Do Appraiser and Homeowner Race Affect Valuation?*

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Abstract

We examine racial bias in property appraisals using a national sample of refinanced mortgages from 2000 to 2007. Our data allow us to observe the race of the homeowner and appraiser in a setting where the appraiser's valuation conveys critical information to the lender. After conditioning on hard and soft information about properties, we observe systematically lower appraised values (relative to adjusted automated valuation model estimates) of 4%, 3%, and 2% for Black, Hispanic, and Asian homeowners, respectively. We find no evidence that minority valuation discounts lessen when the homeowner and appraiser share the same race, suggesting implicit bias is not driven by White appraisers alone.

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1. Introduction

Mortgage lenders often rely on estimates of the value of real estate that serves as collateral on loan contracts. Appraisers, trained in the practice of estimating asset values and licensed by state governments, provide these property value assessments. For many years, appraisers of residential property explicitly factored the owner's race and the neighborhood's racial or ethnic composition into their estimates.[1] However, since the passage of the 1968 Fair Housing Act, which outlawed discriminatory practices in the mortgage lending industry, appraisers are forbidden from considering these factors in property valuations. Despite this, recent investigative reports in the popular press provide striking anecdotal evidence of continued discrimination in the appraisal process (see Haythorn, 2020; Malagón, 2020; Kamin, 2020). These articles echo findings of lower home values for minority homeowners documented in recent studies (Perry, Rothwell, and Harshbarger, 2018; Howell and Korver-Glenn, 2020; Williamson and Palim, 2022; Freddie Mac, 2022). As collateral valuation is a key component in mortgage underwriting, racially driven appraisal bias could further erode the opportunity for minority households to build wealth through homeownership. In response to these continuing reports of discrimination in the appraisal process, the Department of Housing and Urban Development (HUD) launched in June 2021 an inter-agency Property Appraisal Valuation Equity (PAVE) taskforce to better understand the causes and consequences of undervaluation or misvaluation of minority-owned homes.[2]

In this study, we provide new insights into the incidence and magnitude of racial bias in the valuation of residential properties that underlie refinanced mortgages, which are the focus of most anecdotal evidence. Appraisals for refinanced mortgages are often the only estimate of value because there is no new purchase price, whereas for purchase mortgages the appraised values are

[1] Jackson (1980), Fishback et al. (2020), and Aaronson, Hartley, and Mazumder (2021) provide discussions of historical appraisal practices.

[2] `https://pave.hud.gov/`

rarely below the contract price as appraisers target it,[3] leaving less room for racial bias.[4] In a refinance mortgage application, there is no definitive target for the valuation and a low appraisal does not necessarily preclude a loan from being funded. Additionally, because the borrower (who is the current homeowner) usually occupies the property and interacts with the appraiser during a refinance, the appraiser is more likely to observe the race of the applicant than with a purchase mortgage application.[5]

To investigate appraiser racial bias, we benchmark the appraised values of refinanced homes to independent property value estimates generated from an automated valuation model (AVM) using novel data that allow us to observe the race of homeowners and infer the race of appraisers. We test whether the race of the homeowner or appraiser is related to the appraisal-to-AVM ratio after accounting for "soft" information that is observable to an appraiser but not recorded in public records and "hard" information such as property characteristics, origination date, collateral location, and appraiser. Furthermore, we examine the question of whether racial bias in appraisals is sensitive to whether the homeowner and appraiser share the same race.

The data contain over 220,000 mortgages that were refinanced by New Century Financial Corporation (NCEN) from 2000 to 2007 and appraised by over 35,000 individual appraisers across the United States.[6] The 2000-2007 period is often associated with an environment of credit availability expansion to minorities along with increased minority homeownership rates, as well as heightened competition and relatively loose regulations in the U.S. mortgage industry. This setting is advan-

[3]See Agarwal, Song, and Yao, 2020; Cho and Megbolugbe, 1996; Calem et al., 2021; Conklin et al., 2020; Ding and Nakamura, 2016.

[4]In a purchase transaction, the appraiser typically receives a copy of the sales contract, which highlights the price for the property agreed between the buyer and seller. In an early contribution, LaCour-Little and Green (1998) examine the relationship between the likelihood of a below contract appraisal on purchase transactions and neighborhood and buyer race.

[5]It is common for the borrower to meet the appraiser face-to-face when the onsite property inspection is conducted. In contrast, for a purchase transaction, the appraiser generally meets with the current property owner (the seller). Thus, it is unclear whether the appraiser knows the buyer/borrower's race on a purchase transaction.

[6]NCEN was one of the largest subprime lenders in the housing boom of the early- to mid-2000s and declared bankruptcy in 2007. The NCEN data contain information used by the lender during the loan underwriting process (e.g. FICO score, borrower income documentation, loan purpose) as well as the property location and information recorded as part of the Home Mortgage Disclosure Act (HMDA) reporting process, which provides us with the borrower's race.

tageous for our inquiry as current regulations of the appraisal process and mortgage industry are much more pronounced under the 2010 Dodd-Frank Act than before. Another advantage of the NCEN data is that (to the best of our knowledge) they are the only publicly available data that provide researchers with sufficient information to accurately infer the race and ethnicity of multiple individual actors in the mortgage origination process.[7] For instance, the self-disclosed race and ethnicity of the borrower that was recorded on the mortgage application is available, allowing us to avoid the common practice in research of relying on neighborhood demographics to infer a homeowner race effect. Furthermore, the full name of the appraiser contracted by the mortgage broker is recorded, allowing us to use a Bayesian-based race classification algorithm—similar to the one described by Ambrose, Conklin, and Lopez (2021)—to infer the appraiser's race. A third advantage is that the appraised values are also found in the NCEN data. One challenge is that NCEN did not collect AVM estimates limiting the availability of this third-party valuation measure in the existing data. However, we merge the NCEN data with ABSNet and HomeVal data to overcome this obstacle.[8]

We make four key contributions. First, although we find that appraisals for all borrowers are on average 5% to 12% higher than AVM values—which is consistent with prior studies (Conklin et al., 2020; Shi and Zhang, 2015; Kruger and Maturana, 2021), we find that Black and Asian owned homes are undervalued by an average of about 0.6 and 0.8 percentage points below the appraisal-to-AVM ratio of comparable White owned homes, respectively. But, benchmarking appraisals to AVMs may not be appropriate, as AVMs may systematically undervalue (or overvalue) minority-owned homes or omit important facts about a property that an appraiser would notice when visiting a home in person, as AVMs are based on "hard" information about property features and sales prices that are recorded in electronic databases. Thus, we introduce an alternative value benchmark,

[7] Ambrose, Conklin, and Lopez (2021) use these data to study the borrower and mortgage broker race interactions on the pricing of mortgage credit. Using proprietary data, two contemporaneous studies examine the relationship between mortgage applicant race and appraisal values (Freddie Mac, 2022; Williamson and Palim, 2022).

