicity, r. Finally, the error term, e, reflects an idiosyncratic element arising from human error in lender decisions.[11]

The top row of Table 1 shows that lenders denied 17 percent of Black mortgage applicants in 2018-2019, significantly higher than the 8 percent denial rate for white applicants.[12] Lenders also denied Hispanic and Asian applicants at higher rates than white applicants. At the same time, Table 1 indicates that observable applicant characteristics, (X or X^* in the equations above) differ on average across groups. These differences could be driving the differences in denial rates, as opposed to racial bias, r.

As noted by equation 1, AUS decisions are not a function of race or ethnicity, r, yet the second row of Table 1 shows that Black and Hispanic applicants are more likely than white applicants to receive and AUS denial recommendation. Recall that AUS algorithms reflect the underwriting and eligibility standards of government-related mortgage programs. Thus, even if application decisions were based purely on government credit-risk algorithms, the data suggest that the Black-white denial gap in 2018-19 would still have been about 9 percent.

We can also see in Table 1 that lenders deny each applicant group at a higher rate than AUS. This holds even for white applicants, consistent with lenders denying applicants more often than AUS for reasons other than minority status. As highlighted by equations 1 and 2, lenders could have different decision functions than AUS (h versus g), account for other risk factors, w, or use updated measures of risk, X^*.

How much of the gaps in denials by lenders can be traced to the gaps in AUS denial recommendations? In column 2 of Table 2 we regress an indicator of lender denial on applicant race and ethnicity dummies, while conditioning on AUS denial recommendations (interacted with loan purpose by loan program). Compared to the unconditional gaps shown in column 1, controlling for AUS recommendations shrinks the Black-white denial gap from 9 to 4.3 percentage points, and the Hispanic-white gap from 3.1 to 2 percentage points, while the Asian-white gap

[11] Lenders' decisions may depend directly on AUS recommendations. However, because D_{AUS} is a deterministic function $g()$ of X and u, for simplicity we do not include D_{AUS} as a separate argument in $h()$.
[12] We follow the method described in Bhutta, Laufer, and Ringo (2017) to designate a race and ethnicity for each application.

actually increases slightly. Overall, differential rates of AUS recommendations can explain some of the minority denial gap, but far from all of it.

Do "Overlays" Explain Denial Disparities?

AUS recommendations are not binding, and lenders may choose to impose tighter underwriting standards, known as overlays, than the government programs require.[13] In the terms of equations 1 and 2, $g()$ may change from 1 to 0 at different values of X and u than $h()$ does. Here we investigate how much of the remaining minority denial gaps can be explained by lender overlays on observable characteristics, X.

In column 3 of Table 2 we add in the complete set of underwriting controls derived from the new HMDA fields.[14] We include a fully interacted set of controls of discretized bins of credit score, LTV, and DTI ratio.[15] We also include the AUS denial recommendation indicator, to help capture some of the potential unobservable risk factors, u. Lastly, we include county-by-month fixed effects, indicators for requested loan amount (discretized into bins of $50,000), an indicator for the presence of a co-applicant, the log of reported income, and a lender fixed effect. All these covariates are fully interacted with the indicators for loan purpose and program.

The estimated Black and Hispanic denial rate gaps are cut in half relative to column 2. Black applicants are 2 percentage points more likely, Asian applicants 1.4 percentage points more likely, and Hispanic applicants 1 percentage point more likely to be denied than comparable white applicants. Comparing columns 1 and 3 indicates that we can explain over three-quarters of the Black-white denial gap. We refer to the remaining gaps as "excess denials".

[13] Lenders may also approve and potentially portfolio a loan that the AUS does not recommend accepting. See Table 1 for the frequency of disagreement between lender decisions and AUS recommendations by race and ethnicity.

[14] We treat reported underwriting factors as exogenous characteristics of the borrower. However, if lenders are less likely to e.g. help minority applicants find loan terms that result in an acceptable DTI ratio, this could lead to racial disparities in denial rates that we would attribute to an observed factor.

[15] Credit scores are discretized into buckets of 300-399, 400-499, 500-579, and buckets of 10 points for FICO above 580. DTI ratios are discretized into buckets of 5 percentage points for ratios from 0 to 30 percent, single percentage point bins for DTI between 30 and 60 percent, and bins of 20 for DTI between 60 and 100. LTV ratios are discretized into buckets of 10 percentage points from 0 to 80 percent, then in 5 percentage point buckets up to 95 percent, single percentage points up to 100 percent, and then bins of LTV of 101-110, 111-120, and 121-200.

Although denial disparities are still not fully explained, the explanatory power of the new HMDA fields is far greater than with pre-2018 data, as we demonstrate in Appendix Table A.2. [16] Table A.2 also shows that the raw Black-white denial gap *before* we select on applications that were run through AUS is nearly 12 percentage points, which is larger than the 9 percent raw gap we show in Tables 1 and 2. Our estimate of Black excess denials of 2 percentage points is over 83 percent lower than this baseline. Of course, racial bias by lenders could drive selection into our AUS sample. However, additional evidence shown in Table A.2 is inconsistent with racial bias driving lenders' decisions to run applications through AUS.[17]

Finally, as we show in Appendix Table A.4, excess denials appear both in the subsample of applicants approved by the AUS as well as the subsample of those with an AUS denial. In other words, lenders are both more likely to override a positive AUS recommendation to deny a minority applicant, and to override a negative AUS recommendation to approve a white applicant.

4. Explanations for Excess Denials

Should these remaining minority denial gaps, or "excess denials," be attributed to racial discrimination by lenders, or can they be explained by other non-discriminatory factors? In this section we test for both discriminatory and non-discriminatory explanations for the excess denials. First, we investigate the possibility of lender overlays on *un*observable risk factors. Despite the expanded HMDA data, we still do not directly observe various risk factors that might influence credit decisions, such as the applicant's cash reserves, the length of time employed at their current job, or how well they are able to document their income and assets. Second, we try a number of indirect tests of discrimination, and we end this section by directly considering the explanations of denials lenders provide in HMDA.

