Mind the Appraisal Gap: Understanding the Extent and Consequences of Low Appraisals Among Minority Borrowers and in Minority Neighborhoods*

Kristoffer (Kip) Jackson†

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Abstract

Using comprehensive data from single-family home purchase appraisals matched to HMDA, we study the incidence of low appraisals (i.e., where the appraised value is less than the contract price) and the magnitude of the corresponding appraisal gap (i.e., the difference between the appraised value and the contract price). Low appraisals are significantly more common for properties in majority-minority neighborhoods and particularly for minority borrowers within those neighborhoods. In contrast, Black and Hispanic borrowers purchasing properties outside majority-minority neighborhoods are less likely to receive a low appraisal than non-Hispanic Whites purchasing similar properties in those neighborhoods. Appraiser location and race significantly impact the likelihood of a low appraisal. Low appraisals (and larger appraisal gaps) significantly increase the likelihood of credit denial overall, particularly for collateral reasons, but the effect differs by race; Asians are less likely than Whites to be denied following a low appraisal, whereas Blacks and Hispanics are more likely to be denied. We also find some evidence that appraisals for properties in majority-minority neighborhoods use lower quality comparable properties when the borrower is a minority, particularly for Asians and Blacks.

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† Office of the Comptroller of the Currency, Washington, DC. Email: kristoffer.jackson@occ.treas.gov.

1. Introduction

The home appraisal is a crucial component of residential real estate lending. Accurate appraisals provide lenders with important information on the value of collateral against which a mortgage loan might be offered. They can also help reduce any informational asymmetries between the home seller and prospective buyer regarding the value of the property. However, inaccurate appraisals can distort real estate markets. Moreover, if misvaluations cause otherwise sound mortgage loan applications to be denied, they can be a key hinderance to households' ability to accumulate wealth through homeownership. To the extent that misvaluations are highly correlated with race, this may be one contributor to the racial wealth gap (see, for example, Aladangady & Forde (2021)).

Because of this, there has been a surge in interest and concern related to the U.S. appraisal industry, even prompting the creation of a special task force involving thirteen federal government agencies, tasked with studying the causes, extent, and consequences of racial and ethnic bias in home valuations.[1] Much of the interest in the potential for bias in the appraisal process has its roots in recent media accounts in which minority borrowers received substantially higher appraised values after making it appear as though those involved in the transaction were White.[2] However, there is very limited systematic and rigorous research into the extent to which the issues illuminated by these anecdotes are widespread and in what ways this form of bias (which we refer to as appraisal racial bias) might be manifested.

This paper contributes to the still nascent literature by relying on a comprehensive dataset of appraisals that includes detailed property information for both the subject property and corresponding comparable properties (comps) in addition to information about the appraisers themselves. Using this data, we assess whether the prevalence and magnitude of appraisal gaps differ systematically by borrower race or across neighborhoods.[3] In identifying these systematic differences, we follow Freddie Mac (2021; 2022) and LaCour-Little & Green (1998) in comparing appraised values to contract prices for arms-length home purchase transactions.[4] Such a

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[1] https://pave.hud.gov.

[2] See, for example, https://www.cbsnews.com/news/paul-austin-tenisha-tate-austin-black-couple-settles-housing-discrimination-lawsuit-marin-city/.

[3] For the purposes of this research project, we use the term "neighborhood" synonymously with Census tract.

[4] Several other papers (e.g., Fout et al., 2022) also compare contract prices to appraised values, but they are not focused on racial differences in appraisal gaps.

comparison assumes the contract price is the “true value” of the property. In the absence of significant market failures, this is a reasonable assumption since it is likely the outcome of competition and negotiation among willing sellers and willing buyers on the open market. To the extent the market price accurately reflects the value of a property when sold, differences in the appraisal gap (i.e., the gap between the contract price and the appraised value) for minority vs. non-minority borrowers/neighborhoods that cannot be explained by other factors would be consistent with the presence of appraisal racial bias. Thus, much of our analysis focuses on disparities based on this appraisal gap and the incidence of low appraisals (i.e., appraised values that are less than the contract price).

Although disparities in appraisal gaps may be consistent with the presence of appraisal racial bias, we are not able to identify the underlying cause of the disparity, so the estimated disparities in this paper should not be interpreted as evidence of discrimination. For example, we cannot rule out the possibility that, rather than being due to personal biases, appraisal gaps are due to unobserved heterogeneity across neighborhoods or appraisers’ limited familiarity with certain neighborhoods. Based on the data leveraged in this study, we note that appraisers’ offices (which may be in their homes if self-employed) are much more heavily concentrated in predominantly White census tracts than the properties for which they are asked to give opinions of market value. These differences could potentially affect an appraiser’s ability to objectively assess locational amenities and/or select the most appropriate comparable sales in neighborhoods with which they have limited familiarity.

Despite these limitations, the question of whether there is widespread appraisal racial bias has become a matter of some academic debate, albeit typically through brief, targeted analyses and research notes rather than peer reviewed publications. For example, Freddie Mac (2021) uses appraisal data from 2015-2020 to provide descriptive evidence that appraised values are more likely to come in below the contract price in tracts with high concentrations of Black and Latinos compared to predominantly White tracts. That research was followed up with a modeling approach in Freddie Mac (2022), which finds that even after accounting for various relevant factors, properties in minority tracts are more likely to receive a low appraisal compared to those in White tracts. Using median list prices and owner-reported home values, Perry et al. (2018) and Perry & Rothwell (2021) similarly find that homes in Black neighborhoods are valued significantly lower than similar homes in low/non-Black neighborhoods, even after accounting for several home and neighborhood characteristics. Contrary to these findings, Pinto & Peter (2021a; 2021b; 2021c) argue that disparities in home values and appraisal outcomes are due to differences in factors related to socioeconomic status and borrower characteristics (such as creditworthiness) and not race per se.

A separate strand of the literature identifies disparities consistent with potential appraisal racial bias by comparing appraised values to estimates from an automated valuation model (AVM) for refinance transactions. For example, Williamson & Palim (2022) provide descriptive evidence that appraised values for Black-owned properties are slightly lower than corresponding AVM estimates, whereas the opposite is true for White-owned properties. However, based on their definition of undervaluation (an appraisal gap of at least 10%), they found that Black-owned homes and White-owned homes are undervalued at roughly the same rate. In a much more rigorous assessment of the issue, Ambrose et al. (2022) find that, relative to comparable White-owned homes, those owned by Black and Hispanic homeowners are appraised at values that are significantly and systematically lower than AVM estimates.

The advantage of focusing on refinances rather than home purchases is that the mechanism through which an appraiser may exercise potential racial bias is clearer, since he may interact directly with the borrower or at least may be able to surmise the borrower's race based on pictures or decorations in the home. For home purchases, assumptions of the borrower's race must be based on their name, which appears on the sales contract, and potentially the demographic characteristics of the neighborhood where the property is located. One significant downside in comparing appraised values to AVM estimates is that it is not clear whether the latter should be considered the "true" value of the property. This concern is particularly salient given recent reports that Zillow's iBuying program resulted in losses of more than half a billion dollars due to its inability to accurately predict home values, despite having a sophisticated AVM.[5] Research that is focused on properties that fall in the lower tail of the distribution of home values may be particularly susceptible to misestimation, since AVM performance generally deteriorates as the data becomes thinner, such as in the tails of the distribution. Finally, we note that although AVMs are often referred to as being "race-blind", since race is not explicitly incorporated into the model, research suggests that

[5] https://www.wsj.com/articles/zillow-offers-real-estate-algorithm-homes-ibuyer-11637159261.

AVMs may produce higher error rates for homes in minority neighborhoods (Neal et al., 2020; Zhu et al., 2022).

In this paper, we use data from the universe of single-family home purchase appraisals submitted to the Uniform Collateral Data Portal (UCDP) during the second half of 2018 through the end of 2020 to understand the extent to which minority borrowers and those in majority-minority neighborhoods experience appraisal gaps.[6] We find that that low appraisals are more common in majority-minority neighborhoods and the effect increases with neighborhood minority concentration. Moreover, even within such neighborhoods, minority borrowers are nearly twice as likely as White borrowers to experience a low appraisal. In contrast, Black and Hispanic borrowers purchasing properties outside majority-minority neighborhoods are less likely to receive a low appraisal than non-Hispanic Whites purchasing similar properties in those neighborhoods. We also find that the likelihood of a low appraisal is significantly impacted by appraiser race and location (e.g., distance between their office location and the property being appraised). Pulling in mortgage application information, we find that a low appraisal (and larger appraisal gap) more than doubles the overall likelihood the corresponding applicant's credit application will be denied. However, applicants' ability to recover from a low appraisal varies by race with Asians being the least likely to be denied following a low appraisal, then Whites, then Hispanics and Blacks. Finally, leveraging information on the comparable properties (comps) that were used for each appraisal, we find some evidence that appraisals for properties in majority-minority neighborhoods use lower quality comps when the borrower is a minority. For example, in majority-minority neighborhoods, the average distance and sale-date gap between the subject property and corresponding comps is significantly higher for Black and Asian borrowers compared to White borrowers.

2. Data

Our data come from the Uniform Appraisal Dataset (UAD), which captures all fields required for an appraisal submission to either Fannie Mae or Freddie Mac. Specifically, we use all single-family appraisals submitted to Fannie Mae for home purchase transactions between the second half of 2018 and the end of 2020. The data contain all the information captured on the Uniform Residential Appraisal Form (Form 1004), including a rich set of property characteristics,

[6] The UCDP is a data portal for the electronic submission of appraisal data files to Fannie Mae and Freddie Mac. The corresponding data make up the Uniform Appraisal Dataset (UAD).

neighborhood characteristics, details about each comp that was used and line-item valuation adjustments made based on any differences between the subject property and each comp. The data also contain information about the appraiser who performed the appraisal, which we use to infer the appraiser's race and to geolocate the appraiser's office location.

Data on borrower and loan characteristics, as well as credit outcomes, come from the Home Mortgage Disclosure Act Loan/Application Register (HMDA). Specifically, from this data, we obtain information about each applicant's race, as well as factors that reflect their creditworthiness and ability to pay (e.g., credit score, debt-to-income ratio (DTI), combined loan-to-value ratio (CLTV)). HMDA data also provides information on several other factors that are likely part of lenders' underwriting policies (e.g., conforming loan status, loan type, occupancy type, lien status, the outcome of any automated underwriting systems). Finally, we observe within the HMDA data whether the applicant was ultimately approved or denied, and, for denied applicants, the reasons for denial. We also collect census data for several of the controls used in our analyses, including (among others) median household income, median age, and the share of occupied units that are owner-occupied.

We merge UAD and HMDA data based on geocoded property location. For properties in which there are multiple applications in the given year within HMDA, we only assign a borrower race if all applicants are of the same race.[7] For analyses that depend on an exact match between UAD and HMDA, such as those involving additional borrower characteristics (beyond race) and credit outcomes, we drop properties with multiple applications in HMDA. This equates to around half the applications in each year from 2018 to 2020 but ensures the race and application information in HMDA align with the specific borrower whose transaction is captured in the UAD data.

2.1 Identifying Low Appraisals

We start by dropping observations with invalid contract sale prices and/or appraisal values (i.e., when either was reported as $0 or when the sale price was less than the reported concession amount). We also deal with some suspiciously low values by winsorizing the bottom 0.05% of

[7] Some of these duplicate applications are likely the same borrower submitting multiple applications to different lenders, however some of the duplicates are likely different borrowers submitting applications for the same property. For most of our analyses, this distinction is not important since we are not distinguishing borrowers by any other factor besides their race. However, we note that the results throughout the paper are remarkably robust to the alternative approach of only including appraisals corresponding to single applications within HMDA.

sales prices and appraisal values. In order to obtain transactions in which properties were likely sold on the open market (so the contract price reflects the true market value of the property), we exclude non-arms-length transactions (i.e., those between related parties) and those in which the seller is not the owner of public record. It is also important to account for any seller concessions, where the seller provides a rebate to the buyer (e.g., to help cover closing costs or the cost of repairs/improvements), as agreed upon in the sales contract. Since the contract price generally includes the value of any seller concessions, it may not accurately reflect the market value of the property in those instances. In such cases, an appraised value that is equal to the *implied* market value of the property (i.e., the contract price minus the amount of the concession) would appear to be a low appraisal even though it is not. Indeed, one critique of the existing literature offered by Pinto & Peter (2023) is that large seller concessions may explain (at least in part) the prevalence of low appraisals. Researchers at Freddie Mac (2022) account for this potential issue by excluding contracts with concession amounts exceeding 3%. Rather than removing data based on an arbitrary threshold, we obtain an adjusted sales price for each property by subtracting the dollar amount of any seller concession from the contract price. Low appraisals are then identified as those in which the appraised value is less than the adjusted sales price.[8]

2.2 Determining Applicant Race

Following Jackson & Senney (2023), we use HMDA-reported applicant and co-applicant race and ethnicity information to classify each borrower into the following mutually exclusive categories: American Indian, Asian, Black, Native Hawaiian or Other Pacific Islander (Hawaiian), Hispanic White (Hispanic), and non-Hispanic White (White).[9] First, race is assigned to sole applicants reporting a single race and joint applicants reporting the same race.[10] White applicants are then divided by ethnicity to distinguish Hispanics and non-Hispanic Whites. Applicants who do not report a race but report Hispanic ethnicity are also classified as Hispanic. This hierarchical

[8] We dropped observations in which the appraised value or sales price were listed as $0 and those in which the value of the concessions was greater than the sales price. In total, this constituted a very tiny fraction of the data (1,353 out of more than 10.2 million observations).