[8] Details of the merging process are discussed in Section 2.2.

$\hat{V}$, that accounts for soft information and omitted property characteristics not captured by the AVM. The model for this adjusted AVM value is calibrated based on a sample of mortgages (purchase loans) where the true value of the property (i.e., purchase price) is known. In addition to the proxies for soft information, we also control for the AVM's confidence score at the property-level to account for valuation uncertainty discussed in Molloy and Nielsen (2018) and Jiang and Zhang (2022). Our valuation model created using the home purchase sample is then employed to create an out of sample estimate of market value ($\hat{V}$) for our refinance mortgages.

We find that not taking into account soft information severely underestimates racial bias in appraisals. Using our preferred valuation metric, the appraisal-to-$\hat{V}$ ratio, the valuation discount for Black owned homes increases to 4.1 percentage points from the unadjusted discount of 0.6 percentage points. The valuation discounts also increase for Hispanic and Asian owned homes, to 2.6 and 1.9 percentage points from 0 and 0.8 percentage points, respectively. While these average differences are not as large as the anecdotal reports in the popular press, they are statistically significant and consistent with the perception of differential treatment for minority borrowers. To provide context, a home appraised for $278,000 for a White borrower would have been appraised at about $266,600 if owned instead by a Black borrower. This would limit the Black borrower's access to housing wealth by about $9,120 (assuming a loan-to-value ratio of 80%) in a cash-out refinance. For liquidity-constrained Black borrowers with limited equity, these valuation discounts could also prevent refinancing, as this discount is larger than the fees typically associated with refinancing (see Ambrose, Conklin, and Lopez, 2021), making it more difficult to take advantage of interest rate decreases or avoid the shock of an expiring teaser rate on an adjustable rate mortgage. We also confirm that our results are not sensitive to variations in area demographics, house price levels, or loan origination year.

Second, whereas previous studies examining racial bias in appraisals only observe owner race or neighborhood demographics, we can infer the appraiser's race and systematically link appraiser race with borrower/homeowner race. As a result, we can examine racial interactions and provide novel insights to the literature that focuses on ethnic and racial group interactions (Agarwal et al., 2019; Li, 2014; Wong, 2013; Zhang and Zheng, 2015; Bertrand, Luttmer, and Mullainathan, 2000; Bayer, McMillan, and Rueben, 2004; Frame et al., 2021; Jiang, Lee, and Liu, 2021). Our analysis points to Black and Hispanic owners receiving lower appraisals than White owners regardless of the race of the appraiser. For example, in contrast to similar properties with White owners, we find that Black owners received value estimates that were 4.2 percentage points lower from White appraisers and 4.1 percentage points lower from Black appraisers, relative to our valuation benchmark. Similarly, we do not observe that the gap is lower for Hispanics or Asians when the owner shares the same race as the appraiser. Thus, our results do not point to implicit bias on the part of only White appraisers as driving the lower valuations experienced by minority owners. Instead, our results point to an implicit bias against minority homeowners across all appraisers, regardless of race or ethnicity.

Third, we explore whether the variation across race in the appraisal-to-$\hat{V}$ gaps are the result of a few appraisers or if the differences are more systemic. To do so, we estimate models that generate appraiser-specific measures of bias in valuations. We find evidence showing that the individual race coefficients are concentrated and symmetric around a gap of -2 percentage points for Asian and Hispanic owners, and -4 percentage points for Black owners. The distributions of these coefficients allow us to provide guidance as to the number of appraisers who appear to give minorities extremely low appraisals relative to similar White owners. For example, we find that 3% of appraisers give Asian and Hispanic owners very low appraisals relative to Whites (defined as lower app-to-$\hat{V}$ ratios by 30 percentage points or more), whereas 5% of appraisers give Blacks extremely low appraisals relative to Whites. Furthermore, our analysis does not reveal any systemic pattern of one racial group consistently undervaluing properties owned by another racial/ethnic group. For example, we find that 9% of Black appraisers and 5% of non-Black appraisers account for extremely low appraisals for Black homeowners. Examining the joint distribution of the coefficients suggests that there is a weak correlation across races: an appraiser who exhibits bias against one minority group will be more likely to exhibit bias against other groups.

Fourth, we also investigate whether racial disparities exist along another dimension – the appraisal fees paid by minority and White owners. Our results indicate that such differences are trivially small for Black and Hispanic owners. For example, we find that Black owners paid \$1.96 more, on average than White owners (without controlling for observable differences). After controlling for location, time, and property type, we find that Black and Hispanic owners paid no more than similar White owners. Note that we only observe the value from the final appraisal used by the lender. If multiple appraisals were ordered to arrive at a sufficiently high valuation, our estimates of racial valuation disparities could be downward biased. Although we cannot directly observe whether multiple appraisals were conducted, if they were, the borrower would have likely paid multiple appraisal fees. However, we find no evidence that minorities are more likely to pay high total appraisal fees ($>$ \$600).

Our results suggest that the appraisal stage of the mortgage process contributes to observed racial disparities in real estate markets, consistent with research that documents racial discrimiation by real estate agents (Ondrich, Ross, and Yinger, 2003; Page, 1995; Zhao, Ondrich, and Yinger, 2006) and mortgage lenders (Black, Schweitzer, and Mandell, 1978; Black, Boehm, and DeGennaro, 2003; Munnell et al., 1996; Ambrose, Conklin, and Lopez, 2021; Bartlett et al., 2022). However, our study does not support the hypothesis that valuation disparities are driven only by White appraisers.