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[16] In column 2 of Table A.2 we control only for fields available in pre-2018 versions of HMDA. These older fields can explain little of the denial disparities.

[17] In particular, in columns 5 and 7 of Table A.2 we run the same specification, but column 7 limits the sample to applications that were run through AUS. The denial gaps in these two columns are very similar, suggesting that differences in observable risk characteristics drive racial differences in the likelihood of a lender running an application through AUS.

Do Unobserved Risk Characteristics Vary by Race and Ethnicity?

As a starting point, we provide evidence of racial differences in risk factors that remain unobserved in the HMDA data. We do so by testing for disparities in AUS recommendations after controlling for observable underwriting variables. As explained earlier and noted by equation 1, AUS results cannot directly depend on the applicant's race and thus unexplained racial or ethnic gaps in AUS recommendations must reflect additional quantifiable factors that we do not observe in the HMDA data. In terms of equations 1 and 2, this would take the form of variation across borrowers in u that is correlated with race and ethnicity, r.

Column 5 of Table 2 shows that even with the full set of controls for observable underwriting variables, Black applicants are 1.5 percentage points less likely to be recommended for acceptance by an AUS than observably identical white applicants. This result implies that Black applicants tend to be considered by AUS to be somewhat riskier along dimensions we do not observe in the HMDA data. However, for Hispanic and Asian applicants the respective unexplained AUS denial gaps are close to zero. This result implies that these two groups, on average, do not differ significantly enough on the unobservable factors considered by the AUS, u, to trigger differential AUS recommendations.

Figure 1 plots unexplained AUS denial gaps as well as lender excess denials for each race and ethnicity by 10-point credit score bins.[18] For Black applicants (top panel), the AUS denial gap relative to white applicants rises substantially as credit score declines, suggesting wider differences in unobserved risk factors at lower credit scores. Strikingly, the same panel also shows that Black-white lender excess denials are highest among the same subset of applicants that AUS consider riskiest along unobservable dimensions. Although excess denials are conditional on AUS output, the differences in unobservables that drive the Black-white AUS gap may also be contributing to the Black-white lender excess denial gap, due to overlays as described further in the next section.

In the middle and bottom panels of Figure 1, the Hispanic-white and Asian-white AUS denial gaps are very close to zero throughout the credit score range. Unlike the top panel, we cannot detect meaningful differences in unobservable risk factors anywhere in the credit score distribution.

[18] Raw racial denial gaps for each credit score bin, by lender and by AUS, are plotted in Appendix Figure A.1.

Do Overlays on Unobserved Characteristics Help Explain Excess Denials?

Excess denials could be explained by lenders having tougher standards than the AUS on applicant characteristics that are not observed in the HMDA data, if minority applicants more frequently fall short of these overlays. In terms of equations 1 and 2, this would mean that u varies by race and that $g()$ and $h_i()$ differ in their treatment of u. We test this hypothesis by exploiting cross-sectional differences in lender policies. We construct a lender-specific measure of the "strictness" of their underwriting policies, and then correlate lenders' strictness with their excess denials. Different lender overlays on unobservables should create a positive correlation between strictness and excess denials across lenders if unobservable characteristics of minority applicants appear riskier than those of white applicants.[19]

To start, we estimate lender-specific excess denials of minority applicants. For this analysis we focus on the 100 largest lenders in our data, as measured by the total count of originations in 2018 and 2019. We run a regression with our full set of controls (as in column 3 of Table 2) but allow the coefficients on race and ethnicity to vary by lender. Importantly, to ensure that our lender-specific excess denial estimates do not simply pick up differences across lenders in their standards on *observable* underwriting factors (credit score, LTV, and DTI ratio), we allow these coefficients to also vary by lender. The lender-specific coefficients on the race and ethnicity dummies are plotted, along with 95 percent confidence intervals, in the left-hand column of Figure 2. For each of the three minority groups shown, at least 85 of the 100 largest lenders had an excess denial rate greater than zero and there are at least ten lenders that have excess denial estimates of 4 percentage points or more.

Next, we consider whether lenders may differ in their estimated excess denials due to differences in their loan approval "strictness" (i.e. stricter policies may have a disparate impact on minority applicants). Strictness is estimated as the lender-specific probability of denying a *white* applicant, conditional on the full set of control variables (similar to the column 3 specification in Table 2, but only including white applicants in the estimation). We construct this measure based solely on white applicants to isolate differences in lender policy without contamination by any

[19] To be sure, we cannot distinguish between overlays on factors that AUS considers (u) and other factors that lenders consider but are not observed to us (w) and may be correlated with race. Our discussion here emphasizes overlays on u because we know with certainty that AUS considers several factors we do not observe in the HMDA data.

differential treatment of minority applicants. The lender fixed effects from this white-only regression yield our estimates of lender-specific strictness. Different measures of strictness between two lenders, i and j, indicate that $h_i(\cdot,\cdot,\cdot, white) \neq h_j(\cdot,\cdot,\cdot, white)$. Lender strictness equal to zero means that lender's denial rate of white applicants was exactly average, conditional on observables. Higher strictness means lenders are imposing tougher standards on their borrowers.

If excess denials of minorities are at least partially due to racial and ethnic differences in the ability to meet overlays on unobservables, then we would expect a positive correlation between strictness and excess denials.[20] We show a scatterplot of lender excess denials against the measure of lender strictness in the right-hand column of Figure 2. A tight, positive slope is visually apparent for all three of the minority groups presented, with correlations being 0.63 for Black applicants, 0.5 for Hispanic applicants, and 0.65 for Asian applicants. Lenders that impose the strictest standards on their *white* applicants tend to also have the largest excess denials of minority applicants. This finding suggests that at least some of the excess denials are the result of tight lender standards on unobservable factors, rather than disparate treatment of minority applicants.[21]

Indirect Tests of Whether Discrimination Drives Excess Denials

To further understand whether excess minority denials might reflect disparate treatment to any extent, we try several indirect tests of discrimination on the part of lenders. These take the form of testing whether estimated excess denials are larger in circumstances we would have *ex ante* expectations for discrimination to be more prevalent.