[9] Disaggregated subcategories within HMDA (i.e., for Asian and Hawaiian races and for Hispanic ethnicity) are rolled up into the corresponding primary race/ethnicity category.

[10] This approach provides the cleanest possible classification of race and avoids any ambiguity caused by multiple different values. The choice to not assign a race when multiple races are reported (or when joint applicants report different races) results in roughly 7% of applications in the data not being assigned despite there being valid race/ethnicity information in the data.

approach has the advantage of producing mutually exclusive categories but ignores ethnicity for Hispanic non-White applicants, which are categorized by their race, rather than as Hispanics. However, the validity of this approach is supported by the fact that there are very few non-White Hispanics; 96% of Hispanic applicants who reported race information in our data are White. Of all applicants reporting Hispanic ethnicity, 13% did not report a race. We classify these as Hispanic in our analysis, since the missing race data may reflect the sentiment that none of the race categories applied to them, indicating that it should not be treated as invalid data.[11]

2.3 Determining Appraiser Race and Location

We identify each unique appraiser based on the first and last names and the state license or certification numbers listed in the data.[12] Following Ambrose et al. (2022), we infer each appraiser's race using the Bayesian Improved First Name Surname (BIFS) classifier method. For each appraiser, based on this approach, we compute conditional probabilities associated with each of six race categories based on the prevalence of the given first and last name among individuals of that race.[13] The six race categories for which conditional probabilities are computed are as follows: American Indian or Alaska Native, Asian or Pacific Islander, Black, Hispanic, White, and Multiracial. Using the maximum a posteriori (MAP) classification approach, appraisers are assigned the race for which the BIFS method generates the highest probability (see Voicu, 2018). As shown in Appendix Table A.1, the distribution of our inferred appraiser races matches extremely well with other sources that captured similar information around the same time period. This includes the appraiser self-reported races summarized by the Appraisal Institute (2019) and those extracted from the 2019 American Community Survey by the Urban Institute (see Neal &

[11] Results throughout the paper are nearly identical when we omit Hispanic applicants that did not provide race information.

[12] Our primary method of identifying unique appraisers was based on state license or certification numbers, but for 1,438 appraisers in which no license or certification number was captured in the data, we used identified them by their names.

[13] This approach is an adaptation of the Bayesian Improved Surname Geocoding (BISG) and the Bayesian Improved First Name Surname Geocoding (BIFSG) methods (see Voicu, 2018; Elliott et al., 2009; Consumer Financial Protection Bureau, 2014). Because we do not have each appraiser's home address, we do not leverage the geocoding aspect in our race proxying approach. However, when we use the appraiser's office location as a proxy for their home address, we get the same racial classification for more than 95% of appraisers using the BIFSG method and for 94% of appraisers using the BISG method.

Mattingly, 2021).[14] Consistent with other sources, our inferred races show that there are relatively few minority appraisers, with upwards of 90% of appraisers being White.[15]

To understand the demographic characteristics around each property and around appraisers' office locations, we geocode all the addresses and determine the minority percentage in each corresponding census tract.

2.4 Descriptive Statistics

Table 1 shows means for the low appraisal indicator and appraisal gap measure, broken out by race and minority tract status. We find that low appraisals are relatively uncommon for each racial group, ranging from 8.4% to 12.7%, but they are much more rare for properties being purchased by Whites rather than minorities. The raw differences in low appraisal rates between Whites and each minority group is large and highly statistically significant, but the disparities are particularly large for Blacks, Hawaiians, and Hispanics, who have low appraisal rates that are higher than that of Whites by 41%, 37%, and 52%, respectively. We also note that properties in majority-minority tracts are significantly more likely to receive a low appraisal than those in majority-White tracts, with a low appraisal rate that is more than five percentage points (or 65%) higher. The overall proportion of low appraisals, across all borrower races and minority tract designations is 9%, which is in line with the rates noted in the literature (e.g., Calem et al., 2021). The low rate of low appraisals is consistent with the idea that housing markets are efficient, so negotiated prices accurately reflect the true market value of the property. However, given that 99.9% of appraisers in the data report that they reviewed the sales contract as part of the appraisal, at least some of the relative parity between appraised values and contract prices is likely indicative of appraisers targeting the contract price in their appraisals, as is suggested in the literature (Agarwal et al., 2020; Calem et al., 2021; Cho and Megbolugbe, 1996; Conklin et al., 2020; Ding & Nakamura, 2016).

While minority borrowers and those in majority-minority tracts are more likely to receive a low appraisal, Table 1 shows that, conditional on receiving such an appraisal, the magnitude of the

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[14] We note that the Appraisal Foundation also conducted a survey of appraisers in 2021. However, the resulting report does not provide sufficient detail to illustrate the entire distribution of races for comparison, and no additional information could be ascertained from the Appraisal Foundation regarding the results of that survey.

[15] When we infer gender based on first names, we find evidence consistent with results reported by the Appraisal Institute, which is that roughly three-quarters of appraisers are men.

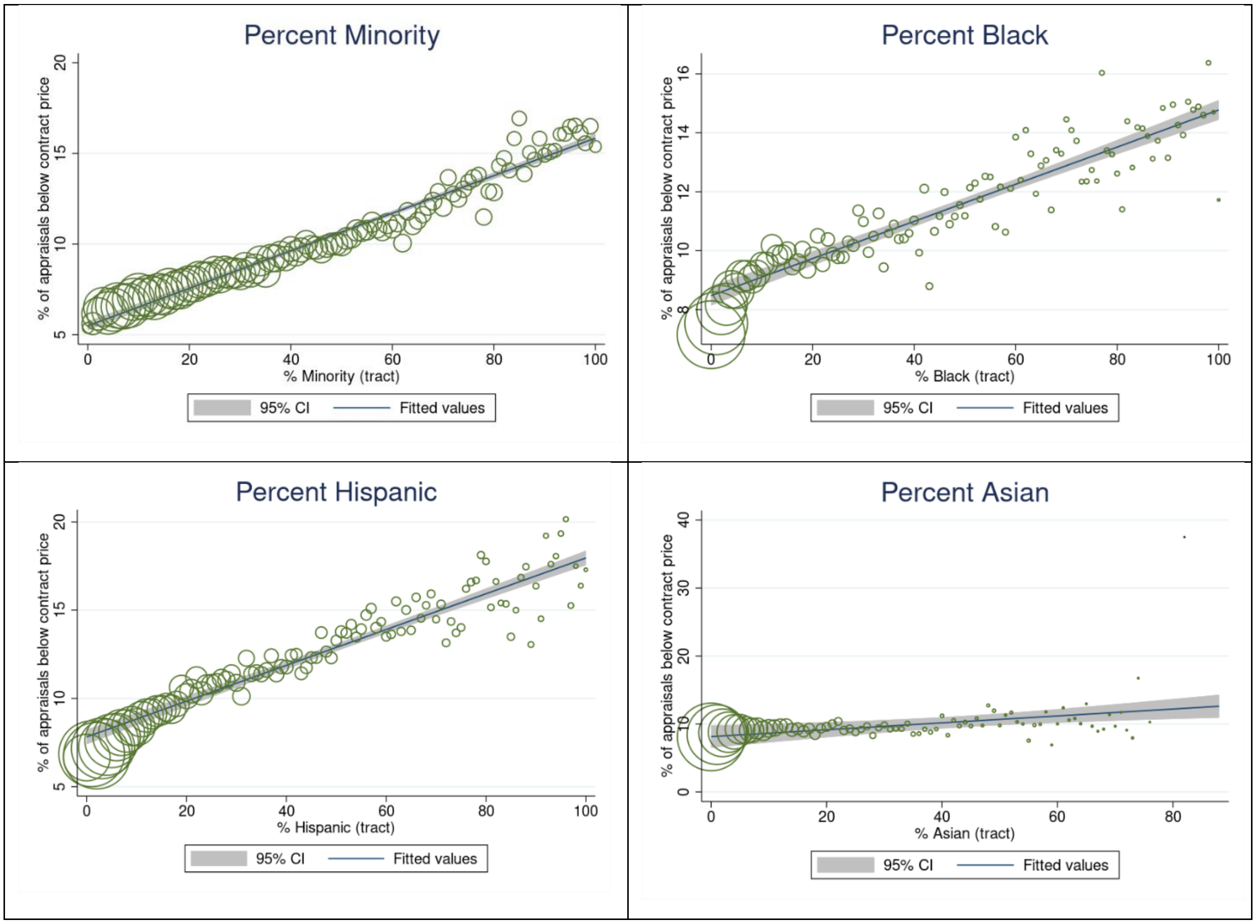
appraisal gap is generally lower for those borrowers. The one notable exception is for Black borrowers, who have a larger appraisal gap, on average, compared to Whites. The difference between majority-minority and majority-White tracts is modest, though highly statistically significant. The differences across races (compared to Whites) are much more pronounced and statistically significant for each minority group, except American Indians.

[Insert Table 1]

Next, we consider the raw relationship between the incidence of low appraisals and neighborhood demographics. Figure 1 illustrates the pairwise relationship between low appraisals and the percent minority overall and in three primary minority groups: Blacks, Hispanics, and Asians. To construct the graphs in that figure, we aggregate tracts with the same percent minority (rounded to the nearest whole number) and compute the percent of appraisals with values less than the contract sales price. The size of the circle captures the number of underlying appraisals, with larger circles indicating a larger number of appraisals. As shown in Figure 1, for minorities overall and for Blacks and Hispanics, as neighborhood minority concentration increases, so does the likelihood of a low appraisal. For Asian tracts, the relatively flat line of observations suggests that the likelihood of low appraisals does not really depend on the proportion of the tract population that are Asian.[16] For each of the minority groups, there are fewer underlying appraisals as we move to higher levels of minority concentration, but this is particularly true with respect to the percent Asian; there are relatively few tracts with high proportions of Asians, and very few appraisals are from such neighborhoods.

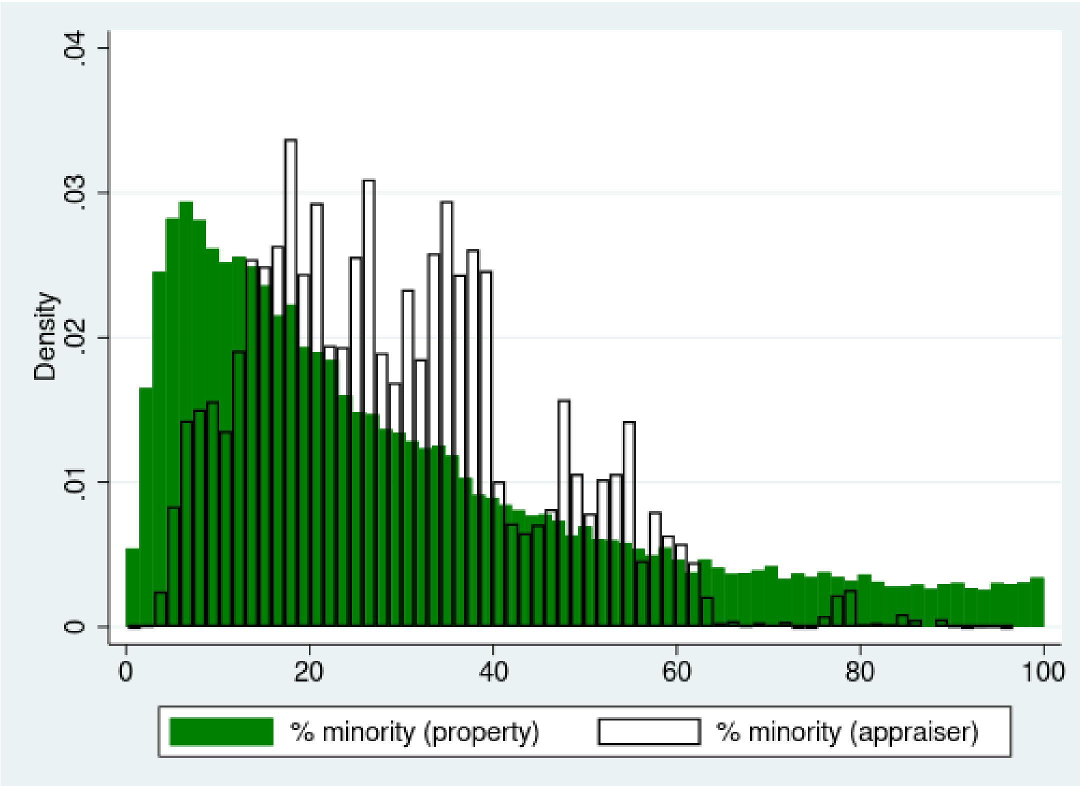
[16] One observation in the Percent Asian graph appears to be an outlier, with 37.5% of appraisals coming in below the contract price. This observation captures a set of two tracts each with 82% Asian population, but a combined total of only 16 appraisals. When we omit this observation, the graph looks nearly identical. Thus, the upward slope in fitted values is not driven by that outlier.