Our findings contribute to three strands of the literature. First, our analysis speaks directly to the current policy debate over the role of appraisals in promulgating the observed differences in homeownership experiences across races (Perry, Rothwell, and Harshbarger, 2018; Pinto and Peter, 2021a,b; Freddie Mac, 2022; Williamson and Palim, 2022). Our analysis is most closely related to Williamson and Palim (2022). Our results documenting lower appraisals for minorities are broadly consistent with Williamson and Palim (2022), but our analysis differs on several dimensions. Our sample covers a different time – one that was markedly different in terms of lending practices and regulatory oversight. We also examine racial disparities in appraisal fees. We additionally explore the interaction of owner and appraiser races, which speaks to the debate as to whether increased appraiser racial diversity, *per se*, will eliminate racial disparities in valuation.

Second, we contribute to the literature assessing appraisal error. Given the importance of collateral valuation to the credit origination channel, a large literature examines how appraisals and appraiser error impact mortgage originations (Kruger and Maturana, 2021; Mayer and Frank, 2021; Fout, Mota, and Rosenblatt, 2021; Agarwal, Ambrose, and Yao, 2020; Conklin et al., 2020; Bogin and Shui, 2020; Eriksen et al., 2020; Diaz-Serrano, 2019; Demiroglu and James, 2018; Ding and Nakamura, 2016; Griffin and Maturana, 2016; Piskorski, Seru, and Witkin, 2015). For example, our analysis showing that appraisal bias is unrelated to individual appraiser race expands on the work of Tzioumis (2018), who shows that appraiser bias is unrelated to experience, and Conklin et al. (2020), who link competition in the appraisal industry with appraisal bias. In addition, Kruger and Maturana (2021) document how lender size interacted with new appraisal regulations to affect the incentive for appraisers to inflate valuations. Given that our analysis is based on mortgage originations by a single lender, we leave to future research the task of exploring the interaction of lender size and appraiser race as a possible channel for the observed differences in appraisal bias across race.

Finally, our analysis contributes to a greater understanding of the role of AVMs in mitigating possible appraisal bias. For example, our finding of a downward bias in AVM valuations for minority owners suggests a more nuanced interpretation of the systematic upward bias of AVM estimates documented in Kruger and Maturana (2021) and Eriksen et al. (2019).

2. Data

2.1. Appraised Values, Property and Owner Information

We use data on first-lien residential mortgage applications from New Century Financial Corporation, one of the largest subprime mortgage lenders leading up to the global financial crisis. New Century sourced its loan applications primarily through independent mortgage brokers that ordered appraisals through third-party residential real estate appraisers. Although the New Century data are limited to a single lender, Ambrose, Conklin, and Yoshida (2016) and Ambrose, Conklin, and Lopez (2021) provide evidence that New Century was representative of the subprime market as a whole. Approximately 45,000 separate mortgage brokerage firms ordered appraisals from 61,000 unique appraisers in the New Century data, which reduces concerns that our findings are specific to one lender.[9] The data include both funded and unfunded mortgage applications from 2000 to 2007. For each application file, New Century recorded property and loan characteristics (e.g., investment property, second home, refinance or purchase), as well as the location (ZIP code) of the property serving as collateral for the loan.

The New Century (NCEN) data contain several fields that are central to our analysis. First, the NCEN data include the borrower's Home Mortgage Disclosure Act (HMDA) race code.[10] Second, the NCEN data contain the full name of the appraiser, which we use to infer the appraiser's race.

[9]Approximately 35,000 unique appraisers remain in our final sample after merging with another mortgage dataset and focusing on appraisals for mortgages that were refinanced. The original data include an appraiser ID field, but we do not use this variable because it is thinly populated. We use each unique appraiser name-state combination to identify an individual appraiser. This means that the number of unique appraisers in our data may somewhat under or overstate the true number of appraisers.

[10]We use the race code of the primary borrower for applications with multiple borrowers. If the ethnicity reported is "Hispanic or Latino," we classify the borrower as Hispanic. If ethnicity is reported as "Not Hispanic or Latino," then we use the following race codes/classifications: "American Indian or Alaska Native," "Asian," "African American," "Hispanic," "Native Hawaiian or Other pacific Islander," or "White." We combine "Asian" and "Hawaiian or Other Pacific Islander" into one group and use the following final categories: American Indian or Alaskan Native, Asian or Pacific Islander (Asian), Black, Hispanic, and White. Our main analysis focuses on Asians, Blacks, Hispanics, and Whites.

The race classification algorithm is discussed in detail below. Third, we observe the appraised value for the subject property, which will be compared to a "race-blind" automated valuation estimate.

2.2. Automated Valuation Model Value Estimates

To obtain AVM property value estimates, we merge New Century funded loans with Lewtan's ABSNet Loan and HomeVal datasets. ABSNet provides detailed loan level information on loans packaged into private-label (non-agency) mortgage securitizations (PLS). ABSNet data are sourced from mortgage servicer and trustee data tapes and cover approximately 90% of the PLS market over our sample period. The HomeVal data, which are linked to the ABSNet mortgage data, provide an estimate of value (at the time of origination) of the property serving as collateral for each mortgage in the sample. These value estimates were likely not available to appraisers as they come from a proprietary AVM developed by Collateral Analytics—an industry-leading provider of valuation solutions—for the purpose of informing investors about the underlying collateral of PLS products.[11]

We follow the matching procedure from Kruger and Maturana (2021), which merges the New Century and ABSNet/HomeVal datasets using the following variables: *ZIP Code*, *First Payment Date*, *Interest Rate Type* (fixed or adjustable rate), *Credit Score*, and *Loan Amount*.[12] By keeping only unique matches, we successfully match 40% of the funded loans in the New Century data, which is similar to Kruger and Maturana's match rate of 38% over a slightly different sample period. We include observations where the loan amount that the borrower applied for is between \$30,000 and \$1,000,000; the loan-to-value ratio is less than 103%; and the combined loan-to-value ratio (CLTV) is between 25% and 125%. Both an appraised value and an AVM valuation must be available for inclusion in our main sample. Following Kruger and Maturana (2021), we exclude observations where the appraisal to AVM (or app-to-AVM) ratio is less than 0.3 or greater than 3.

[11] Additional background on the AVM is available in Section A.1 of the Online Appendix.