First, we compare Fintech lenders to traditional mortgage lenders. By automating more of the application process, Fintechs cut out some human judgement and consequently have the potential to reduce racial discrimination. We re-estimate equation 1 on different subpopulations of lenders,

[20] To be clear, our measure of lender strictness reflects stringency on both unobservable (u and w) and observable risk factors X (e.g. credit score, LTV, and DTI). However, because our lender-specific excess denial estimates include lender-specific coefficients on X, overlays on observables cannot themselves generate a correlation between our measures of lender-specific strictness and excess denials. [21] We do not have any evidence, however, as to whether these tighter standards reduce loan risk to justify their disparate impact on minorities.

[21] We do not have any evidence, however, as to whether these tighter standards reduce loan risk to justify their disparate impact on minorities.

including lenders identified as Fintechs by Fuster, Plosser, and Schnabl (2019), and present results in Table 3. We find excess denials are, if anything, higher at Fintech lenders, the opposite result we would expect if excess denials reflect racially biased human judgement.

Next, we compare outcomes in more- and less-competitive lending markets. In less competitive markets, a few large lenders could potentially leverage their market power to make inefficient decisions, such as indulging in taste-based discrimination. We rerun our denial regressions, including an interaction term between applicant race and the market share of the top 4 lenders in that MSA. Results are presented in column 2 of Table 3. The estimated interaction effects are all negative. This suggests competitive pressure does not reduce excess denials, in contrast to what we would expect if excess denials were driven by taste-based discrimination.

Finally, we compare outcomes in markets differentiated by a population-level measure of racial animus. If excess denials are due to discrimination by lenders, we might see relatively high excess denials in areas with more racial hostility. We interact applicant race with a measure of the frequency of racially-charged Google search terms, provided by Stephens-Dawidowitz (2014), and re-estimate the denial regressions.

Results are shown in column 3 of Table 3. It does appear that excess denials are somewhat higher in media markets exhibiting greater racial animus. However, when we repeat the exercise for AUS rather than lender excess denials, we observe the same pattern – i.e., higher AUS excess denials in markets of greater racial animus (compare columns 3 and 6 of Table 3). This suggests that white-minority differences in unobservable risk factors are larger in markets with higher racially charged search frequencies, potentially explaining the similar correlation with excess denials. Overall, we do not find compelling evidence that excess denials can be explained by disparate treatment of minority applicants.

How Do Lenders Explain Excess Denials?

Lenders are now required under HMDA to report a denial reason for every denied application. Of course, a lender engaged in illegal discrimination would be unlikely to explicitly admit this, so the self-reported reasons may not always reflect reality. Nonetheless, we can use these stated reasons to better understand how lenders justify their excess denials. We find that lenders particularly cite issues with incomplete applications and verification of applicant information more commonly with minority than observably similar white applicants. This may suggest that minority applicants experience more difficulties in the latter stages of the mortgage approval process (i.e. after initial underwriting and AUS recommendations have completed), contributing to excess denials. In terms of our earlier conceptual framework, there may be racial and ethnic variation in the probability that $X \neq X^*$. Details of the data and analysis, and a discussion of what can be inferred from the results, are presented in the online appendix.

5. Conclusion

Using newly available HMDA data for 2018-2019, we demonstrate that higher denial rates for minority mortgage applicants are mostly explainable by a combination of government-created algorithmic underwriting and lender-imposed overlays on standard underwriting factors. Further evidence suggests that the remaining 1-2 percentage point difference in denial rates between minority and white applicants (what we refer to as "excess denials") are at least partially due to differences in racial and ethnic distributions of unobservable underwriting factors. This evidence suggests that racially biased credit decision-making is substantially less common than has been suggested by recent research.

Our findings have implications for policy and future research. We show that disparities in mortgage denials can be traced in large part to disparities in observable risk characteristics such as credit scores. Research into the causes of disparities in credit scores, and identification of potential interventions to help reduce such disparities could have first-order impacts to alleviate disparities in credit access. That said, research is also needed to verify whether lenders' credit standards, which as we demonstrate can exceed those set by the government agencies that bear most of the credit risk, have valid business rationale.

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Table 1: Summary statistics

	All	White	Black	Hispanic	Asian
Lender Denial Rate	0.10	0.08	0.17	0.12	0.10
AUS Denial Rate	0.06	0.05	0.14	0.07	0.05
Lender-AUS Disagreement Rate	0.09	0.08	0.15	0.10	0.08
Loan Amount (000)	253	246	230	243	333
Income (000)	92	93	78	76	104
Credit Score	720	726	685	703	738
LTV (%)	84.13	83.32	90.69	87.76	79.92
DTI (%)	39.10	37.99	42.75	42.54	39.86
N. Obs.	8,944,153	5,484,991	675,360	807,663	410,732

Note - Table shows average characteristics for purchase and refinance applications in 2018 and 2019 for first lien, 30 year FRM, on owner occupied single unit homes for which an AUS recommendation was reported. Sample excludes withdrawn or incomplete applications.