Figure 1. Relationship Between Neighborhood Demographics and Low Appraisals



With geocoded information on appraised properties and appraisers' office locations, we next explore the extent to which the demographic characteristics of appraisers' office locations mirror those around the properties they are called upon to appraise. As shown by the transparent bars in Figure 2, compared to the appraised properties, appraisers are much more heavily concentrated in areas with relatively few minorities. For both distributions shown in Figure 2, there is a relatively small amount of mass in the right tail of the distribution, but appraisers are particularly unlikely to have offices in areas with more than 60% minorities.

Figure 2. Minority Distribution for Properties and Appraisers



3. Analysis

3.1 Borrower-level analysis of low appraisals

In this section, we test for systematic differences by race in the incidence of low appraisals by regressing an indicator for low appraisals on each of our race categories. In doing so, it is crucial to control for potentially relevant factors that might reasonably explain any disparities by race. Such factors may include circumstances that are time-specific but common to all localities (e.g., macroeconomic shocks like the fallout from the COVID-19 pandemic). For this reason, the analyses in this section and throughout the paper control for year-quarter fixed effects. Other potential factors may include property characteristics and/or geographic idiosyncrasies. To determine which property characteristics are predictive of low appraisals and, as such, should be included in the regression analyses, we employ a backward stepwise variable selection procedure with a 0.001 p-value threshold.[17] Within the appraisal data, we identified 89 quantifiable property characteristics, of which 61 ended up surviving the variable selection procedure. These are listed in the Appendix (Table A.2) along with the corresponding coefficients and standard errors from the final variable selection regression model. It is unclear whether and to what extent geographic fixed effects should be included in these specifications. On the one hand, they may control for important unobservables, but on the other hand, they may capture geographic variation in racial prejudice. Thus, for each of the analyses in this section we include four specifications: one with no geographic controls and one each with geographic fixed effects at the Metropolitan Statistical Area (MSA), County, and Census Tract levels.[18]

Table 2 shows the results linear probability models with the dependent variable being an indicator for low appraisals. As shown in column (1), when we do not include geographic controls, every minority group except American Indians are significantly more likely to get a low appraisal compared to Whites with similar homes. When we include MSA and then county fixed effects in columns (2) and (3), the estimated coefficients shrink, but remain consistent in direction and significance. However, when we include tract fixed effects in column (4), the estimates reverse direction, suggesting that low appraisals are significantly *less* likely for Asian, Black, and Hispanic borrowers. We discuss a potential explanation for this finding in the next section.

[Insert Table 2]

We next test whether an appraiser's racial minority status has any impact on the likelihood of a low appraisal by interacting the applicant race variable with an indicator for whether the appraiser is a minority. The results from these linear probability models, shown in Table 3, mirror those from Table 2 in that the estimates tend to shrink somewhat with the inclusion of more granular geographic fixed effects and sometimes change direction when tract fixed effects are included. When controlling for MSA or county-level fixed effects, the regression estimates suggest that, when the appraiser is White (as the vast majority of them are), low appraisals are significantly more common among Asian, Black, Hawaiian, and Hispanic borrowers, compared to White

[17] The results presented in this paper are robust to the inclusion of the set of property characteristics that come from the use of a 0.05 and a 0.01 p-value threshold as part of the variable selection procedure.
[18] For rural areas that lie outside an MSA, the "MSA" fixed effect controls for the rest (i.e., the non-MSA portion) of the state.

borrowers, after accounting for the other factors. However, when we include tract fixed effects in column (4), the results suggest that low appraisals are significantly *less* likely for Asian, Black, and Hispanic borrowers. The main effect of *minority appraiser* shows that, compared to White appraisers, minority appraisers are significantly more likely to give a low appraisal for the baseline group, White borrowers. When any level of geographic fixed effects are included in the model, the likelihood of a low appraisal for Whites is 1.3 percentage points higher when the appraiser is a minority compared to White appraisers. Moreover, the positive and significant interaction effects indicate that minority appraisers are even more likely to give a low appraisal when the borrower is Black or Hispanic than when the borrower is White. This finding contrasts with the literature suggesting that, in other aspects of the mortgage financing process, minorities who work with other minorities end up with more favorable outcomes (e.g., Frame et al., 2022; Jiang et al., 2022, Ambrose et al., 2021). However, we note that Ambrose et al. (2022) similarly find that minority appraisers do not show favorable treatment toward minority borrowers in terms of the appraisal-to-AVM ratio, suggesting that there may be implicit bias against minorities "across all appraisers, regardless of race/ethnicity" (pg. 5).

[Insert Table 3]

3.2 Borrower-level analysis of appraisal gaps

The regressions in Table 4 test for differences by race in the magnitude of the appraisal gap when there is a low appraisal. Consistent with Freddie Mac (2022), we normalize the appraisal gap by dividing by the contract price and multiplying by 100. Thus, it represents the percentage difference between the appraised value and the contract price. When we include MSA or county-level fixed effects, the results suggest that the average appraisal gap for Black borrowers with White appraisers is upwards of 0.31 percentage points larger than that of White borrowers. However, as we found in our analysis of low appraisals, this disparity reverses when we include tract fixed effects. The positive coefficient on *minority appraiser* suggests that, for White borrowers, the appraisal gap is significantly higher when the appraiser is a minority compared to White appraisers, with the estimated coefficient changing only modestly across specifications. The results suggest that Hispanic borrowers who get low appraisers tend to have smaller appraisal gaps compared to Whites and especially so when the appraiser is a minority. However, the only significant interaction effect in column (4) of Table 4 is for Asian borrowers, who end up with significantly smaller appraisal gaps when the appraiser is a minority.

[Insert Table 4]

In columns (1) – (3) of Tables 2, 3 and 4, we find that aggregate comparisons of minorities to Whites across all areas and within an MSA or county show that minorities are significantly more likely to receive a low appraisal and, among those that receive a low appraisal, the appraisal gap is significantly larger for Blacks compared to Whites. However, within-tract comparisons generally lead to different conclusions. One potential explanation for these findings is that minority borrowers tend to live in tracts where low appraisals (and, for Black borrowers, larger appraisal gaps) are more common. If this were the case, then aggregating across all tracts to a larger geography (like MSA or county) would show that they are more likely to receive a low appraisal even though based on within-tract comparisons they may be, on average, less likely to receive one. To further explore the results, we next perform analyses comparing tracts with higher concentrations of minorities to those with fewer minorities.

3.3 Tract-level analysis of low appraisals

In this section, we explore the extent to which neighborhood demographics are related to the incidence of low appraisals and the magnitude of appraisal gaps. Tracts are categorized based on the proportion of the population that are racial/ethnic minorities. We compare majority-minority tracts (i.e., those with more than 50% minority population) to those with at most 50% minority population. We also perform analyses comparing high minority tracts to low minority tracts, which have, respectively, at least 80% and at most 20% minority population.

In each regression in this section of the paper, we control for the same set of property characteristics as in the previous section, which are the most predictive of a low appraisal. We also control for MSA and year-quarter fixed effects to account for differences in housing market dynamics across geographies and over time. Finally, given that low appraisals may be the result of overbidding rather than undervaluation, we control for a set of tract-level characteristics intended to capture things like inexperience with the home buying process, similar to Freddie Mac (2022). These include median household income, median age, share of households with children under 18 years old, and share of population in the labor force. Pinto & Peter (2023; 2021) argue that a key factor to control for in these types of regressions is the share of home purchase transactions that are for FHA loans. They argue that since FHA borrowers tend to be first-time homebuyers and have lower credit scores, on average, compared to all agency-guaranteed homebuyers, FHA borrowers “are likely more inexperienced and likely have less financial literacy,” which they suggest “may translate into lower skill to negotiate on price” (Pinto & Peter, 2021). We thus control for the share of home purchase applications that are for FHA loans in each tract.[19]

To account for relevant housing market differences across neighborhoods, we also control for whether the tract is urban, suburban, or rural, the share of occupied units that are owner-occupied, and Freddie Mac’s (2022) measure of the housing turnover rate (the annual average number of home purchase applications per square mile). We also include a control for gentrification using an approach similar to Goodnature et al. (2018) by flagging tracts that had median household incomes that were in the lowest quartile during 2007-2011, but in the top two quartiles in 2014-2018.[20] Finally, we control for whether the tract is in a non-disclosure state, in which real estate sale prices are not disclosed or recorded as public record, which may make it more difficult for appraisers to leverage information from historical sales to identify good comps and make appropriate adjustments as part of the reconciliation process. These non-disclosure states include Alaska, Idaho, Kansas, Louisiana, Missouri, Mississippi, Utah, and Wyoming.[21]

Table 5 contains the results of our tract-level analysis of low appraisals. As indicated in column (1), applicants in majority-minority neighborhoods are significantly more likely to obtain a low appraisal, even after controlling for all the various control variables described above. The probability of a low appraisal is 1.7 percentage points higher for those in majority-minority

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[19] The focus on home purchase FHA applications aligns well with the analyses in this paper, which involve home purchase loans. However, the results reported in the paper are robust to instead controlling for the overall share of FHA applications in each tract (for all loan purposes).

[20] The results presented in the paper are extremely robust to various alternative definitions of gentrification, including those that flag tracts that move from the bottom quartile to the top two quartiles in terms of per capita income (rather than median household income) and in terms of the share of residents with a college degree (another approach used in Goodnature et al., 2018). Many other researchers also identify gentrification based on increasing income levels in the lowest income tracts (e.g., Kolko, 2007; Meltzer & Ghorbani, 2017) and some have found a link between the presence of same-sex couples and gentrification (e.g., Collins, 2014; Christafore & Leguizamon, 2017; Florida & Mellander, 2010). When we include the percent change in the share of same-sex couples between 2007-2011 and 2014-2018 as a proxy for gentrification, the results are qualitatively the same.

[21] In the state of Missouri, a small number of jurisdictions, including St. Louis City and County, Jackson County, and St. Charles County, have passed local ordinances mandating sales disclosure, but the remainder of the state remains non-disclosure.

neighborhoods than for those in majority-White neighborhoods. Given the low-appraisal rate of 9.3% in the estimation sample, that estimate equates to more than an 18% increase over the sample mean. This estimate is in line with, though somewhat smaller than, those in Freddie Mac (2022), which finds the probability of a low appraisal to be 2.4 percentage points higher in Black tracts and 2.9 percentage points higher in Hispanic tracts. It is unsurprising that our estimate is slightly smaller than those from Freddie Mac (2022), since we use a much richer set of controls, which potentially reduces omitted variable bias in our estimate.

Table A.3 in the Appendix contains the estimated coefficients for the tract-level controls from column (1) of Table 5.[22] Many of the estimates are quite small, but the signs are generally consistent with our expectations of how they might affect the incidence of low appraisals. For example, all else equal, low appraisals are more common in non-disclosure states, where information constraints around property sale prices may hinder an appraiser's ability to properly assess the value of a property. The results also show that the likelihood of a low appraisal increase with the FHA share of home purchase applications and with the percent of households that have young children and decrease with median income and median age. These results are consistent with the idea that some portion of the low appraisals observed in the data may be the result of less experienced or potentially less financially savvy buyers overbidding on properties. We also find that in areas in which it is likely easier to find good comps, such as ones in which there is a higher rate of owner-occupied housing units and more housing turnover, there is a lower likelihood of a low appraisal. Finally, we find as the percent of population in the labor force increases, so does the likelihood of a low appraisal. There is no statistically discernible relationship between our measure of gentrification (or any of the alternative measures we tested) and the incidence of low appraisals.

Next, we consider whether the proximity between the appraiser and the subject property affects the likelihood of a low appraisal. Within the data, we observe the appraiser's office address (which may be their home address if self-employed). This address serves as a reasonable proxy for the area in which the appraiser is most familiar with housing market dynamics and locational

[22] Given that newly constructed homes may be particularly easy (or difficult) to appraise depending on the availability of nearby comps, we tested the robustness of our results to the exclusion of those properties (i.e., where Condition = 1). Although the adjusted R-square tends to be slightly higher when newly constructed homes are excluded, the results are extremely robust to that exclusion in terms of the level of statistical significance and even the magnitude of the various coefficient estimates.

amenities. Under the assumption that appraisers' expertise diminishes roughly linearly as they move away from that location, we would expect a positive relationship between the incidence of low appraisals and the distance between the subject property and appraiser location. The positive and highly significant coefficient shown in column (2) of Table 5 suggests that relationship is borne out in the data, although the estimate is extremely small.