[12] Credit score must be within 10 points, while loan amount must be within \$1,000.

For precision, hereafter, we refer to these data as the ABSNet-NCEN matched sample.

2.3. Identifying Appraiser Race

In some of our analysis, we examine the interaction between the property owner's and appraiser's race. Although the property owner's race is disclosed in the New Century data, we do not directly observe the race or ethnicity of the appraiser. However, we can infer the appraiser's race and ethnicity using the Bayesian Improved First Name Surname (BIFS) classifier approach, which is similar in spirit to the methodology used by regulators to determine consumer race and ethnicity (Consumer Financial Protection Bureau, 2014). As noted by Ambrose, Conklin, and Lopez (2021), Bayesian-based classification methods have also been used to infer an individual's race or ethnicity in various court cases (e.g., Guardians Ass'n of N.Y.C. Police Dep't v. Civil Serv. Comm'n (1977)).

The intuition of the Bayesian Based classifier approach is to calculate the probability (Bayesian score) that a person self-identifies with a certain race or ethnicity based on the first name and surname of the individual. A Bayesian score for each race is calculated for every appraiser in our sample using:

$$p(r|f,s) = \frac{p(r|s)p(f|r)}{\sum_{r=1}^{6} p(r|s)p(f|r)}$$

where $p(r|f,s)$ is the conditional probability of an individual self-identifying as race *r* given the individual's first name f and surname *s*. Race (r) may be one of six categories including *American Indian or Alaskan Native*, *Asian or Pacific Islander*, *Black*, *Hispanic*, *White*, and *Two or More Races*.[13] We then construct a discrete race categorization by applying a "maximum a posteriori" (MAP) classification scheme that assigns the appraiser to the race associated with the highest Bayesian score.[14] Although we cannot directly test the accuracy of BIFS within our sample, we can compare the racial distribution of appraisers using our methodology to appraiser demographic

[13]We must assume that $p(f|r) = p(f|r,s)$. If the first or surname name is missing, we use racial information from only the available name.

[14]A more detailed discussion of our race classification algorithm is provided in Appendix A.2. Ambrose, Conklin, and Lopez (2021) use a similar method to examine disparities in mortgage pricing across borrower and broker race.

data released by the Appraisal Foundation and the Appraisal Institute. The Appraisal Foundation is "Authorized by Congress as the Source of Appraisal Standards and Appraiser Qualifications," while the Appraisal Institute is the largest professional association of real estate appraisers in the United States. We report the share of appraisers in each racial category in Appendix Table A.1. Based on the MAP BIFS algorithm, the overwhelming majority (91%) of appraisers are identified as White, whereas 2%, 3%, and 4% of appraisers are classified as Asian, Black, and Hispanic, respectively. We note that these numbers are nearly identical to the appraiser racial distribution figures released by the Appraisal Foundation and the Appraisal Institute, reported in the third and fourth columns of Table A.1, respectively. The similarities in racial shares across columns lends credibility to our racial classification algorithm. It also confirms that minorities are underrepresented in the appraisal industry.[15]

Table 1 provides details on the appraisal counts by appraiser and owner race for the subset where both race variables are not missing. White appraisers account for most (86%) of the 205,914 appraisals. Hispanic appraisers account for 7.6% of the appraisals, whereas Black and Asian appraisers each have about a 3% share. Interestingly, owners tend to work with appraisers of the same race. For example, Black owners account for 20% of the sample (41,965/205,914), but conditional on the appraiser being Black, the share of Black owners nearly doubles to 38% (2,032/5,287). This same-race matching pattern is also found in mortgage broker-borrower interactions (Ambrose, Conklin, and Lopez, 2021) and mortgage loan officer-borrower pairings (Frame et al., 2021; Jiang, Lee, and Liu, 2021). A potential explanation for this pattern is that appraisers tend to concentrate their business geographically (Conklin, Diop, and Qiu, 2021). If they also tend to work close to where they reside, they are more likely to encounter owners of the same race. Alternatively, if same-race matches lead to more favorable valuations, then owners may select into appraisers of the same race. We test this latter explanation below.

[15] See https://www.appraisalinstitute.org/file.aspx?DocumentId=2342.

2.4. Descriptive Statistics

We report the descriptive statistics for the NCEN-ABSNet matched sample in Table 2. The average appraised value is \$278,000, which is slightly higher than the average AVM value of \$271,000.[16] Our primary valuation metric is the appraisal value divided by the AVM value, which we term the app-to-AVM ratio. The mean app-to-AVM ratio of 1.09 indicates that, on average, appraisal values are 9% above AVM estimates, which is consistent with prior work (Demiroglu and James, 2018; Kruger and Maturana, 2021). The average of our preferred valuation metric, app-to-$\hat{V}$, is slightly lower at 1.06. Although the average is greater than 1, it is not uncommon for appraised values to be below the benchmark valuation ($\hat{V}$). In fact, 8% of the appraisals have an appraised value that is 20% below $\hat{V}$ (App-to-$\hat{V}$ $<$0.8).

Another metric that we examine is the dollar amount of fees that an owner paid for one or more appraisals during the loan origination process. The appraisal fee(s) charged to the borrower is recorded for approximately 35% of the appraisals in our sample and range from \$75 to \$1,200 with an average of \$345.[17] Two percent of applications have appraisal fees greater than or equal to \$600. High appraisal fees could be indicative of a particularly difficult to value property (e.g., multi-unit rental property) or that more than one appraisal was completed. We will return to this point later in our analysis.

Most property owners in our sample are White (53%), whereas Hispanic and Black owners represent 23% and 20%, respectively. Asian owners account for only 4% of the observations. Blacks and Hispanics represent a much larger share of our data than in other recent studies using mortgage applicant or origination data (e.g., Freddie Mac (2021), Bhutta, Hizmo, and Ringo (2021),

[16] Our results remain unchanged after excluding observations where the appraisal or AVM value are above \$1 million.