Table 2: Denial Regressions using the AUS sample

	Lender Denial			AUS Denial	
	(1)	(2)	(3)	(4)	(5)
Black	0.090**	0.043**	0.020**	0.084**	0.015**
	(0.005)	(0.003)	(0.001)	(0.008)	(0.001)
Asian	0.012**	0.021**	0.014**	-0.004*	0.002**
	(0.004)	(0.003)	(0.001)	(0.002)	(0.001)
Hispanic	0.031**	0.020**	0.010**	0.022**	0.000
	(0.004)	(0.003)	(0.001)	(0.002)	(0.001)
Other	0.075**	0.035**	0.018**	0.062**	0.009**
	(0.007)	(0.006)	(0.002)	(0.009)	(0.001)
Joint Race	-0.005*	-0.000	0.003**	-0.000	-0.000
	(0.003)	(0.002)	(0.001)	(0.002)	(0.001)
Missing Race	0.064**	0.043**	0.017**	0.015**	0.005**
	(0.010)	(0.008)	(0.002)	(0.005)	(0.001)
AUS Outcome		Yes	Yes		
County by Month FE			Yes		Yes
Loan Amount Bins			Yes		Yes
Co-applicant			Yes		Yes
Log Income			Yes		Yes
FICO-LTV-DTI grid			Yes		Yes
Lender FE			Yes		Yes
R-Squared	0.010	0.233	0.390	0.009	0.350
N. Obs.	8,944,153	8,944,153	8,692,402	8,944,153	8,692,402

Note - All the controls except for the race/ethnicity indicators are fully interacted with program by loan purpose indicators . The standard errors are clustered at the lender and county levels. Significance: * p<0.1, ** p<0.05.

Table 3: Indirect tests for discrimination

	Lender Denial			AUS Denial		
	(1)	(2)	(3)	(4)	(5)	(6)
Black	0.020***	0.022***	0.021***	0.016***	0.014***	0.015***
	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)
Hispanic	0.010***	0.013***	0.011***	0.001	0.004***	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Asian	0.014***	0.019***	0.014***	0.002***	0.003*	0.002***
	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)
Fintech						
× Black	0.024***			-0.006		
	(0.004)			(0.004)		
× Hispanic	0.007*			-0.004*		
	(0.004)			(0.002)		
× Asian	0.003			-0.000		
	(0.006)			(0.002)		
Top 4 Lenders' Share						
× Black		-0.002			0.005	
		(0.009)			(0.009)	
× Hispanic		-0.015**			-0.022***	
		(0.007)			(0.007)	
× Asian		-0.026***			-0.006	
		(0.009)			(0.007)	
Racially Charged Search Rate						
× Black			0.002***			0.003***
			(0.001)			(0.001)
× Hispanic			0.002***			0.003***
			(0.001)			(0.001)
× Asian			0.002***			0.001***
			(0.001)			(0.000)
AUS Outcome	Yes	Yes	Yes			
County by Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Loan Amount Bins	Yes	Yes	Yes	Yes	Yes	Yes
Co-applicant	Yes	Yes	Yes	Yes	Yes	Yes
Log Income	Yes	Yes	Yes	Yes	Yes	Yes
FICO-LTV-DTI grid	Yes	Yes	Yes	Yes	Yes	Yes
Lender FE	Yes	Yes	Yes	Yes	Yes	Yes
R-Squared	0.388	0.388	0.388	0.351	0.351	0.351
N. Obs.	7,154,900	7,154,900	7,035,694	7,154,900	7,154,900	7,035,694

Note - The racially charged search rate is constructed by Stephens-Dawidowitz (2014) by using Google searches for racially charged terms in 195 designated market areas. The variable is standardized. All the controls except for the race/ethnicity indicators are fully interacted with program by loan purpose indicators . The standard errors are clustered at the lender and county levels. Significance: * $p<0.1$, ** $p<0.05$.

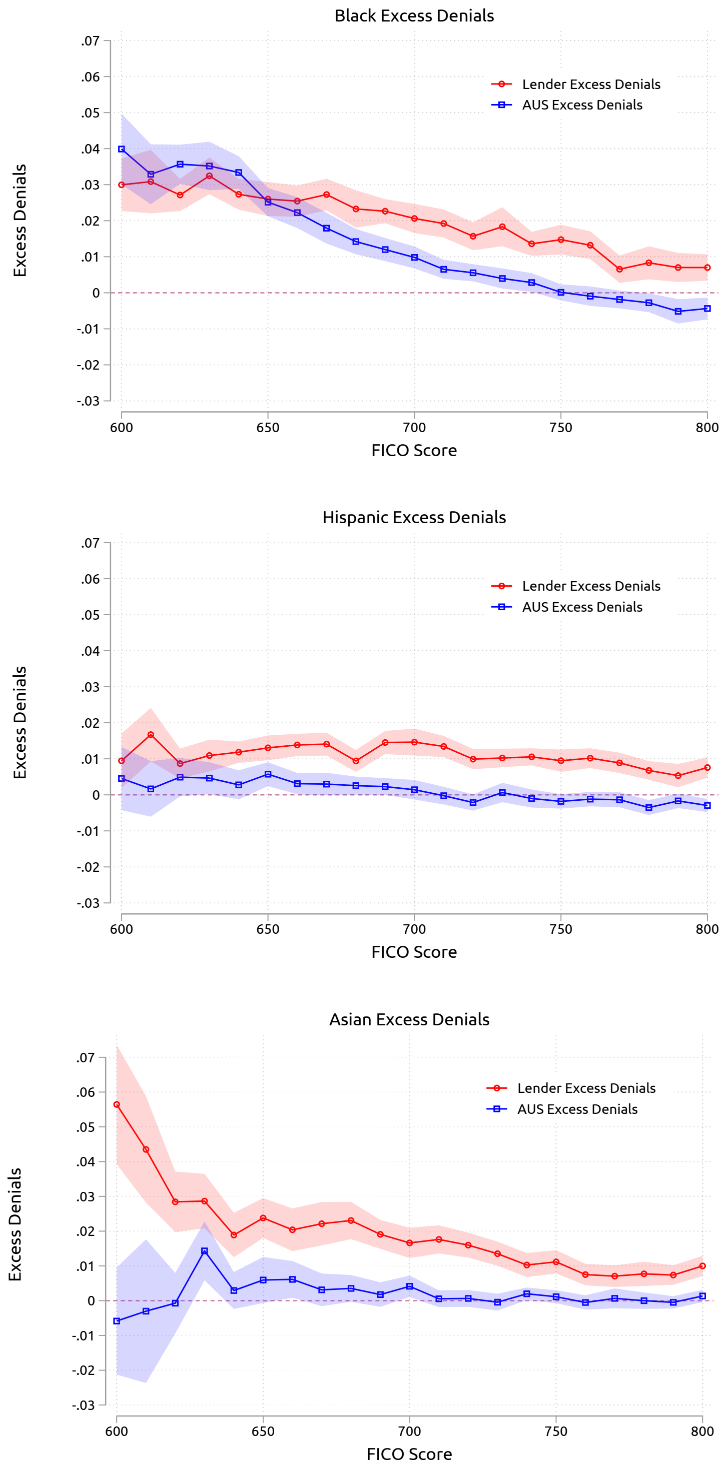

Figure 1: Lender and AUS minority exess denials relative to white by FICO score.