Given the ambiguity as to whether the appraiser's office location accurately reflects their area of expertise, we also include an indicator for whether the appraiser's state is the same as that of the subject property, which may serve as a more accurate proxy for the appraiser's familiarity with the area surrounding the subject property. Column (2) shows that when the appraiser is located in the same state as the subject property, they are less likely to provide an appraised value that is lower than the sales contract price. However, when we interact the *appraiser_samestate* and *majority-minority* indicators, as shown in column (3), we find that while being located in the same state reduces the likelihood of a low appraisal for those in neighborhoods with relatively few minorities (as shown by the negative main effect of *appraiser_samestate*), the positive interaction term suggests that those in majority-minority neighborhoods are still more likely to receive a low appraisal, even when the appraiser is from the same state. Comparing columns (1) and (2), we note that the estimated impact of being in a majority-minority tract is remarkably robust to the inclusion of appraiser geography variables. Although the main effect drops in column (3), the combined effect when the appraiser is from the same state (i.e., adding the main effect and the interaction effect) yields nearly the same estimate as shown in columns (1) and (2), despite the inclusion of additional significant regressors.

When we add to the regression in column (3) a measure of the absolute difference between the percent minority in the property's tract and the appraiser's tract, we find a highly significant coefficient of 0.00007. This small but positive estimate suggests that, in terms of minority share, the more different the appraiser's tract is from the property's tract, the greater the likelihood the appraisal will come in below the contract price. Specifically, for a 10 percentage point increase in the absolute difference in minority share between the appraiser's tract and the property's tract, the likelihood of a low appraisal increases by 7 basis points.

[Insert Table 5]

Column (4) of Table 5 shows results from a regression that replicates that in Column (1) but adds indicators for each borrower race and interactions between each race and the majority-minority flag. This specification allows us to test whether minority borrowers in majority-minority tracts are more likely to receive a low appraisal than White borrowers in those tracts. The main effect of majority-minority in column (4) suggests that the probability of a low appraisal for White borrowers in a majority-minority tract is 1.3 percentage points higher than for those in a majority-White tract. The main effects for Blacks and Hispanics are negative, which suggests that they are less likely than Whites to receive a low appraisal when the property is in a majority-White neighborhood. However, the interaction effects for both groups are much larger in magnitude than the main effects, so the overall effect in majority-minority tracts is positive. The estimated coefficients on the interaction terms show, within majority-minority tracts, how much more likely minorities are to receive a low appraisal than Whites. For Blacks and Hispanics, the additional likelihood of receiving a low appraisal is roughly 1 and 1.1 percentage points, respectively. Thus, compared to the 1.3 percentage point baseline for Whites, the likelihood of a low appraisal for Blacks and Hispanics is nearly double that of Whites in the same areas. Asians and American Indians also have significant interaction effects, but for Asians the magnitude is less than half that of Blacks and Hispanics. The estimate for American Indians, while largest in magnitude, is only significant at the 5% level.

Table 6 shows results from the same regressions as in Table 5, except that we replace the majority-minority flag with one that compares high minority tracts (those with 80% or more minority population) to low minority tracts (those with 20% or less minority population). Comparing such starkly different tracts yields baseline coefficient estimates that are generally more than 2.5 times larger than those in Table 5. After accounting for relevant factors, the probability of receiving a low appraisal in a high minority tract is 4.3 percentage points higher than that in a low minority tract. The main effects of *appraiser_distance* and *appraiser_samestate* are similar to those in Table 5, but the interaction effect between *HM8020* and *appraiser_samestate* is nearly twice as large. The estimates in Column (4) indicate that the interaction effects are slightly higher for Blacks and Asians, but nearly double for Hispanics. The likelihood of obtaining a low appraisal for Hispanic borrowers in high minority tracts compared to low minority tracts is roughly 2 percentage points higher than that for White borrowers in similar tracts.

[Insert Table 6]

When we regress low appraisals on the percent minority directly, rather than discretizing that variable into distinct categories, we find a significant positive relationship (see Table 7). This means that, regardless of its starting point, any given increase in the minority composition of a neighborhood increases the likelihood of a low appraisal. In particular, the estimates suggest that for a 10 percentage point increase in minority concentration, the probability of a low appraisal increases by roughly 0.5 percentage points. The magnitude of this estimate aligns almost exactly with those found by Freddie Mac (2022).[23] We also find significant interaction effects for Asians, Blacks, and Hispanics, extending our earlier findings by showing that as the minority concentration increases so too does the increased likelihood of a low appraisal for those minorities, compared to their White counterparts.

[Insert Table 7]

3.4 Tract-level analysis of appraisal gaps

Having established that the likelihood of a low appraisal is significantly higher in neighborhoods with higher concentrations of minorities, we next turn to the question of whether, among those who receive low appraisals, the appraisal gaps are larger or smaller in such neighborhoods. Table 8 shows results from regressions that mirror those in Table 5, but where the dependent variable is the appraisal gap as a percent of the contract sales price.[24] We find that among borrowers who received a low appraisal the appraisal gap is 0.36 percentage points higher in majority-minority tracts than in majority-White tracts. This finding is consistent with Freddie Mac (2022), with the magnitude of our estimate falling between those from Freddie Mac (2022) for Black tracts (0.741) and Hispanic tracts (0.183). Consistent with our previous results, we find that as the distance between the subject property and the appraiser's work address increase, so too does the magnitude of the appraisal gap. We also similarly find that when the appraiser is from the state in which the property lies, the appraisal gap is 0.21 percentage points lower than when the appraiser is from a

[23] Freddie Mac (2022) looked at the how the shares of Black and Latino populations relate to the likelihood of a low appraisal. In the specification that includes their full set of controls, Freddie Mac (2022) found the same coefficient for the Black share (0.0005) and a slightly larger one for Latino share (0.0006).

[24] When we normalize by the appraised value rather than the sales price, the estimated coefficients are generally larger (since these are instances where the appraised value is lower than the sales price, making the denominator smaller when calculating the appraisal gap) but consistent with those reported in the paper.

different state. In contrast to our findings regarding the incidence of low appraisals, the non-significant interaction term in column (3) suggests that, in terms of the magnitude of the appraisal gap, the effect of being from the same state does not differ by majority-minority status. The coefficients on the interaction terms in column (4) show that, among borrowers in majority-minority tracts, the appraisal gap is significantly larger for Black borrowers than for Whites. However, for Asians and Hispanics in majority-minority tracts, the magnitude of the appraisal gap is significantly smaller than for Whites in those tracts.

[Insert Table 8]

When we replace the majority-minority indicator with a continuous measure of percent minority, the results are consistent with those reported in Table 8 (see Table A.4 in the Appendix).[25] The estimates from those regressions suggest that for a 10 percentage point increase in minority concentration, the appraisal gap increases by about 0.12 percentage points.

Having shown that low appraisals occur more frequently in areas with higher concentrations of minorities, and that certain minority groups (e.g., Blacks, Hispanics, and Asians) have a higher likelihood of low appraisals within those areas, we next turn to the credit consequences of such appraisals.

3.5 Analysis of Underwriting Denials Following a Low Appraisal

A borrower faced with a low appraisal, but determined to purchase the property, can either provide additional funds to cover the gap between the appraised value and the contract price or attempt to renegotiate the purchase price.[26] Indeed, researchers have found that low appraisals often provide borrowers significant leverage in renegotiating the price downward (Fout et al., 2022; Fout & Yao, 2016; Shui & Murthy, 2019). To the extent a contract price is inflated, a low appraisal that triggers downward price renegotiation could protect both the lender and the buyer by more accurately reflecting the current market value of the property. Moreover, Fout et al. (2022) finds that low appraisals have only a modest negative effect on the likelihood of the loan closing (as captured by

[25] The results are also consistent when we replace the majority-minority indicator with one that flags high minority tracts compared to low minority tracts (see Table A.5 in the Appendix).

[26] If the buyer no longer wanted to go through with the transaction, the appraisal contingency could be exercised (assuming one is stipulated in the purchase agreement). The buyer is also always free to walk away from the sale if there is no appraisal contingency, but in that case would likely lose any earnest money put down on the property.

it being delivered to Fannie Mae). For these reasons, some researchers have argued that low appraisals yield important benefits to buyers (e.g., Pinto & Peter, 2023; Fout et al., 2022). In making such an argument, however, one must assume that all borrowers have the same opportunity to renegotiate prices. To the extent these opportunities differ based on the borrower's race, for example, it could lead to disparities in credit denials if borrowers are not able to come up with the additional cash to cover the appraisal gap.

In order to test whether low appraisals lead to disparate credit outcomes for minority borrowers, we leverage information in HMDA regarding the final disposition of the mortgage loan application. Specifically, we identify denied applications (including denied preapproval requests) and approvals, which include applications that were originated as well as applications and preapproval requests that were approved but not accepted by the applicant.[27] Corresponding to each denial in HMDA are lender-provided denial reasons, one of which is "collateral." If a loan were denied due to a low appraisal, this is the most appropriate denial reason for the lender to select.[28] About 27% of denials in the data were for collateral reasons.

We note that while it is likely that all appraisal-related denials would be classified as collateral denials, it is also possible for an application to be denied for collateral reasons that are totally unrelated to the appraisal or appraised value. For example, certain property types (e.g., geodesic dome homes) may be unacceptable forms of collateral under a lender's underwriting guidelines, and these would also likely be denied for collateral reasons. Of the 43,000 collateral-based denials in the data, just over 40% have low appraisals. Likewise, of the almost 30,000 denied applications with low appraisals, roughly 60% were denied for collateral reasons. Thus, while there is clearly a link between collateral-based denials and low appraisals, they are not perfectly correlated.

Before moving to a multiple regression framework, we first consider the unconditional relationship between low appraisals and loan application denials. The share of low-appraisal applications that are ultimately denied (for any reason) is fairly low (8.27%), but the unconditional odds of denial

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[27] We exclude from these analyses purchased loans and applications that were withdrawn by the applicant or closed for incompleteness.

[28] The other possible denial reasons from which a lender could select are the following: Debt-to-income ratio, Employment history, Credit history, Insufficient cash (downpayment, closing costs), Unverifiable information, Credit application incomplete, Mortgage insurance denied, Other.

given a low appraisal are 2.21 times higher than if the appraised value is at or above the contract price. When we focus on collateral-based denials, the odds of denial jump to 6.66.

3.5.1 Collateral-Based Denials

Table 9 shows results from linear regressions of collateral-based denials on low appraisals, using several different sets of controls. Each specification includes year-quarter fixed effects to account for industry-wide changes that might have affected underwriting policies and approaches over the sample period.[29] Column (2) adds controls for all the factors captured in HMDA that could potentially relate to lenders' underwriting criteria, including any special considerations for certain property types (e.g., manufactured homes) and/or loan and product types. These include the following: debt-to-income ratio (DTI), credit score, and indicators for each loan type (conventional, FHA, VA, USDA) and occupancy type (principal residence, second residence, investment property), as well as indicators for manufactured home, reverse mortgage, home equity line of credit (HELOC), conforming loan status, first lien status, single family home, interest only loan, receiving a positive outcome from an automated underwriting system (AUS), and receiving a negative outcome from an AUS system.[30] We note that our baseline set of underwriting controls omits combined loan-to-value (CLTV), given that we are exploring whether appraised values may be biased. Although CLTV is typically considered as part of underwriting, an appraised value that is biased downward would result in CLTV ratios that are biased upwards.

As shown in column (2) of Table 9, after accounting for potentially relevant underwriting factors, having a low appraisal increases the probability that a denial was for collateral reasons by 41 percentage points. Given that only 27% of all denials are for collateral reasons, this constitutes a substantial increase in the likelihood of collateral denial (the corresponding odds ratio is 6.55). Comparing columns (1) and (2), we see that the estimated coefficient of interest is extremely robust to the inclusion of underwriting controls. Despite our concerns with CLTV ratios, which are

[29] We note that the estimated coefficient of interest is nearly identical in each specification when year-quarter fixed effects are omitted as controls.

[30] We define positive AUS outcomes as any of the following: Approve/Eligible, Accept, Eligible, Accept/Eligible, Accept/Unable to Determine. Negative AUS outcomes are defined as the following: Refer/Ineligible, Refer with Caution, Caution, Ineligible, Refer with Caution/Ineligible. These were determined based on the likelihood of denial in 2020 HMDA data among applicants that received each AUS outcome. Applicants receiving each of the outcomes in the AUS positive classification had very low denial rates (<10%), while those that received one of the outcomes classified as AUS negative had very high denial rates (>70%). We note that both indicators can be included in the model since there are several AUS outcomes that are omitted from both.

potentially biased by misvaluations, column (3) shows that when we include CLTV as an additional control, the coefficient of interest drops modestly, but is still large and highly statistically significant. The results in Table 9 are also robust to the inclusion of the full set of property characteristic controls used earlier in the paper as well as the inclusion of tract fixed effects.

[Insert Table 9]

3.5.2 All Denials

The link between appraisals and collateral denials is an interesting one, but of perhaps greater relevance is the impact of low appraisals on overall credit denial rates. Table 10 shows results from regressions predicting loan application denials based on the incidence of low appraisals, after controlling for year-quarter fixed effects and the same set of underwriting controls as used earlier.[31] Column (1) shows that a low appraisal increases the probability of denial by 4.2 percentage points. Given that 3.99% of applications in the estimation sample were denied, this equates to more than doubling the likelihood of denial.