[17] The appraisal fee field is missing or zero for many of our observations as they may have been paid outside of escrow. For extremely low values of appraisal fees (e.g., zero), we suspect that the true cost of the appraisal is higher, but the broker/lender did not directly bill the borrower. In these cases, it is quite possible the originator increased other fees (e.g., origination fees; broker fees) to cover the cost of the appraisal. In other words, extremely low values of appraisal fees are likely not informative of actual appraisal fees. In our fee analysis, we include observations where the appraisal fee is at least \$75 but no more than \$1,200.

and Gerardi, Willen, and Zhang (2020)), which is likely for two reasons. First, our sample period covers the housing boom of the early to mid-2000s, which saw a large increase in homeownership rates for these minority groups. Second, New Century was primarily a subprime lender, and subprime loans were disproportionately originated to Blacks and Hispanics.[18]

Panel B of Table 2 reports mean values of the variables by owner race. Although most of the appraisals are for owner-occupied single-family residences, property values (whether estimated by appraisal or AVM) vary considerably across race categories. Asian owned properties are higher in value than those owned by the other three racial groups, on average. Hispanic and White owned properties are unconditionally similar in value, whereas the average Black owned property is valued lower. For all races, the average appraised value is higher than the average AVM estimate. We plot the distribution of app-to-AVM ratios by owner race in Figure 1. Although the app-to-AVM distributions vary across race, there are no glaring unconditional differences suggesting that White owned homes receive more favorable valuations than minority-owned homes. As with app-to-AVM, the average app-to-$\hat{V}$ is greater than 1 across all races. Even though, White owned properties appear to have the highest app-to-$\hat{V}$ratio, Whites are (unconditionally) as likely to receive low valuations (app-to-AVM$<$.8). The difference in the low valuation likelihood between Whites and the other race categories is quite small.

[18]See Faber (2013) for evidence from the Home Mortgage Disclosure Act (HMDA) data regarding the disproportionate share of minority borrowers that originated subprime mortgages prior to the Great Financial Crisis of 2007.

3. Racial Disparities in Appraisals on Refinance Loans

3.1. Appraisals and Owner Race

We formally test whether appraisers treat White and minority borrowers differently by estimating a model of the following form:

$$Y_i = \delta_1 A_i + \delta_2 B_i + \delta_3 H_i + X_i \beta + \zeta_i + \gamma_i + \omega_j + \epsilon_i, \qquad (1)$$

where Y_i represents the appraisal-to-AVM ratio for property i; A_i, B_i, and H_i are indicator variables denoting whether property owner self-identifies in the HMDA disclosure fields as non-Hispanic Asian (A), non-Hispanic Black (B), or Hispanic (H), respectively, with non-Hispanic White owners as the omitted group; X_i stands for control variables for property type, including indicator variables for second homes, investment properties, multi-unit properties, condominiums, planned unit developments (PUDs), and additional attributes as discussed below; ζ_i and γ_i represent the location (ZIP Code) and origination year fixed effects, respectively, that account for time-invariant spatial factors and temporal changes in national economic conditions that impact valuations; ω_j is an appraiser fixed effect; and ϵ_i is an error term. The δs are the parameters of interest to be estimated.

Although including appraiser fixed effects in Equation (1) precludes the direct investigation of the role of the appraiser's race, this modeling choice allows us to factor appraiser heterogeneity and approximate the identification strategy in experimental paired-audit studies (e.g., Ayers and Siegelman (1995)). As a result, the δ parameter estimates rely on the variation in the valuation and race among appraisers who completed at least one appraisal for a White owner and one appraisal for a minority owner; this subsample represents 85% of the sample. Thus, the null hypothesis is that the owner's race does not affect the appraiser's property valuation once accounting for confounding factors.

Column (1) of Table 3 presents the ordinary least squares (OLS) coefficient estimates of the effect of the property owner's race on the app-to-AVM ratio based on Equation (1). We find that the app-to-AVM of Black and Hispanic owned homes are about 0.9 and 0.7 percentage points lower, respectively than that of White owned homes. These marginal differences are statistically significant at the 1% level. For statistical inference, we use robust heteroscedasticity-consistent standard errors based on a Huber-White-sandwich estimator. In contrast, we do not observe a statistically significant difference in the average app-to-AVM ratio between White and Asian owned homes when accounting for appraiser fixed effects and other factors.

We add to our model a measure of the accuracy of the AVM estimate. HomeVal provides a property-level confidence score for its AVM estimates, which range from 50 to 99, with a higher score indicating greater confidence in the value estimate. As AVM error could be large for some properties (Molloy and Nielsen, 2018; Jiang and Zhang, 2022), these confidence scores allows our model to condition point estimates on valuation uncertainty. When we include the AVM confidence score in column (2) of Table 3, the minority coefficients are nearly identical to the estimates in the first column, suggesting that our results are not driven by AVM value uncertainty.[19] Since the condition of the property (unobservable to us) may correlate with app-to-AVM ratios and owner race, we include two additional variables as proxies for it: a binary variable indicating if the proceeds from a cash-out refinance will be used for home improvements, and the number of years the owner has lived at the residence. Column (3) of Table 3 shows that both of the property condition proxies are negatively related to app-to-AVM ratios, but they have little impact on the race coefficients.

In column (4), we include several owner-level controls that may be correlated to unobserved

[19] AVM confidence score is missing for some observations. We set "AVM Confidence" to zero for missing values and also include a dummy variable to identify those observations. We adopt the same approach for the variables with missing values included in columns (3) and (4) of Table 3. Descriptive statistics, including the share of observations with missing values for these variables, are presented in Appendix Table A.3.

property characteristics affecting property value. These controls include the natural logarithm of the owner's total financial assets, the natural logarithm of the owner's monthly income, the owner's age, and the number of dependants that the owner declares on the mortgage application. Additionally, we interact the number of years the owner has lived at the property with income and number of dependants.[20] These interactions are included to consider the effects of property depreciation, as higher income owners may better be able to maintain their properties, while more dependents (e.g., children) may be associated with greater wear and tear over time. We observe that including these owner-level controls impacts all of the race coefficients. The Asian owner coefficient now becomes -0.8%, while the Black coefficient is reduced (in absolute magnitude) to -0.6% with a 95% confidence interval of -0.2% and -1%, capturing the previous point estimates. The Hispanic coefficient becomes essentially 0.