Note: Figure plots race and ethnicity regression coefficients by FICO after controlling for all borrower and loan characteristics as in specifications 3 and 5 of Table 2.

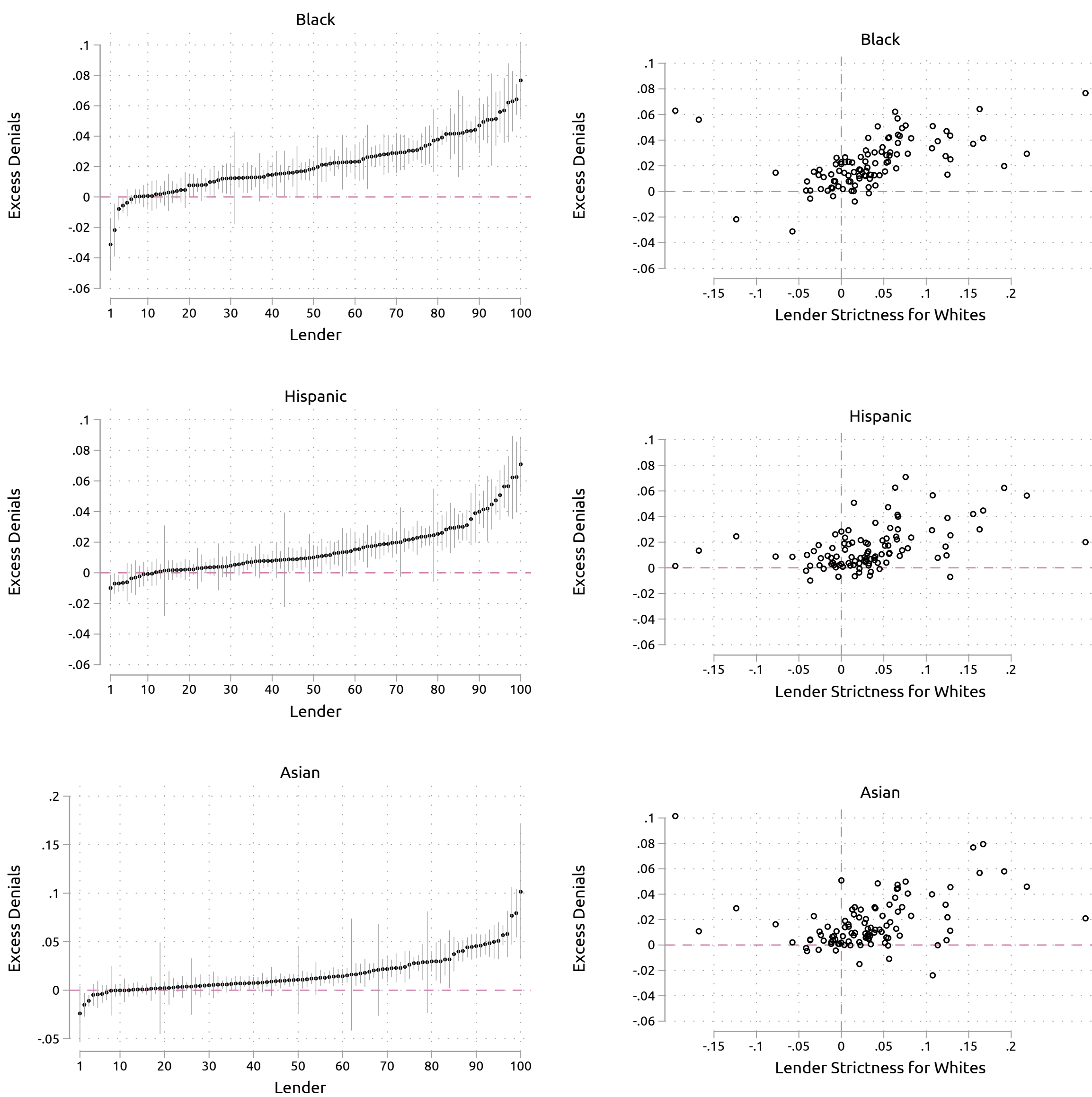

Figure 2: Excess denials for the top 100 lenders

Note: The vertical axes are regression coefficients of lender denials on race after controlling for borrower and loan characteristics as well as AUS outcomes separately for each of the top 100 lenders in our data. Lender strictness coefficients are lender fixed effects from a regression of lender denials on all controls including AUS outcomes for only white borrowers.

Internet Appendix for

"How Much Does Racial Bias Affect Mortgage Lending?

Evidence from Data on Human and Algorithmic Credit Decisions"

Neil Bhutta, Aurel Hizmo, Daniel Ringo

How Do Lenders Explain Excess Denials? An Analysis of Lenders' Stated Reasons for Denial

In this section, we describe the analysis of lenders stated reasons for denial as an investigation into the causes of excess denials of minority mortgage applicants.[1] Lenders must report at least one reason for why an application was denied from a default list or select "other" and describe the reason in a free text field.[2] The default reasons are issues with borrower credit history, DTI ratio, the collateral, insufficient cash, employment history, mortgage insurance, verification of applicant data, or an incomplete application.[3]

To infer lenders' explanations for excess denials, we estimate differences by race and ethnicity in the conditional probability of being denied for each of the listed reasons. To do so, we create a new set of outcome variables, Y^D for each reason D, set equal to one if an application was denied and the first stated reason for denial was D, and zero otherwise. For each D we then estimate:

$$Y^D = \sum_{r \in R} \beta_r^D \mathbf{1}\{x = r\} + \boldsymbol{W}\boldsymbol{\beta}_{\boldsymbol{W}}^{\boldsymbol{D}} + \varepsilon \tag{A.1}$$

where x is the applicant's race and ethnicity, R is our set of minority race and ethnicities and $\boldsymbol{W}$ is the vector of underwriting controls, including AUS recommendation, identical to specification 3 of Table 2. We estimate equation (2) separately for each of the nine denial reasons.