The estimated coefficients and standard errors for the underwriting controls in column (1) of Table 10 are contained in Table A.6 in the Appendix. For variables with a clear nexus to credit risk, the signs and significance of the estimated coefficients are generally as expected. For example, the likelihood of denial increases with DTI and decreases with credit score. Compared to conventional loans, FHA and VA loans are more likely to be denied. Similarly, compared to loans for primary residences, those for second residences and investment properties are more likely to be denied. Unsurprisingly, AUS Positive and AUS Negative are among the variables that are most predictive of credit denial.

The specification summarized in column (2) of Table 10 includes applicant race interacted with the incidence of low appraisals. As shown in column (2), among those who did not receive a low appraisal (i.e., the vast majority of the data), each minority group except American Indians is more likely to be denied than Whites, after controlling for basic underwriting factors.[32] The interaction

[31] While CLTV is not included as a control in the regressions summarized in Table 10, the results are robust to the inclusion of CLTV as an additional control.
[32] We note that these disparities do not necessarily imply discrimination, since there are likely other relevant underwriting factors not captured in HMDA, which are not included in these regressions.

terms capture the differential effect of low appraisals on the probability of denial for applicants from each minority group, relative that of Whites. We find that for Black and Hispanic applicants, a low appraisal increases the likelihood of denial, above that of similar Whites, by 1.71 and 0.84 percentage points, respectively. Given the baseline effect of low appraisals for Whites (3.86 percentage points), this means a low appraisal increases the probability of denial by 5.57 percentage points for Blacks and 4.7 percentage points for Hispanics. Asian applicants who receive a low appraisal, while still more likely to be denied than if the appraisal had not come in low, are significantly less likely to be denied than similar Whites. Thus, the impact of a low appraisal on the ultimate outcome of the loan application hinges on the applicant's race, with Black and Hispanic borrowers being the least able to overcome the challenges posed by a low appraisal. We note that these findings are in line with Ambrose et al. (2022), although our estimates are much smaller than theirs.[33] These differences are not surprising, given that Ambrose et al. (2022) focuses on a single lender's originations (rather than all approvals), use less granular race information and, crucially, do not include in their analyses the various underwriting factors included in our specification.

[Insert Table 10]

Next, we explore how the *magnitude* of the appraisal gap affects an applicant's probability of denial. As in earlier sections of the paper, we normalize the magnitude of appraisal gap by the contract price and multiply by 100, although the results are extremely similar when we instead normalize by the appraised value.[34] As shown in Table 11, there is a positive and highly significant relationship between the magnitude of the appraisal gap and the likelihood of denial. Specifically, for an additional 1 percentage point increase in the appraisal gap, the probability of denial increases by 0.9 percentage points. Thus, the larger the appraisal gap, the more likely the applicant is to be denied for the loan. The positive and significant interaction effects for Black, Hawaiian, and Hispanic borrowers suggest that for those borrowers, the relationship between the appraisal gap and the likelihood of denial is exacerbated by race, even after accounting for differences in underwriting factors. Thus, combining the results from Tables 10 and 11, both the extensive and

[33] Ambrose et al. (2022) find that the probability of origination is reduced by 13.2 percentage points for Whites, 5.2 percentage points for Asians, and 21.3 percentage points for Blacks. This equates to estimates that are between two and four times as large as those shown in Table 10.

[34] When we instead use the raw appraisal gap and include a control for sale price, the results are also similar.

intensive margins of low appraisals increase the likelihood of denial for Blacks and Hispanics significantly more than for Whites.

[Insert Table 11]

Having established the prevalence of low appraisals among minority borrowers and tracts and the differential impact of low appraisals on credit outcomes based on a borrower's race, we next explore a key mechanism through which low appraisals may occur: the number and quality of comparable properties (comps) used to determine the value of the subject property.

3.6 Analysis of Comparable Properties

The sales comparison approach is the most used method for determining the value of residential real estate.[35] This approach involves identifying recently sold properties that are similar to the subject property in terms of location (i.e., sharing the same locational amenities) and physical characteristics. These properties serve as comps for the subject property. In circumstances where there are many potential comps to choose from, appraisers subjectively consider differences in location, characteristics, and time since the comp was sold in determining which properties should be included as comps and which should not. Since no two properties are identical, the sales comparison approach necessarily involves a reconciliation process, whereby the appraiser makes positive or negative adjustments to the valuation based on differences between the subject property and each comp.[36]

In this section, we use several different outcome variables to test for whether comp selection and the reconciliation process differ systematically based on neighborhood and borrower characteristics. Specifically, we consider the number of comps used in the appraisal and measures of comp quality with respect to geographic distance, temporal distance (i.e., the time lag since the comp was sold), and physical similarity. For each of these analyses, we include year-quarter and

[35] Although some properties have value estimates based on multiple different methods, our data show that more than 99.99% of all single-family residential appraisals submitted to Fannie Mae between mid-2018 through 2020 reported a value estimate based on the sales comparison approach.

[36] For example, consider a comp that is very similar to the subject property, except that the comp has a two-car garage, which the subject property does not have. Then, as part of the reconciliation process, the value of the subject property would be determined by taking the comp sales price and making a negative adjustment to reflect the fact that a portion of the comp sale price captures the value of the two-car garage. As necessary, the appraiser also makes positive adjustments to account for amenities or positive characteristics that the subject property has but the comp does not.

MSA fixed effects to account for differences in the available of good comps over time and across geographies. We also control for property characteristics, since the ability to identify similar comps depends critically on the uniqueness of the subject property. The specifications reported below also include the complete set of property characteristics that emerged from the variable selection exercise described in Section 3.1, but the results are all robust to alternatively controlling for the much smaller subset of property characteristics used in Freddie Mac (2022).[37] As before, we also include tract-level controls to account for relevant housing market differences across neighborhoods, which may affect appraisers' ability to identify reasonable comps. For the regressions in this section, these include whether the tract is urban, suburban, or rural, the share of occupied units that are owner-occupied, the measure of the housing turnover rate described in Section 3.3, and whether the tract is in a non-disclosure state.

3.6.1 Number of Comps Used in the Appraisal

We first consider the number of comps used in the appraisal. Before turning to the empirical results, we note that it is unclear whether having more or fewer comps would likely be advantageous to the borrower. On the one hand, if all the comps are appropriate comparators to the subject property, additional data points may provide for a more accurate valuation. On the other hand, an appraiser may choose to add more (marginally informative) comps to justify a valuation that is not necessarily supported by the core set of best comps. Empirically, there is a strong positive relationship between the incidence of low appraisals and the number of comps used in the appraisal. However, it is unclear which way the causation runs; more comps could potentially lead to misvaluation or the appraiser might feel obligated to provide additional evidence in cases where the valuation is lower than the contract price.

Table 12 reports the results from regressions of several different dependent variables on race categories, interacted with an indicator for whether the tract is majority-minority. Column (1) shows how the number of comps used in the appraisal differ based on neighborhood and borrower minority status. For minority borrowers purchasing homes in majority-White neighborhoods, there tend to be more comps used in the appraisals. Similarly for White borrowers in majority-minority

[37] The property controls from Freddie Mac (2022) include gross living area, number of stories, number of bathrooms, number of bedrooms, year built, and separate indicators for whether the home has a fireplace, pool, and garage. Each of these factors is included in the complete set of property controls included in the specifications reported here.

tracts. Since White borrowers are the baseline group in this interaction model, the coefficient on *majority-minority* indicates that, on average, 0.018 additional comps were used for Whites in majority-minority neighborhoods compared to those in majority-White neighborhoods. In contrast, the number of comps used for Black and Asian borrowers in majority-minority neighborhoods are lower by an average 0.01 and 0.04, respectively. These estimates are highly statistically significant, but quite small economically.

The key question in determining what additional comps mean for minority borrowers is whether there are significant differences in the quality of comps used in the appraisals. The quality of a given comp is generally determined by its similarity to the subject property in terms of three primary dimensions: distance, date, and physical similarity. In order to understand whether low appraisals can be explained by the choice of comps, we next test for differences along each of these dimensions to determine whether the quality of comps differs systematically based on borrower or neighborhood minority status.

3.6.2 Comp Quality – Distance

As a general rule, comps that are farther away from the subject property are lower quality (i.e., less informative of the subject property's value) compared to those that are closer. This is because comps that are closer to the subject property are more likely to share the same set of locational amenities (e.g., school quality, access to parks, access to public transit, etc.), the value of which would be reflected in their sales prices. In order to test for differences in comp distances for minority neighborhoods and borrowers compared to Whites, we compute the distance between each comp and the corresponding subject property.[38] For each subject property, we calculated the mean comp distance (averaged across all the corresponding comps), as well as the minimum, maximum, and range (i.e., maximum minus minimum).

As shown in column (2) of Table 12, Asians, Blacks, Hawaiians, and Hispanics purchasing homes in majority-White neighborhoods received comps that were significantly closer to the subject

[38] We note that one of the free-form text fields in the data captures the appraiser's estimate of the distance between the subject property and the comp. When we extract that information and replicate the comp distance results using the corresponding distance measure, the estimated coefficients are generally larger but consistent with the magnitudes and statistical significance reported here. Although the two measures of distance are generally consistent (there is, on average, less than half a mile difference between the two), we prefer our measure given some discrepancies we observed in the reported data field and because our measure is more transparent in terms of how the distances are determined.

property. However, in majority-minority tracts, even for White borrowers, the average comp distance is significantly higher by 0.1 miles. For American Indian, Asian, Black, and Hispanic borrowers, the average comp distance is an additional roughly 0.1miles. Thus, while comp quality in terms of distance is generally lower for all borrowers in majority-minority neighborhoods, compared to Whites it is significantly more so for each of those minority groups.

In addition to the mean, we also performed similar tests for significant differences in the minimum, maximum, and range of comp distances. These additional measures of comp distance provide a more complete picture of all the comps that were used for any given appraisal. As shown in Appendix Table A.7, across each of these measures of comp distance, we find highly significant positive coefficients for *majority-minority* and the interaction terms involving Asians, Blacks, and Hispanics. Thus, after controlling for factors that affect the availability of comps, we find consistent evidence that properties in majority-minority neighborhoods tend to receive appraisals with comps that are significantly farther away from the subject property, particularly for Asians, Blacks, and Hispanics compared to Whites.[39]

3.6.3 Comp Quality – Date

Another key indicator of the quality of a given comp is how recently it was sold. All else equal, comps that were sold more recently provide a better gauge of current market conditions than those that occurred with a longer time lag. We test for differences in this dimension of comp quality based on the average number of days between the comp settlement date and the appraisal date. As before, we include as controls several factors related to property characteristics and local housing market dynamics, which might reasonably explain an appraiser's inability to identify comps that have been sold recently.

Column (3) of Table 12 shows results from the regression of the mean comp time gap. Positive coefficient estimates in this column indicate longer average time lags between the appraisal date and the comp settlement date. Thus, significant positive estimates indicate the presence of lower quality comps in terms of the timing dimension. We find that, on average, more timely comps are used for Asian, Black, and Hispanic borrowers in majority-White tracts. However, in majority-minority tracts, Asians and Blacks have a significantly longer average comp time gap compared

[39] For American Indians the coefficient significance is less consistent across the various measures of comp distance.

to White borrowers in those tracts. These differences are highly statistically significant but equate to an average increase of less than 2 additional days.

3.6.4 Comp Quality – Similarity

The third key indicator for the quality of a comp is the extent to which it has similar physical characteristics as the subject property, including the condition of the property and the quality of building materials. Differences between the comp and the subject property are captured in the data through the various adjustments that are made as part of the reconciliation process. These adjustments can be negative or positive, depending on whether the comp has more or fewer amenities/enhancements relative to the subject property. An ideal comp (i.e., one that matches the subject property across all the relevant dimensions) will require very few adjustments during reconciliation. Using the various line-item adjustments, we calculate the absolute value of the total net adjustment amount associated with each comp.[40] Then, we test for differences in the average comp similarity by neighborhood and borrower minority status, based on the extent to which adjustments had to be made to calibrate the comps to subject properties. This analysis is somewhat less informative about comp quality than the previous two both because it uses an indirect measure and because it relies on appraisers' assessment of the value of various property characteristics.

As shown in Column (4) of Table 12, compared to Whites, the differences in average absolute total net adjustments are not statistically distinguishable from zero for any minority group or for majority-minority neighborhoods compared to majority-White ones.[41] Thus, the average quality of comps in terms of similar property characteristics does not differ by race, regardless of whether the property is in a majority-minority or majority-White neighborhood. The same is also true for the range and maximum (see Appendix Table A.9). When testing for differences in the minimum absolute total net adjustment across all comps, we find significant negative estimates for each racial group and *majority-minority*, suggesting that the comp that was most like the subject property (i.e., requiring the minimum amount of adjustment) tended to be less different for minorities in majority-White neighborhoods and for Whites in majority-minority neighborhoods.