However, one concern is that Black and Hispanic owners obtain multiple appraisals on the property to get a fair value, which could bias the δ parameters towards zero. In recent press accounts of racial valuation bias, a minority owner typically receives an initial appraisal that is well below market value. The applicant then orders another appraisal but takes steps to conceal his or her race from the appraiser. In this subsequent appraisal, where the owner's true race is not known, the valuation comes in much higher. Although we cannot directly observe whether multiple appraisals are completed, we can use the appraisal fees as a proxy for multiple appraisals. Intuitively, an extremely high appraisal fee likely signals that more than one appraisal was required. Of course, the appraisal fee could be high for other reasons, such as a particularly difficult-to-value property. Furthermore, an average (or low) appraisal fee does not necessarily rule out the possibility of multiple appraisals. But high appraisal fees may serve as a reasonable proxy for the use of multiple appraisals. Thus, we substitute the dependent variable in Equation (1) with either the Appraisal Fees or an indicator for whether the Appraisal Fees exceeds $600, which is slightly under twice the average appraisal fee.

[20] We also interact years at residence with the missing income and missing dependants dummies.

Table 4 reports the effect of the owner's race on the amount of the appraisal fees in column (1) and the likelihood of encountering high appraisal fees in column (2); we use the saturated model specification that appeared in the last column of Table 3. We find no evidence of systematic racial disparities in appraisal fees. We also do not find evidence indicating that minorities are more likely to require multiple appraisals (proxied by high appraisal fees) in the loan application process.

Another concern is that AVMs could systematically undervalue (or overvalue) minority owned homes. For example, within a given neigbhorhood, minorities may select into properties that are different than those owned by Whites in ways not captured in an AVM. But, because the appraiser has local market knowledge and typically performs an on-site inspection, the appraiser observes these differences and accounts for them in his valuation. This could bias our estimates of the δ parameters when using AVMs as the benchmark valuation for appraisals. We address this concern in the next section.

3.2. Adjusting AVM to Account for Soft Information

To account for the concern that AVMs may systematically undervalue (or overvalue) minority-owned homes or overlook soft information about a property that an appraiser would notice when visiting a home in person, we leverage the fact that in our sample of purchase mortgages, we observe both the purchase price of the property and the AVM estimate for these mortgages. This allows us to project the value (purchase price) as a function of AVM and indicators of the owner's race, along with a rich set of control variables and fixed effects. The projection of this model provides an adjustment to valuation estimates for any systemic differences by owner race. Assuming that the property's purchase price (P) in an arm's length transaction is the true market value (V) of a property, then

$$V_i \equiv P_i = \text{AVM}_i \times \mathcal{T}_i$$

where $\mathcal{T}_i$ is the price adjustment factor that accounts for discrepancies between the AVM and the property's true market value.

To recover $\mathcal{T}_i$, we employ the following model:

$$\ln(P_i) = \rho \ln(AVM_i) + \delta_1 A_i + \delta_2 B_i + \delta_3 H_i + X_i \beta + \zeta_i + \gamma_i + \varepsilon_i \tag{2}$$

where $\ln(AVM_i)$ is the natural log of the AVM, which captures the easily observable, or hard information, associated with the property. The parameter ρ is the conditional price elasticity of the AVM, and ε_i is an error term. The variables included in X (e.g., income, assets, AVM confidence, etc.) serve as proxies for soft information about the property – attributes that impact value that are not captured in the AVM estimate. The other variables on the right-hand-side are the same as in Equation (1), except for the exclusion of appraiser fixed effects. The market value in levels can be estimated as:

$$\hat{V} = \hat{P} = \exp\{\widehat{ln(P_i)} + \hat{\sigma}^2/2\} \tag{3}$$

where $\hat{\sigma}^2$ is the standard error of the regression (Equation (2)).

To implement this procedure, we first estimate the fully saturated specification of Equation (2) using a sample of purchase mortgage loans, which report the purchase price.[21] The binary race variables (A_i, B_i, H_i) specify the race or ethnicity of the purchaser who is the borrower in this setting. After estimating the coefficients, we use them to predict the market value of the properties (out-of-sample) in the refinance mortgage sample using Equation (3). Finally, we estimate our baseline regression, Equation (1), using the refinanced mortgages but with the "corrected" AVM values in the dependent variable as follows:

$$\frac{AppraisedValue_i}{\hat{V}_i}. \tag{4}$$

[21] Descriptive statistics for the home purchase sample are reported in Table A.2 and discussed in Section A.3 of the appendix.

In Table 5, we report the results from correcting the AVM for systemic differences in home prices across race. The first column shows the coefficient point estimates of Equation (2) using the purchase sample. The R^2 is high, indicating a strong goodness of fit. The coefficients on Asian, Black, and Hispanic are positive and statistically significant at the 1% level, which rules out the concern that minority borrowers select into lower priced homes and accounts for variation in prices from unobserved soft information that the AVM does not capture but correlates with race.

Column (2) of Table 5 reports the coefficient estimates of Equation (1) using the sample of refinanced mortgages and the app-to-$\hat{V}$ measure. Compared to the corresponding estimates in Table 3, these estimates of appraisal bias relative to the estimated purchase price are greater in absolute value. They suggest that the homes of Asians, Blacks, and Hispanics are appraised at a statistically significant lower value than those of White homeowners. On average, appraisers discount property values by about 1.9 percentage points for Asian owners, 4.1 percentage points for Black owners, and 2.6 percentage points for Hispanic owners when compared to the valuations of White-owned homes. These differences are statistically significant at the 1% level of confidence.[22] This finding suggests that racial valuation disparities were visible but much lower than the figures ($\approx$ 25% discount for Black owners) reported in recent anecdotal accounts in the popular press (Kamin, 2020; Malagón, 2020; Haythorn, 2020).

We also investigate the possibility that certain groups may be more likely to get extremely low valuations, which would be consistent with that anecdotal evidence. Specifically, in column (3) of Table 5, we use an indicator variable ($1[\textit{App-to-}\hat{V} < .8]$) that takes a value of one if the appraised value is less than 80% of the predicted valuation, which is equivalent to one-standard-deviation below the average app-to-AVM ratio; and zero if otherwise.[23] We find a coefficient of 0.015 on

[22]Appendix Table A.4 reports results using alternative specifications of Equation 2 to arrive at our estimate of $\hat{V}$. Column (1) includes interactions between owner race and Ln(AVM) to estimate $\hat{V}$. In column (2) we interact Ln(AVM) and onwer race with all controls, while in column (3) we estimate the $\hat{V}$ models separately by race. Although the magnitudes of the discounts vary slightly across columns, the interpretations are consistent with the main results in column (2) of Table 5.