We plot the estimated contribution of each denial reason to the racial denial gaps in the stacked bar charts in Figure [A.3], shown separately by race and ethnicity. For all three minority groups, "verification" and "incomplete" account for a substantial share of excess denials. In other words, according to these lender-reported denial reasons, minority applicants are conditionally more likely to experience difficulties in the later stages of the application process and when underwriters attempt to verify the applicant's information. These steps mostly occur after initial underwriting, when an AUS recommendation is obtained, which may help explain why Hispanic and Asian borrowers experience positive excess denials from lenders, but not from AUS recommendations. Unfortunately, we do not have any method to ensure lenders are truthfully reporting these reasons for denial. Furthermore, difficulties with verification and application completion could reflect lenders providing poorer service to minority applicants. We therefore cannot be sure that denials citing "incomplete" or "verification" are not actually due to some form of discrimination.

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[1] Along with the new data fields reported, beginning with the 2018 data lenders are required to list at least one reason for denial for all denied applications. Previously, this field was reported at the lender's option.

[2] The most common explanations given under the "other" category are quite general, such as indicating that the lender does not extend credit under the terms requested without further detail.

[3] In Appendix Figure A.2 we show the unconditional breakdown of denial reasons by race.

Indeed, some stated reasons raise suspicions. For example, credit history and DTI ratios are offered as explanations for a sizable fraction of excess denials, particularly for Black applicants, despite the fact that we are controlling very flexibly for credit score and DTI ratio in the denial regressions. Innocent explanations are possible – for example, more Black applicants may be denied due to a consideration of their full set of underwriting characteristics, observed and unobserved in HMDA. Lenders are only required to report one reason, and so many may simply select "DTI" or "credit history" if these were important, but not the only, factors in the decision to deny credit. Moreover, lenders (and AUS) may consider aspects of credit histories for which the credit score is not a sufficient statistic, or consider the front-end as well as the (HMDA reportable) back-end DTI ratio.[4] Recall that excess AUS denials were particularly elevated for low-credit score black applicants. Nevertheless, greater regulatory scrutiny may be warranted for lenders that are more likely to report denying a minority applicant due to credit history than a white applicant with an identical credit score.

[4] Front end DTI refers to the ratio between the applicant's proposed mortgage debt service payments and income. Back-end DTI refers to the ratio between all debt payments (both mortgage and non-mortgage) and income. While HMDA requires reporting of only the back-end ratio, some lending programs (such as FHA loans) impose restrictions on both front- and back-end DTI ratios.

Table A.1: Market shares for automated underwriting systems

	All	Conforming	FHA	VA	Jumbo
Desktop Underwriter	0.63	0.71	0.40	0.84	0.26
Loan Product Advisor	0.14	0.21	0.01	0.06	0.03
TOTAL	0.11	0.00	0.53	0.00	0.00
Other	0.04	0.02	0.00	0.01	0.29
N/A	0.07	0.06	0.06	0.08	0.42

Note - The sample is restricted to purchase and refinance applications in 2018 and 2019 for first lien, 30 year FRM, on owner occupied single unit homes. Sample excludes withdrawn or incomplete applications.

Table A.2: Denial Regressions using the full sample and the AUS sample

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Black	0.116**	0.083**	0.050**	0.031**	0.027**	0.023**	0.025**	0.021**
	(0.008)	(0.004)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Asian	0.012**	0.034**	0.033**	0.024**	0.018**	0.017**	0.014**	0.014**
	(0.005)	(0.003)	(0.003)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Hispanic	0.036**	0.026**	0.014**	0.008**	0.011**	0.010**	0.010**	0.009**
	(0.005)	(0.003)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Other	0.104**	0.073**	0.049**	0.035**	0.024**	0.023**	0.021**	0.020**
	(0.011)	(0.005)	(0.004)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
Joint Race	-0.003	0.019**	0.011**	0.008**	0.004**	0.004**	0.003**	0.003**
	(0.003)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Missing Race	0.070**	0.047**	0.042**	0.034**	0.023**	0.022**	0.019**	0.018**
	(0.008)	(0.004)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.001)
County by Month FE		Yes	Yes	Yes	Yes	Yes	Yes	Yes
Loan Amount Bins		Yes	Yes	Yes	Yes	Yes	Yes	Yes
Co-applicant		Yes	Yes	Yes	Yes	Yes	Yes	Yes
Log Income		Yes	Yes	Yes	Yes	Yes	Yes	Yes
FICO bins			Yes					
LTV bins								
DTI bins								
FICO-LTV-DTI grid				Yes	Yes	Yes	Yes	Yes
Lender FE					Yes	Yes	Yes	Yes
Tract FE						Yes		Yes
AUS sample							Yes	Yes
R-Squared	0.012	0.128	0.206	0.360	0.403	0.412	0.341	0.353
N. Obs.	9,718,273	9,467,775	9,467,774	9,417,853	9,416,243	9,330,797	8,692,402	8,609,381

Note - All the controls except for the race/ethnicity indicators are fully interacted with program by loan purpose indicators. The AUS sample includes all applications that were run through one of the three goverment produced AUSs. The standard errors are clustered at the lender and county levels. Significance: * p<0.1, ** p<0.05.