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[40] We use the absolute value of total net adjustments because we are attempting to measure the similarity between the comp and the subject property (regardless of whether the total net adjustment was positive or negative). Nonetheless, the results are similar when we use the raw total net adjustment amount.

[41] Results are similar when we include sales price as an additional control, when we use the raw total net adjustment amount, and when we normalize by the sales price.

The interaction effects suggest that in majority-minority neighborhoods, compared to Whites, Asians and Hawaiians had more similar comps, while Blacks and Hispanics had comps that required larger net adjustments.

[Insert Table 12]

4. Conclusion

Given how important home appraisals are in the residential real estate lending process, it is understandable that the industry has come under scrutiny in recent years. Although there has been a fair amount of news coverage around specific instances of alleged appraisal racial bias, it is unclear whether those are anomalies or symptoms of more widespread issues. This paper contributes to a very limited academic literature exploring this question, by comparing appraised values to the sale prices agreed upon by willing buyers and willing sellers on the open market. We primarily focus on the incidence of low appraisals, but the results are generally consistent when we instead evaluate the magnitude of the appraisal gap (normalized by the contract price); factors that tend to increase the likelihood of a low appraisal are also often associated with larger appraisal gaps.

We find that low appraisals are more common in majority-minority neighborhoods with more pronounced effects as minority concentration increases, particularly for Asians, Blacks, and Hispanics. For properties within majority-minority neighborhoods, minority borrowers are more likely than Whites to receive a low appraisal. We also find that appraiser geographic characteristics are related to the likelihood of low appraisals in intuitive ways; when the appraiser's office is in the same state and closer to the subject property, the likelihood of a low appraisal declines. The same is true when the minority concentration around the appraiser's office more closely aligns with that around the subject property. Since local knowledge is key to fully understanding the locational amenities associated with any given property (and to correctly identify the comps that truly share the same amenities), the ideal appraiser is one who has familiarity with the neighborhood even before arriving at the subject property. However, given the mismatch in neighborhood demographics surrounding appraiser's offices and the properties they appraise (see Figure 2), it may be unlikely that such is the case for those purchasing properties in predominantly minority neighborhoods.

Using somewhat indirect measures of credit outcomes, previous research has found that low appraisals may not adversely impact underwriting outcomes (Fout et al., 2022). However, a key insight from this paper is the fact that low appraisals (and larger appraisal gaps) significantly increase the likelihood of denial, as reported by each lender. Moreover, the impact of low appraisals (and the appraisal gap size) varies according to borrower race; among borrowers who received a low appraisal, Asians are less likely than Whites to be denied whereas Blacks and Hispanics are more likely to be denied, after controlling for key underwriting factors related to creditworthiness and ability to pay. Future research should explore whether these disparities are due to differences in borrowers' ability to recover from the low appraisal (e.g., by coming up with additional cash or negotiating a lower sales price) or in lender-specific underwriting practices (or some combination of both).

Our research identifies some aspects of comp selection as potential sources of the disparities for majority-minority neighborhoods and for certain minority borrowers in those neighborhoods. Further research is needed to fully understand the causes of low appraisals in these neighborhoods and for these borrowers. For example, whereas we have tested for differences in the quality of comps that were actually used in various appraisals, future work could consider the broader range of *possible* comps that *could have* been selected to determine whether there are systematic differences in the decision to include or exclude certain comps.

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Tables

Table 1. Means of Key Variables by Race and Minority Tract Status

	Low Appraisals	No. Obs.	Appraisal Gap (% of Sales Price)	No. Obs.
American Indian	0.0966***	9,744	5.162	941
Asian	0.0976***	345,102	4.572***	33,674
Black	0.1184***	377,821	5.328***	44,725
Hawaiian	0.1148***	8,287	4.492***	951
Hispanic	0.1274***	389,462	4.737***	49,623
White	0.0839	3,968,383	5.126	333,058
Majority-Minority Tract	0.1273***	1,859,982	5.053***	236,802
Majority-White Tract	0.0772	7,867,048	4.942	607,239

Notes: ***p<0.001 when testing for differences in means between the given group and that of the corresponding control group using robust standard errors. For racial minorities, the control group is Whites. For majority-minority tracts, the control group is majority-White tracts. Appraisal Gap calculations are conditional on there being a low appraisal.

Table 2. Low appraisals for minority borrowers

	(1)	(2)	(3)	(4)
American Indian	0.0036	0.0046	0.0028	-0.0011
	(0.0030)	(0.0030)	(0.0030)	(0.0030)
Asian	0.0098***	0.0035***	0.0023***	-0.0051***
	(0.0005)	(0.0006)	(0.0006)	(0.0006)
Black	0.0261***	0.0172***	0.0135***	-0.0054***
	(0.0006)	(0.0006)	(0.0006)	(0.0006)
Hawaiian	0.0190***	0.0105**	0.0091**	-0.0024
	(0.0035)	(0.0035)	(0.0035)	(0.0035)
Hispanic	0.0264***	0.0092***	0.0073***	-0.0078***
	(0.0006)	(0.0006)	(0.0006)	(0.0006)
Year-Qtr FEs	X	X	X	X
Property controls	X	X	X	X
MSA FEs		X		
County FEs			X	
Census Tract FEs				X
N	4,939,927	4,900,271	4,939,927	4,939,799
Adj. R-square	0.020	0.033	0.036	0.060

Notes: **p<0.01, ***p<0.001 using robust standard errors. Property controls include 61 property characteristics from a backward stepwise variable selection procedure (see text for details).

Table 3. Low appraisals for minority borrowers with minority appraisers

	(1)	(2)	(3)	(4)
American Indian	-0.0003	0.002	0.0005	-0.0028
	(0.0034)	(0.00344)	(0.0034)	(0.0035)
Asian	0.0093***	0.0036***	0.0025***	-0.004***
	(0.0007)	(0.0007)	(0.0007)	(0.0007)
Black	0.0221***	0.0155***	0.0122***	-0.0058***
	(0.0006)	(0.0006)	(0.0007)	(0.0007)
Hawaiian	0.0167***	0.0092*	0.0079	-0.0016
	(0.0041)	(0.0041)	(0.004)	(0.0041)
Hispanic	0.0183***	0.0073***	0.0055***	-0.0084***
	(0.0007)	(0.0007)	(0.0007)	(0.0007)
Minority appraiser	0.0178***	0.0132***	0.0133***	0.0138***
	(0.0007)	(0.0007)	(0.0007)	(0.0007)
Am. Indian*Minority appraiser	0.0171	0.0134	0.0128	0.0096
	(0.0126)	(0.0126)	(0.0125)	(0.0126)
Asian*Minority appraiser	-0.0037*	0.0001	0.0001	-0.0037
	(0.0019)	(0.0019)	(0.0019)	(0.0019)
Black*Minority appraiser	0.0256***	0.0141***	0.0123***	0.0055*
	(0.0024)	(0.0024)	(0.0024)	(0.0024)
Hawaiian*Minority appraiser	-0.0017	-0.0034	-0.0036	-0.0109
	(0.0131)	(0.0131)	(0.0130)	(0.0130)
Hispanic*Minority appraiser	0.0333***	0.0115***	0.0110***	0.00334
	(0.002)	(0.002)	(0.002)	(0.0021)
Year-Qtr FEs	X	X	X	X
Property controls	X	X	X	X
MSA FEs		X		
County FEs			X	
Census Tract FEs				X
N	3,907,222	3,875,068	3,907,222	3,907,135
Adj. R-square	0.020	0.033	0.035	0.063

Notes: *p<0.05, **p<0.01, ***p<0.001 using robust standard errors. Property controls include 61 property characteristics from a backward stepwise variable selection procedure (see text for details).

Table 4. Normalized appraisal gap for minority borrowers and minority appraisers

	(1)	(2)	(3)	(4)
American Indian	0.0657	0.0942	0.0829	-0.0867
	(0.244)	(0.239)	(0.228)	(0.243)
Asian	-0.0602	0.0246	0.0495	0.0393
	(0.0378)	(0.0381)	(0.0386)	(0.0444)
Black	0.422***	0.309***	0.214***	-0.159***
	(0.0341)	(0.0344)	(0.0357)	(0.0410)
Hawaiian	-0.342*	-0.131	-0.203	-0.366*
	(0.163)	(0.165)	(0.166)	(0.172)
Hispanic	-0.169***	-0.114***	-0.115***	-0.190***
	(0.0314)	(0.0322)	(0.0323)	(0.0362)
Minority appraiser	0.198***	0.243***	0.232***	0.204***
	(0.0381)	(0.0389)	(0.0395)	(0.0432)
Am. Indian*Minority appraiser	0.758	0.632	0.489	1.175*
	(0.524)	(0.506)	(0.484)	(0.495)
Asian*Minority appraiser	-0.514***	-0.474***	-0.475***	-0.229*
	(0.0796)	(0.0809)	(0.0823)	(0.0930)
Black*Minority appraiser	-0.184*	-0.143	-0.160	-0.0798
	(0.0897)	(0.0888)	(0.0887)	(0.0967)
Hawaiian*Minority appraiser	-0.470	-0.450	-0.395	-0.247
	(0.468)	(0.476)	(0.474)	(0.597)
Hispanic*Minority appraiser	-0.302***	-0.409***	-0.404***	-0.0944
	(0.0659)	(0.0704)	(0.0707)	(0.0802)
Year-Qtr FEs	X	X	X	X
Property controls	X	X	X	X
MSA FEs		X		
County FEs			X	
Census Tract FEs				X
N	350,527	348,424	350,527	350,521
Adj. R-square	0.063	0.077	0.097	0.307

Notes: *p<0.05, **p<0.01, ***p<0.001 using robust standard errors. Property controls include 61 property characteristics from a backward stepwise variable selection procedure (see text for details).

Table 5. Low appraisals in majority-minority tracts

	(1)	(2)	(3)	(4)
Majority-minority	0.0170***	0.0171***	0.00699***	0.0128***
	(0.0004)	(0.0005)	(0.0017)	(0.0006)
appraiser_distance		0.000003**	0.000004***	
		(0.000001)	(0.000001)	
appraiser_samestate		-0.0059***	-0.0075***	
		(0.0008)	(0.0008)	
Maj. Min.*samestate			0.0107***	
			(0.0017)	
American Indian				-0.0055
				(0.0033)
Asian				-0.00013
				(0.0006)
Black				-0.0017*
				(0.0007)
Hawaiian				0.0038
				(0.0042)
Hispanic				-0.0060***
				(0.0007)
Maj. Min.*Am. Indian				0.0176*
				(0.0075)
Maj. Min.*Asian				0.0044***
				(0.0013)
Maj. Min.*Black				0.0104***
				(0.0012)
Maj. Min.*Hawaiian				-0.0005
				(0.0075)
Maj. Min.*Hispanic				0.0114***
				(0.0012)
Year-Qtr FEs	X	X	X	X
MSA FEs	X	X	X	X
Property controls	X	X	X	X
Tract-level controls	X	X	X	X
N	6,249,373	4,867,346	4,867,346	4,899,002
Adj. R-square	0.036	0.038	0.038	0.036

Notes: *p<0.05, **p<0.01, ***p<0.001 using robust standard errors. Property controls include 61 property characteristics from a backward stepwise variable selection procedure. Tract-level controls include median household income, median age, share of households with children under 18 years old, share of population in labor force, share of home purchase transactions that are for FHA loans, share of occupied units that are owner-occupied, annual average number of home purchase applications per square mile, and indicators for whether the tract is rural, urban, gentrifying, or in a non-disclosure state (see text for details).

Table 6. Low appraisals in high-minority (>=80%) tracts vs. low-minority (<=20%) tracts

	(1)	(2)	(3)	(4)
HM8020	0.0426***	0.0410***	0.0222***	0.0357***
	(0.0009)	(0.0011)	(0.003)	(0.0016)
appraiser_distance		0.000004*	0.000005***	
		(0.000002)	(0.000002)	
appraiser_samestate		-0.0036***	-0.0055***	
		(0.0009)	(0.00096)	
HM8020*samestate			0.0200***	
			(0.003)	
American Indian				-0.0025
				(0.0049)
Asian				0.0009
				(0.001)
Black				-0.0027*
				(0.0012)
Hawaiian				0.007
				(0.006)
Hispanic				-0.0053***
				(0.0011)
HM8020*Am. Indian				0.0194
				(0.0137)
HM8020*Asian				0.0067*
				(0.0027)
HM8020*Black				0.0113***
				(0.0022)
HM8020*Hawaiian				-0.0098
				(0.0126)
HM8020*Hispanic				0.0197***
				(0.0023)
Year-Qtr FEs	X	X	X	X
MSA FEs	X	X	X	X
Property controls	X	X	X	X
Tract-level controls	X	X	X	X
N	3,258,801	2,518,101	2,518,101	2,634,239
Adj. R-square	0.038	0.041	0.041	0.037

Notes: *p<0.05, **p<0.01, ***p<0.001 using robust standard errors. Property controls include 61 property characteristics from a backward stepwise variable selection procedure. Tract-level controls include median household income, median age, share of households with children under 18 years old, share of population in labor force, share of home purchase transactions that are for FHA loans, share of occupied units that are owner-occupied, annual average number of home purchase applications per square mile, and indicators for whether the tract is rural, urban, gentrifying, or in a non-disclosure state (see text for details).