[23]Eight percent of the app-to-$\hat{V}$s are below 0.80.

the indicator for Hispanic Owner and a coefficient of 0.019 on the indicator for Black Owner, which are both statistically significant at the 1% level. The effect of Asian Owner is positive and statistically significant at the 5% level. The results imply that homes owned by Blacks and Hispanics are about 27% and 21% more likely than similar White owned homes to be appraised one or more standard deviations below the average app-to-AVM value, respectively. Asian owned homes are about 11% more likely to fall into this category than White owned homes.[24] Thus, the results provide evidence that homes are more likely to be severely undervalued when the owner is Asian, Black, or Hispanic.

3.3. Do the App-to-Adjusted AVM Results Vary with ZIP Demographics, House Price Levels, or Appraisal Year?

Accounts of appraisal discrimination often imply that minority owners living in mostly White neighborhoods are treated differently from White owners in the same neighborhood. Furthermore, it is possible that properties in areas preferred by various racial or ethnic groups might be more difficult to appraise or have greater price dispersion, which would lead to the observed differences in *App-to-*$\hat{V}$. To investigate these possibilities, we examine whether the impact of owner race on app-to-AVM varies with ZIP code racial composition. We supplement our data with population racial distribution information at the ZIP code level from the 2011 American Community Survey 5-year estimates, then estimate Equation (1) (but without appraiser fixed effects) separately in ZIP codes with a high white population share ($\geq$80%), those in a high minority population share ($\geq$80%), and "mixed race ZIPs" (<80% White and <80% Minority share).[25] We use the app-to-$\hat{V}$ (as in Equation 4) as the dependent variable.

[24]Hispanic owned $21.4\% = 0.015/0.07$, Black owned $21.1\% = 0.019/0.09$, Asian owned $11.4\% = 0.008/0.07$ effects.

[25]Since we estimate the models separately for each neighborhood type, which reduces the sample size in each regression, we do not include individual appraiser fixed effects here. Approximately 56%, 19%, and 25% of the appraisals are in mixed ZIPs, high White population share ZIPs, and high minority population share ZIPs, respectively.

Figure 2 plots coefficient estimates from the app-to-$\hat{V}$ regressions reported in Appendix Table A.5 in the appendix. In the top left panel (mixed race ZIPs), all the coefficient estimates are negative for all minority groups and are of similar magnitudes as reported in column (2) of Table 5. In primarily White ZIPs (top right panel) and Minority ZIPs (bottom left panel), appraisal discounts on minority-owned homes are surprisingly of similar magnitudes as in mixed neighborhoods. However, the confidence intervals are wider in these samples, reflecting the smaller sample sizes. Overall, the differences in valuation are statistically similar to prior estimates and the individual race coefficients are not significantly different across the different ZIP types. For example, the discount in valuations on Black owned properties are 4.4 percentage points in primarily White ZIP codes and 3.8 percentage points in primarily minority ZIP codes. Both estimates fall within each other's 95% confidence intervals.[26] We observe a similar pattern for Asians and Hispanics across neighborhoods.

We also test whether racial impacts on valuation vary with house price levels using house price data from Zillow. The Zillow data include a median house price value estimate in 2005 for all ZIP codes. This measure allows us to create house price level quintiles. We classify ZIPs in the first, second and third quintile as "low price ZIPs," ZIPs in the fourth quintile as "mid price ZIPs", and ZIPs in the fifth quintile as "high price ZIPs." The share of our appraisals in low, mid, and high price ZIPs is 32%, 29%, and 39%, respectively.[27] We then estimate the regressions separately for the three different house price level categories and plot the coefficients in Figure 3.[28] The results are similar across ZIP code house price levels, except for Asians in low-price ZIPs. Minority owners generally receive lower appraisals irrespective of the ZIP price level.

Lastly, we examine whether the appraisal racial disparities vary over time by regressing the

[26]Each of the panels in Figure 2 is based on a separate regression. When we formally test whether the Asian Owner coefficient in mixed neighborhoods is different from that in White or minority neighborhoods, we fail to reject the null hypothesis. The same holds for the White Owner and Hispanic Owner coefficients.

[27]Roughly 28% of our appraisals are in California, where house price levels are relatively high, which explains why high price ZIPs have the largest share of appraisals.

[28]The underlying results for this figure are reported in Appendix Table A.6.

app-to-$\hat{V}$ on the owner's race separately for each application year from 2003 to 2006.[29] Figure 4 shows the coefficient estimates across years (see also Table A.7 in the appendix). Again, even though the coefficients vary somewhat over time, app-to-$\hat{V}$disparities across race remain much the same. Thus, we conclude that the observed discounts are not the result of homeowners sorting into racial enclaves or differences in property quality reflected in neighborhood price levels.

4. The Role of Appraiser Race

To this point, our analysis has focused on documenting differences in appraisals across racial and ethnic groups. Furthermore, we do not find that these differences arise from issues related to the accuracy of the AVM model, observable or unobservable property characteristics, the potential for minorities obtaining multiple appraisals, or that minorities select into lower quality homes. Thus, in this section we investigate the role of individual appraisers and the interaction of the appraiser with homeowners having the same or different race/ethnicity as possible causal mechanisms.