Table A.3: Denial regressions for different subsamples of the data

	Conforming, Purchase				FHA, Purchase			
	All Lenders	Depository	Nonbank	Fintech	All Lenders	Depository	Nonbank	Fintech
Black	0.015**	0.016**	0.014**	0.024**	0.023**	0.024**	0.021**	0.033**
	(0.001)	(0.001)	(0.002)	(0.007)	(0.001)	(0.001)	(0.002)	(0.005)
Asian	0.012**	0.011**	0.011**	0.017**	0.019**	0.021**	0.018**	0.032**
	(0.001)	(0.002)	(0.002)	(0.005)	(0.002)	(0.002)	(0.002)	(0.007)
Hispanic	0.007**	0.007**	0.007**	0.006	0.013**	0.014**	0.012**	0.015**
	(0.001)	(0.002)	(0.001)	(0.004)	(0.001)	(0.001)	(0.001)	(0.003)
Other	0.011**	0.015**	0.007**	0.023*	0.016**	0.014**	0.017**	0.036**
	(0.002)	(0.003)	(0.003)	(0.011)	(0.003)	(0.004)	(0.004)	(0.014)
Joint Race	0.001**	0.001	0.002*	0.003	0.004**	0.004**	0.003*	0.007
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)	(0.002)	(0.006)
Missing Race	0.010**	0.010**	0.009**	0.016**	0.021**	0.024**	0.019**	0.024**
	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
AUS Outcome	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County by Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Loan Amount Bins	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Co-applicant	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Log Income	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FICO-LTV-DTI grid	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Lender FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-Squared	0.285	0.288	0.290	0.239	0.319	0.322	0.319	0.259
N. Obs.	3,672,642	1,954,840	1,680,021	241,655	1,489,483	643,870	815,195	104,335

Note - The depository insitutions in columns 2 and 6 are banks and credit unions. All the controls except for the race/ethnicity indicators are fully interacted with program by loan purpose indicators. The standard errors are clustered at the lender and county levels. Significance: * p<0.1, ** p<0.05.

Table A.4: Lender denial regressions separately by AUS recommendation

	AUS Accept Sample		AUS Reject Sample	
	(1)	(2)	(3)	(4)
Black	0.050**	0.018**	0.025**	0.030**
	(0.004)	(0.001)	(0.011)	(0.002)
Asian	0.008**	0.013**	0.117**	0.030**
	(0.003)	(0.001)	(0.027)	(0.003)
Hispanic	0.017**	0.008**	0.054**	0.021**
	(0.003)	(0.001)	(0.015)	(0.002)
Other	0.047**	0.017**	0.013	0.028**
	(0.006)	(0.003)	(0.038)	(0.005)
Joint Race	-0.003	0.003**	-0.028**	0.003
	(0.002)	(0.000)	(0.010)	(0.004)
Missing Race	0.051**	0.016**	0.123**	0.031**
	(0.012)	(0.002)	(0.015)	(0.003)
County by Month FE		Yes		Yes
Loan Amount Bins		Yes		Yes
Co-applicant		Yes		Yes
Log Income		Yes		Yes
FICO-LTV-DTI grid		Yes		Yes
Lender FE		Yes		Yes
R-Squared	0.006	0.230	0.009	0.558
N. Obs.	8372022	8140916	572131	439262
Average Lender Denial Rate	0.069	0.069	0.604	0.604

Note - The first two specifications limit the sample to applications that were recommended to be accepted by the AUS, while the last two include only applications that were rejected by the AUS. All the controls except for the race/ethnicity indicators are fully interacted with program by loan purpose indicators . The standard errors are clustered at the lender and county levels. Significance: * p<0.1, ** p<0.05.

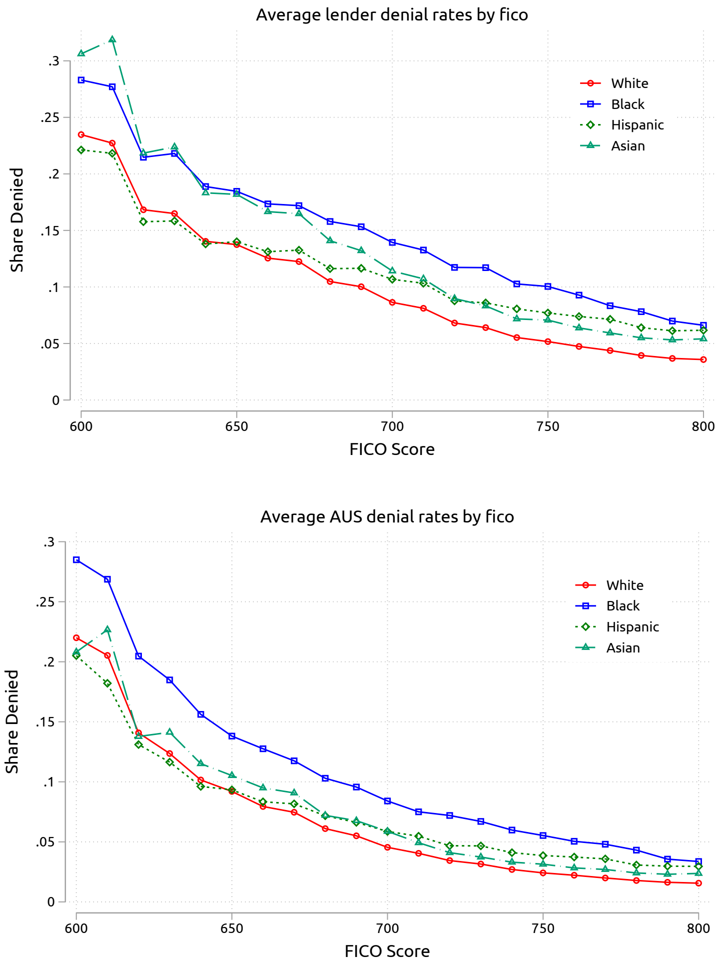

Figure A.1: Lender and AUS average denials by credit score

Note: Line show simple average denials by race. Sample includes all applications that were processed through an AUS.