Table 7. Low appraisals by percent minority

	(1)	(2)	(3)	(4)
Percent minority	0.0005***	0.0005***	0.0003***	0.0004***
	(0.00001)	(0.00001)	(0.00003)	(0.00001)
appraiser_distance		0.000003***	0.000005***	
		(0.000001)	(0.000001)	
appraiser_samestate		-0.0057***	-0.0101***	
		(0.0008)	(0.001)	
%Min.*samestate			0.0002***	
			(0.00003)	
American Indian				-0.0093
				(0.0051)
Asian				-0.006***
				(0.001)
Black				-0.0094***
				(0.0011)
Hawaiian				0.0038
				(0.0064)
Hispanic				-0.0163***
				(0.0011)
%Min.*Am. Indian				0.0002
				(0.0001)
%Min.*Asian				0.0001***
				(0.00002)
%Min.*Black				0.0002***
				(0.00002)
%Min.*Hawaiian				-0.00002
				(0.0001)
%Min.*Hispanic				0.0003***
				(0.00002)
Year-Qtr FEs	X	X	X	X
MSA FEs	X	X	X	X
Property controls	X	X	X	X
Tract-level controls	X	X	X	X
N	6,249,373	4,867,346	4,867,346	4,899,002
Adj. R-square	0.037	0.038	0.038	0.036

Notes: *p<0.05, **p<0.01, ***p<0.001 using robust standard errors. Property controls include 61 property characteristics from a backward stepwise variable selection procedure. Tract-level controls include median household income, median age, share of households with children under 18 years old, share of population in labor force, share of home purchase transactions that are for FHA loans, share of occupied units that are owner-occupied, annual average number of home purchase applications per square mile, and indicators for whether the tract is rural, urban, gentrifying, or in a non-disclosure state (see text for details).

Table 8. Normalized appraisal gap in majority-minority tracts

	(1)	(2)	(3)	(4)
Majority-minority	0.362***	0.362***	0.337***	0.431***
	(0.0208)	(0.0230)	(0.0765)	(0.0316)
appraiser_distance		0.0003***	0.0003***	
		(0.0001)	(0.0001)	
appraiser_samestate		-0.211***	-0.216***	
		(0.0514)	(0.0543)	
Maj. Min.*samestate			0.0266	
			(0.0773)	
American Indian				0.218
				(0.272)
Asian				0.0853*
				(0.0402)
Black				-0.0170
				(0.0393)
Hawaiian				-0.232
				(0.158)
Hispanic				-0.146***
				(0.0378)
Maj. Min.*Am. Indian				-0.420
				(0.344)
Maj. Min.*Asian				-0.307***
				(0.0619)
Maj. Min.*Black				0.286***
				(0.0574)
Maj. Min.*Hawaiian				0.0139
				(0.271)
Maj. Min.*Hispanic				-0.226***
				(0.0533)
Year-Qtr FEs	X	X	X	X
MSA FEs	X	X	X	X
Property controls	X	X	X	X
Tract-level controls	X	X	X	X
N	581,610	462,699	462,699	448,833
Adj. R-square	0.082	0.085	0.085	0.083

Notes: *p<0.05, **p<0.01, ***p<0.001 using robust standard errors. Property controls include 61 property characteristics from a backward stepwise variable selection procedure. Tract-level controls include median household income, median age, share of households with children under 18 years old, share of population in labor force, share of home purchase transactions that are for FHA loans, share of occupied units that are owner-occupied, annual average number of home purchase applications per square mile, and indicators for whether the tract is rural, urban, gentrifying, or in a non-disclosure state (see text for details).

Table 9. Collateral-denial analyses (among all denials)

	(1)	(2)	(3)
Low appraisal	0.409***	0.397***	0.353***
	(0.003)	(0.003)	(0.003)
Yr-Qtr FEs	X	X	X
UW controls		X	X
CLTV control			X
N	155,962	135,862	132,215
Adj. R-square	0.124	0.187	0.226

Notes: *** $p < 0.001$. UW controls include: DTI, and credit score, as well as indicators for various loan types occupancy types, as well as manufactured home, reverse mortgage, HELOC, conforming loan status, first lien, single family home, interest only loan, and positive and negative AUS outcomes. CLTV is included as an optional control given that the denominator in the ratio could be biased if there are systematic misvaluations.

Table 10. Probability of denials based on low appraisals

	(1)	(2)
Low appraisal	0.0420***	0.0386***
	(0.0005)	(0.0006)
American Indian		0.0017
		(0.0024)
Asian		0.0042***
		(0.0005)
Black		0.0084***
		(0.0007)
Hawaiian		0.0148***
		(0.0037)
Hispanic		0.0042***
		(0.0004)
Am. Indian*Low appr		0.0165
		(0.0109)
Asian*Low appr		-0.0098***
		(0.002)
Black*Low appr		0.0171***
		(0.0024)
Hawaiian*Low appr		-0.001
		(0.0139)
Hispanic*Low appr		0.0084***
		(0.0016)
Yr-Qtr FEs	X	X
UW controls	X	X
N	3,354,657	2,695,398
Adj. R-square	0.129	0.132

Notes: *** $p < 0.001$. UW controls include: DTI, and credit score, as well as indicators for various loan types occupancy types, as well as manufactured home, reverse mortgage, HELOC, conforming loan status, first lien, single family home, interest only loan, and positive and negative AUS outcomes.

Table 11. Probability of denial based on normalized appraisal gap

	(1)	(2)
Normalized appr gap	0.0086***	0.0071***
	(0.0002)	(0.0002)
American Indian		0.0137
		(0.0157)
Asian		-0.0044
		(0.0033)
Black		-0.0141***
		(0.0039)
Hawaiian		-0.0487*
		(0.0210)
Hispanic		-0.0126***
		(0.0029)
Am. Indian*Appr Gap		-0.0028
		(0.0028)
Asian*Appr Gap		0.00008
		(0.0008)
Black*Appr Gap		0.0054***
		(0.0008)
Hawaiian*Appr Gap		0.0135**
		(0.0052)
Hispanic*Appr Gap		0.005***
		(0.0006)
Yr-Qtr FEs	X	X
UW controls	X	X
N	301,416	239,598
Adj. R-square	0.156	0.161

Notes: ** p< 0.01, *** p < 0.001. Underwriting controls include: UW controls include: DTI, and credit score, as well as indicators for various loan types occupancy types, as well as manufactured home, reverse mortgage, HELOC, conforming loan status, first lien, single family home, interest only loan, and positive and negative AUS outcomes.

Table 12. Comp Analyses

Dependent Variable:	(1) Number of Comps	(2) Mean Comp Distance	(3) Mean Comp Time Gap	(4) Mean Absolute Total Net Adjustment
American Indian	0.0349*	-0.0406	0.235	-44570.2
	(0.0157)	(0.0319)	(1.037)	(45162.5)
Asian	0.0072*	-0.126***	-2.183***	2763.0
	(0.003)	(0.0028)	(0.230)	(4905.3)
Black	0.0763***	-0.161***	-3.979***	-22981.3
	(0.0032)	(0.0035)	(0.241)	(20736.6)
Hawaiian	0.0634***	-0.0761***	-3.356	11953.6
	(0.0189)	(0.0217)	(2.628)	(17687.9)
Hispanic	0.0429***	-0.0525***	-2.471***	-44419.1
	(0.0031)	(0.0038)	(0.266)	(46348.7)
Majority-minority	0.0178***	0.107***	-0.0567	5795.1
	(0.0024)	(0.0033)	(0.218)	(9089.1)
Maj. Min.*Am. Indian	0.0670*	0.134**	-0.824	61925.5
	(0.0303)	(0.0461)	(1.667)	(63384.9)
Maj. Min.*Asian	-0.0404***	0.0895***	1.449***	30713.3
	(0.0052)	(0.0044)	(0.388)	(32082.9)
Maj. Min.*Black	-0.0099*	0.0554***	1.705***	29216.7
	(0.0048)	(0.0051)	(0.402)	(27473.6)
Maj. Min.*Hawaiian	0.0319	0.0447	-0.648	-12750.3
	(0.0293)	(0.0252)	(2.886)	(17382.9)
Maj. Min.*Hispanic	-0.00802	0.0645***	0.333	8574.8
	(0.0048)	(0.0053)	(0.406)	(9690.8)
Year-Qtr FEs	X	X	X	X
MSA FEs	X	X	X	X
Property controls	X	X	X	X
Tract-level controls	X	X	X	X
N	4,943,435	4,943,435	4,940,895	4,943,435
Adj. R-square	0.146	0.328	0.074	0.000

Notes: *p<0.05, **p<0.01, ***p<0.001 using robust standard errors. Mean comp distance captures the average distance between the subject property and each of the corresponding comps. Mean comp time captures the average difference between the appraisal date and the comp settlement date. Property controls include 61 property characteristics from a backward stepwise variable selection procedure. Tract-level controls include share of occupied units that are owner-occupied, annual average number of home purchase applications per square mile, and indicators for whether the tract is rural, urban, or in a non-disclosure state (see text for details).

Appendix

Table A.1 Distribution of Appraiser Race

	UAD Race Proxy		Appraisal Institute[42]	Urban Institute[43]
American Indian	14	0.03%	0.4%	-
Asian	1,548	2.83%	1.1%	-
Black	1,407	2.57%	1.3%	2%
Hispanic	2,244	4.10%	4.3%	5%
Multiracial	36	0.07%	0.7%	-
White	49,462	90.41%	85.4%	89%
Prefer not to say	-	-	5.1%	-
Other	-	-	1.7%	4%
Total	54,711	100%	100%	100%

Notes: We identify each unique appraiser based on the state license or certification number. For 1,438 appraisers in which no license or certification number was captured in the data, we used names to uniquely identify them.

[42] https://www.appraisalinstitute.org/file.aspx?DocumentId=2342
[43] https://www.urban.org/urban-wire/increasing-diversity-appraisal-profession-combined-short-term-solutions-can-help-address-valuation-bias-homeowners-color

Table A.2 Property characteristics from backward variable selection procedure

	Coefficient	Standard Error
Quality		
2	-0.0159***	(0.0021)
3	-0.0299***	(0.002)
4	-0.0178***	(0.002)
5	0.0086***	(0.0023)
Bath_improv_time		
<1yr	0.0273***	(0.0022)
1to5yrs	0.0217***	(0.0022)
6to10yrs	0.0148***	(0.0023)
11to15yrs	0.0131***	(0.0024)
Unknown	0.0156***	(0.0023)
Condition		
2	0.0627***	(0.0004)
3	0.0502***	(0.0003)
4	0.0427***	(0.0004)
5	0.1175***	(0.0031)
6	0.2459***	(0.0194)
Fence_flag	0.0091***	(0.0002)
Fireplace_flag	0.0045***	(0.0004)
Other_amenities_flag	-0.0052***	(0.0002)
Patio_deck_flag	0.0018***	(0.0003)
Pool_flag	0.0221***	(0.0004)
Porch_flag	0.0021***	(0.0002)
Woodstove_flag	-0.0106***	(0.0005)
Dishwasher_flag	-0.0074***	(0.0003)
Disposal_flag	0.0077***	(0.0002)
Microwave_flag	0.0035***	(0.0002)
Num_stories	-0.0001***	(0.00003)
Range_oven_flag	-0.0034***	(0.0003)
Refrigerator_flag	0.0024***	(0.0002)
Washer_dryer_flag	0.0058***	(0.0002)
Basement_pctfinish	0.00005***	(0.000004)
Kit_improv_time		
6to10yrs	-0.0087***	(0.0005)
11to15yrs	-0.0079***	(0.0008)
Unknown	-0.0077***	(0.0006)
Attic_dropstair_flag	-0.0035***	(0.0005)
Attic_floor_flag	-0.0018***	(0.0005)
Num_fireplace	-0.0046***	(0.0003)

Attic_none_flag	-0.005***	(0.0005)
Attic_scuttle_flag	-0.004***	(0.0004)
Bath_notupdated_flag	0.0197***	(0.0022)
Effective_age	0.0005***	(0.00001)
Num_bedrooms	0.0052***	(0.0002)
Carport_flag	-0.004***	(0.001)
Noupdates_last15yrs_flag	0.0094***	(0.0022)
Yearbuilt_estimated_flag	-0.0142***	(0.0007)
Concrete_slab_flag	0.0113***	(0.0005)
Not_nbrhood_conforming_flag	0.0979***	(0.0024)
Basement_area (‘000)	0.005***	(0.0003)
Cooling_centralair_flag	0.0135***	(0.0005)
Cooling_individual_flag	0.0091***	(0.0007)
Cooling_other_flag	0.0028***	(0.0005)
Crawlspace_flag	-0.0091***	(0.0005)
Driveway_flag	0.0019***	(0.0005)
Dampness_flag	0.0097***	(0.0012)
No_infestation_flag	0.0229***	(0.0035)
Carport_numcars	-0.0022***	(0.0006)
Year_built	0.0004***	(0.000005)
Full_basement_flag	-0.0233***	(0.0007)
Garage_flag	-0.0086***	(0.0004)
Heating_FWA_flag	-0.0058***	(0.0007)
Heating_HWBB_flag	-0.0049***	(0.0008)
Heating_other_flag	-0.0027***	(0.0007)
Heating_radiant_flag	-0.0046***	(0.0008)
Garage_numcars	0.0024***	(0.0002)
Kit_remodeled_flag	0.0052***	(0.0003)
Driveway_numcars	0.0006***	(0.0001)
Partial_basement_flag	-0.0224***	(0.0005)
Num_rooms	-0.0025***	(0.0001)
Physical_deficiencies_flag	0.0258***	(0.001)
Proposed_construction_flag	0.0504***	(0.001)
Sumppump_flag	-0.0028***	(0.0003)
Attached_unit_flag	0.0151***	(0.0005)
Num_baths	0.0017***	(0.0002)
Detached_endunit_flag	0.0265***	(0.0006)
Gross_living_area (‘000)	-0.016***	(0.0002)
Accessory_unit_flag	0.017***	(0.0008)

Notes: *** $p<0.001$ using robust standard errors.