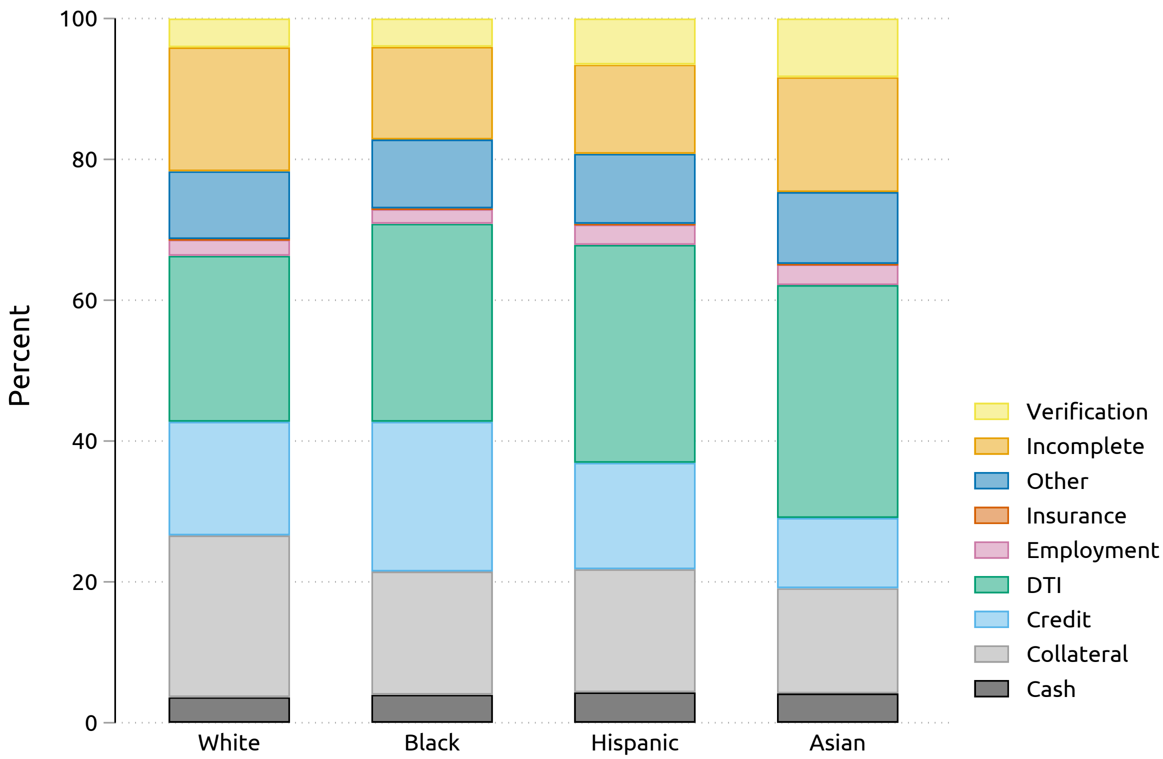

Figure A.2: Raw shares of denial reasons provided by lenders

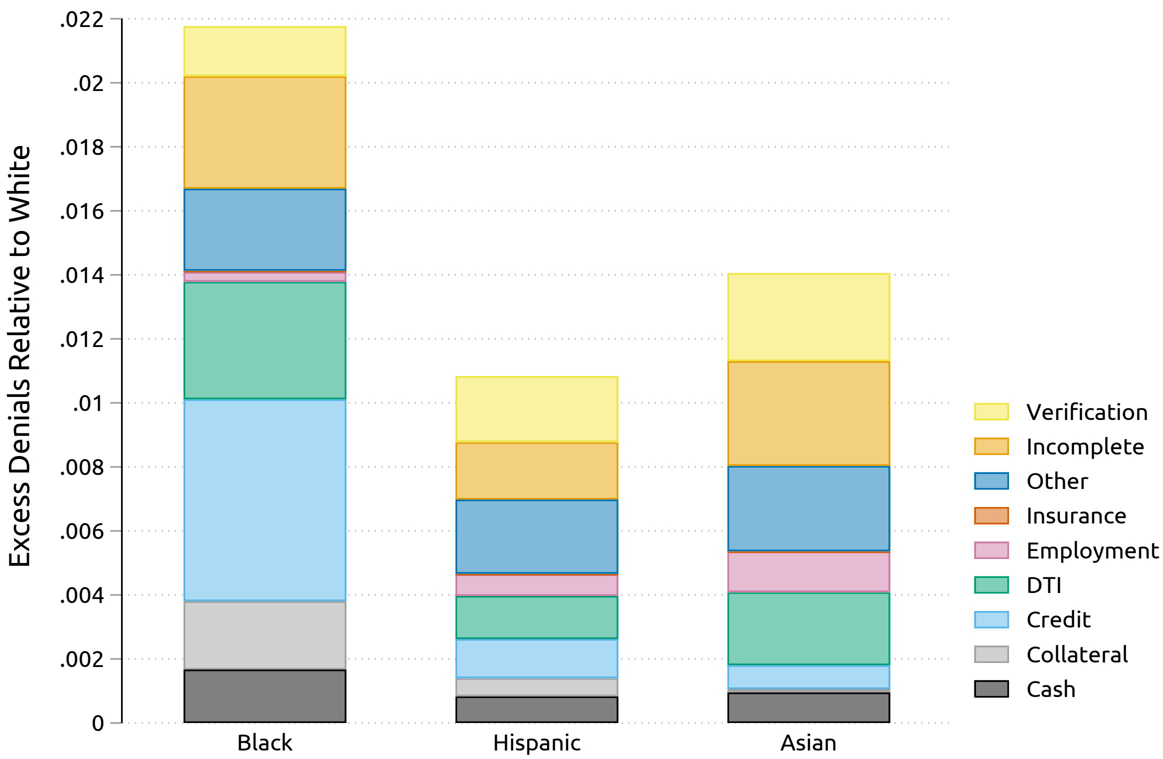

Figure A.3: Excess denial gaps broken down by lender provided denial reason

Note: The figure plots coefficients from separate regressions by denial reason controlling for all borrower and loan characteristics as in columns (3) of Table 2.