Table A.3 Estimated coefficients and standard errors for tract-level controls from regression in Column (1) of Table 5.

	Coef.	**Std. Error**
Non-disclosure state	0.0223***	(0.0018)
Median income ($000)	-0.0001***	(0.000006)
Median age	-0.0001***	(0.00003)
Share of HHs with children <18 years old	0.0003***	(0.00002)
Share of population in labor force	0.0002***	(0.00002)
Share of occupied units that are owner occupied	-0.0002***	(0.00002)
HP applications per square mile	-0.00006***	(0.000002)
Rural	-0.0008	(0.0005)
Urban	0.0033***	(0.0003)
Share of HP applications for FHA loans	0.0008***	(0.00001)
Gentrification (based on change in HH income)	-0.0019	(0.0021)

Notes: *** $p < 0.001$ using robust standard errors. See text for descriptions of each variable.

Table A.4 Normalized appraisal gap by percent minority

	(1)	(2)	(3)	(4)
Percent minority	0.0118***	0.0116***	0.00998***	0.0130***
	(0.0005)	(0.0005)	(0.001)	(0.0007)
appraiser_distance		0.0003***	0.0003***	
		(0.00005)	(0.0001)	
appraiser_samestate		-0.202***	-0.255***	
		(0.0514)	(0.0688)	
%Min.*samestate			0.0017	
			(0.0014)	
American Indian				0.322
				(0.345)
Asian				0.164*
				(0.0653)
Black				-0.283***
				(0.0621)
Hawaiian				-0.534
				(0.276)
Hispanic				-0.0699
				(0.0579)
%Min.*Am. Indian				-0.0067
				(0.0057)
%Min.*Asian				-0.0056***
				(0.0013)
%Min.*Black				0.0058***
				(0.0011)
%Min.*Hawaiian				0.0056
				(0.006)
%Min.*Hispanic				-0.0044***
				(0.001)
Year-Qtr FEs	X	X	X	X
MSA FEs	X	X	X	X
Property controls	X	X	X	X
Tract-level controls	X	X	X	X
N	581,610	462,699	462,699	448,833
Adj. R-square	0.083	0.085	0.085	0.084

Notes: *p<0.05, **p<0.01, ***p<0.001 using robust standard errors. Property controls include 61 property characteristics from a backward stepwise variable selection procedure. Tract-level controls include median household income, median age, share of households with children under 18 years old, share of population in labor force, share of home purchase transactions that are for FHA loans, share of occupied units that are owner-occupied, annual average number of home purchase applications per square mile, and indicators for whether the tract is rural, urban, gentrifying, or in a non-disclosure state (see text for details).

Table A.5 Normalized appraisal gap in high minority vs. low minority tracts

	(1)	(2)	(3)	(4)
HM8020	1.361***	1.294***	1.176***	1.520***
	(0.0567)	(0.0637)	(0.146)	(0.0842)
appraiser_distance		0.0005***	0.0005***	
		(0.0001)	(0.0001)	
appraiser_samestate		-0.236**	-0.255***	
		(0.0752)	(0.0771)	
HM8020*samestate			0.125	
			(0.140)	
American Indian				-0.0632
				(0.305)
Asian				0.143
				(0.0760)
Black				0.187*
				(0.0866)
Hawaiian				-0.0418
				(0.279)
Hispanic				-0.243***
				(0.0696)
HM8020*Am. Indian				-0.620
				(0.498)
HM8020*Asian				-0.558***
				(0.130)
HM8020*Black				-0.0623
				(0.121)
HM8020*Hawaiian				0.908
				(0.562)
HM8020*Hispanic				-0.424***
				(0.104)
Year-Qtr FEs	X	X	X	X
MSA FEs	X	X	X	X
Property controls	X	X	X	X
Tract-level controls	X	X	X	X
N	272,333	215,472	215,472	216,180
Adj. R-square	0.083	0.085	0.085	0.086

Notes: *p<0.05, **p<0.01, ***p<0.001 using robust standard errors. Property controls include 61 property characteristics from a backward stepwise variable selection procedure. Tract-level controls include median household income, median age, share of households with children under 18 years old, share of population in labor force, share of home purchase transactions that are for FHA loans, share of occupied units that are owner-occupied, annual average number of home purchase applications per square mile, and indicators for whether the tract is rural, urban, gentrifying, or in a non-disclosure state (see text for details).

Table A.6 Estimated coefficients and standard errors for underwriting controls from regression in Column (1) of Table 10.

	Coefficient	Standard Error
DTI	0.0028***	(0.00002)
Credit Score	-0.0002***	(0.000003)
Manufactured Home	0.0999***	(0.0091)
FHA Loan	0.0027***	(0.0004)
VA Loan	0.253***	(0.0036)
USDA Loan	-0.0217***	(0.0008)
Reverse Mortgage	-0.260***	(0.0200)
HELOC	0.134***	(0.0039)
Conforming	0.075***	(0.0009)
AUS Negative	0.141***	(0.0017)
AUS Positive	-0.135***	(0.0007)
First Lien	-0.0663***	(0.0039)
Second Residence	0.0154***	(0.0004)
Investment Property	0.0232***	(0.0005)
Single Family Home	-0.0622***	(0.0077)
Interest Only Loan	-0.0713***	(0.0018)

Notes: *** p<0.001.

Table A.7 Range, Maximum, and Minimum Comp Distance

Dependent Variable:	Range Comp Distance	Maximum Comp Distance	Minimum Comp Distance
American Indian	0.0003	-0.0336	-0.0339
	(0.0472)	(0.0549)	(0.0207)
Asian	-0.165***	-0.214***	-0.0496***
	(0.0044)	(0.005)	(0.0016)
Black	-0.181***	-0.256***	-0.0749***
	(0.0053)	(0.006)	(0.0021)
Hawaiian	-0.0877**	-0.115**	-0.0273*
	(0.0324)	(0.0371)	(0.0129)
Hispanic	-0.0632***	-0.0856***	-0.0224***
	(0.0059)	(0.0068)	(0.0023)
Majority-minority	0.133***	0.177***	0.0445***
	(0.0048)	(0.0056)	(0.0021)
Maj. Min.*Am. Indian	0.0541	0.149*	0.0945**
	(0.0633)	(0.0755)	(0.0303)
Maj. Min.*Asian	0.115***	0.152***	0.0375***
	(0.0069)	(0.0078)	(0.0026)
Maj. Min.*Black	0.0477***	0.0779***	0.0302***
	(0.0076)	(0.0087)	(0.0032)
Maj. Min.*Hawaiian	0.0502	0.0607	0.0106
	(0.0392)	(0.0444)	(0.0144)
Maj. Min.*Hispanic	0.0850***	0.106***	0.0215***
	(0.0082)	(0.0093)	(0.0032)
Year-Qtr FEs	X	X	X
MSA FEs	X	X	X
Property controls	X	X	X
Tract-level controls	X	X	X
N	4,943,435	4,943,435	4,943,435
Adj. R-square	0.258	0.319	0.188

Notes: *p<0.05, **p<0.01, ***p<0.001 using robust standard errors. Mean comp distance captures the average distance between the subject property and each of the corresponding comps. Mean comp time captures the average difference between the appraisal date and the comp settlement date. Property controls include 61 property characteristics from a backward stepwise variable selection procedure. Tract-level controls include share of occupied units that are owner-occupied, annual average number of home purchase applications per square mile, and indicators for whether the tract is rural, urban, or in a non-disclosure state (see text for details).

Table A.8 Range, Maximum, and Minimum Comp Settlement Date

Dependent Variable:	Range Comp Time Gap	Maximum Comp Time Gap	Minimum Comp Time Gap
American Indian	3.474	2.572	-0.902
	(2.822)	(2.463)	(1.531)
Asian	-3.331***	-3.877***	-0.546
	(0.684)	(0.384)	(0.582)
Black	-4.716***	-6.702***	-1.986**
	(0.752)	(0.401)	(0.650)
Hawaiian	6.877	-2.262	-9.139
	(7.877)	(2.333)	(7.481)
Hispanic	-1.243	-3.310***	-2.067**
	(0.780)	(0.425)	(0.670)
Majority-minority	2.292***	1.062***	-1.230*
	(0.619)	(0.321)	(0.541)
Maj. Min.*Am. Indian	-16.28***	-9.549**	6.731***
	(3.699)	(3.393)	(1.939)
Maj. Min.*Asian	-2.241	-0.0306	2.211*
	(1.190)	(0.654)	(1.010)
Maj. Min.*Black	1.441	2.706***	1.265
	(1.239)	(0.617)	(1.079)
Maj. Min.*Hawaiian	-16.04	-5.604	10.43
	(8.254)	(3.402)	(7.531)
Maj. Min.*Hispanic	-4.280***	-1.877**	2.402*
	(1.171)	(0.631)	(1.010)
Year-Qtr FEs	X	X	X
MSA FEs	X	X	X
Property controls	X	X	X
Tract-level controls	X	X	X
N	4,940,895	4,940,895	4,940,895
Adj. R-square	0.014	0.065	0.004

Notes: *p<0.05, **p<0.01, ***p<0.001 using robust standard errors. Mean comp distance captures the average distance between the subject property and each of the corresponding comps. Mean comp time captures the average difference between the appraisal date and the comp settlement date. Property controls include 61 property characteristics from a backward stepwise variable selection procedure. Tract-level controls include share of occupied units that are owner-occupied, annual average number of home purchase applications per square mile, and indicators for whether the tract is rural, urban, or in a non-disclosure state (see text for details).

Table A.9 Range, Maximum, and Minimum Absolute Total Net Adjustments (ATNA) ($)

Dependent Variable:	Range ATNA Gap	Maximum ATNA Gap	Minimum ATNA Gap
American Indian	-173411.6	-174109.9	-698.3***
	(180650.4)	(180650.6)	(86.84)
Asian	15659.1	15114.8	-544.3***
	(19619.7)	(19619.7)	(31.58)
Black	-84945.7	-85792.3	-846.6***
	(82953.6)	(82953.6)	(23.57)
Hawaiian	52732.3	52249.2	-483.1**
	(70740.2)	(70742.4)	(152.9)
Hispanic	-176295.9	-176763.7	-467.8***
	(185227.4)	(185227.4)	(21.47)
Majority-minority	29943.5	29212.1	-731.4***
	(36354.7)	(36354.7)	(19.25)
Maj. Min.*Am. Indian	245947.2	246161.8	214.6
	(253545.3)	(253544.5)	(138.2)
Maj. Min.*Asian	126292.4	126033.1	-259.3***
	(128337.1)	(128337.1)	(49.75)
Maj. Min.*Black	113949.0	114315.4	366.4***
	(109897.2)	(109897.2)	(30.36)
Maj. Min.*Hawaiian	-44433.2	-45439.6	-1006.4***
	(69506.1)	(69508.5)	(200.2)
Maj. Min.*Hispanic	37838.3	38058.8	220.5***
	(38519.5)	(38519.6)	(32.74)
Year-Qtr FEs	X	X	X
MSA FEs	X	X	X
Property controls	X	X	X
Tract-level controls	X	X	X
N	4,943,435	4,943,435	4,943,435
Adj. R-square	0.000	0.000	0.157

Notes: *p<0.05, **p<0.01, ***p<0.001 using robust standard errors. Mean comp distance captures the average distance between the subject property and each of the corresponding comps. Mean comp time captures the average difference between the appraisal date and the comp settlement date. Property controls include 61 property characteristics from a backward stepwise variable selection procedure. Tract-level controls include share of occupied units that are owner-occupied, annual average number of home purchase applications per square mile, and indicators for whether the tract is rural, urban, or in a non-disclosure state (see text for details).