4.1. Appraiser Race

First, we investigate the effect of the interaction of the owner's and appraiser's race on valuation by expanding the regression specification as follows:

[29] We report the results only for 2003 thru 2006 because 92% of the observations in ABSNet-NCEN matched sample are from those years. The sample sizes in the other years (2000-2002; 2007) are too small to provide meaningful estimates.

$$
\begin{aligned}
Y_i = & \delta_1^W A_i \times P_j^W + \delta_1^A A_i \times P_j^A \\
& + \delta_2^W B_i \times P_j^W + \delta_2^B B_i \times P_j^B \\
& + \delta_3^W H_i \times P_j^W + \delta_3^H H_i \times P_j^H + \\
& + \delta_4^A W_i \times P_j^A + \delta_4^B W_i \times P_j^B + \delta_4^H W_i \times P_j^H \\
& + X_i \beta + \zeta_i + \gamma_i + \epsilon_i
\end{aligned} \tag{5}
$$

where Y_i is set to the app-to-$\hat{V}$ ratio (Equation (4)); W_i is 1 if the owner is White, and 0 if otherwise; and P_j^k stands for the race of appraiser j with $k \in \{W, A, B, H\}$ indicating the appraiser's race. For example, $B_i \times P_j^W$ reflects the interaction of a Black owner and a White appraiser. The specification also includes interaction terms for when the owner is White ($W_i = 1$) and the appraiser belongs to one of three minority groups (A, B, or H). The omitted category is $W_i \times P_i^W$, White owned properties appraised by White appraisers. Thus, each δ can be interpreted as the marginal difference in valuation relative to White owned homes appraised by White appraisers.[30] This specification allows us to test for systematic differences in the valuation of minority-owned homes based on the appraiser's race, in particular, if the treatment is more favorable when the appraiser and owner are of the same race. More formally, we test for conditional mean differences between Asian owned homes appraised by White versus Asian appraisers (δ_1^W vs δ_1^A), Black owned homes appraised by White versus Black appraisers (δ_2^W vs δ_2^B), and Hispanic owned homes appraised by White versus Hispanic appraisers (δ_3^W vs δ_3^H). Equation (5) includes property and borrower characteristics and, except for appraiser fixed effects, the same set of fixed effects as Equation (4).

Table 6 presents the estimated coefficients for OLS regressions of the app-to-$\hat{V}$ on indicators

[30]Due to concerns about statistical power, we exclude observations (4%) where both the appraiser and the owner are minorities, but not of the same race. These groups contain very few observations.

for owner and appraiser race that build up to (Equation (5)). All columns include ZIP code and year fixed effects, as well as property type and owner controls. Column (1) includes owner race coefficients, and thus the results are very similar to those in column (2) of Table 5 despite the omission of appraiser fixed effects. Column (2) of Table 6 replaces the owner race indicators with appraiser race indicators. The Black and Hispanic appraiser coefficients are essentially zero, however, the results indicate that Asian appraisers assign slightly higher appraisals than White appraisers (0.6 percentage points with 10% statistical significance).

Next, we include the aforementioned indicators for the owner-appraiser race pairs (as in Equation (5)). Again, the omitted category in the regression is a White owner matched to a White appraiser and all regression coefficients in column (3) can be interpreted as the marginal difference in the app-to-$\hat{V}$ ratio relative to White owners using White appraisers. To ease interpretation, we plot the coefficients from column (3) in Figure 5. Relative to $\hat{V}$, appraisals received by White owners matched with minority appraisers are no different from those received from White appraisers.

All the minority owner coefficients, regardless of appraiser race, are negative, and similar in magnitude to our previous estimates, which suggests that minorities receive slightly lower valuations. However, the magnitudes of the app-to-$\hat{V}$ discount experienced by some groups vary with appraiser race. Black owners receive on average a similar appraisal discount from White appraisers as from Black appraisers (4.2 vs 4.1 percentage points). On the other hand, Asian and Hispanic owners received lower appraisals from appraisers of the same race. Average discounts on Hispanic owned homes appraised by White and Hispanic appraisers are 2.4 and 3.1 percentage points, respectively, with the difference being statistically significant at 1% level. Similarly, Asian homeowners receive a 1.8 percentage point discount from White appraisers and a 2.9 percentage point discount from Asian appraisers—these two estimates are statistically different at 5% level from each other.

To summarize, minority owners do receive lower appraisals, on average, irrespective of the race of the appraiser. However, assigning an appraiser of the same race to the owner would not necessarily fix the problem. If anything, appraisal disparities suffered by minority homeowners seem to increase if the appraiser is of the same race as the owner.

4.2. Appraiser-specific Race Coefficients

In the previous sections we provide evidence of racial disparities in valuation. A key question is whether these differences are driven by large racial valuation gaps by a few appraisers, or if the differences are more systemic to the industry. To answer this question, we estimate appraiser-level racial disparities conditional on a host of control variables. More specifically, we estimate a slightly modified version of Equation (1) that takes the following form:

$$Y_i = \alpha M_i + \lambda_j \omega_j + \sum_j \delta_j \cdot (\omega_j \times M_i) + X_i \beta + \zeta_i + \gamma_i + \epsilon_i, \tag{6}$$

where Y_i is the app-to-$\hat{V}$ ratio for property i, as calculated in Section 3.2. M_i is a binary variable indicating whether the homeowner identifies with a racial minority group. All other variables are defined as before. For example, ω_j stands for individual appraiser fixed effects. By interacting the appraiser fixed effects with the minority owner indicators, we allow the minority effect on the app-to-$\hat{V}$ ratio to vary uniquely for each appraiser who has appraised White and minority owned homes. Put differently, the gap in the app-to-$\hat{V}$ ratio that a minority homeowner encounters relative to a White homeowner depends on who appraises the property; this appraiser-specific gap is defined by $\hat{\alpha} + \hat{\delta}_j$.[31]

We estimate Equation (6) using OLS separately for each minority group (Asian, Black, Hispanic), while setting White homeowners as the base group each time. We collect the individual appraiser race effects ($\hat{\alpha} + \hat{\delta}_j$) and plot the distribution of these marginal effects in Figure 6. Panel A illustrates the distribution of the individual appraiser race effects from a regression where only

[31] $\hat{\alpha}$ is the minority coefficient for the individual appraiser that serves as the base or omitted category, in the regression.

White and Asian owned homes, appraised by 1,029 appraisers, are included in the sample.[32] Similarly, Panel B shows the distribution of the individual appraiser race effects using Black and White owned homes appraised by 4,634 appraisers, whereas Panel C does the same for Hispanic and White owned homes appraised by 4,458 appraisers. In line with our previous findings, the average appraiser-level race coefficients imply an appraisal bias of approximately -2 percentage points for Asians, -4 percentage points for Blacks, and -2 percentage points for Hispanics. The distribution is tight and symmetric for the three samples. There are appraisers with extreme negative coefficients (lower valuations for minorities), but there also positive extreme values (higher valuations for minorities), where extreme is defined as valuations greater than 30 percentage points. Furthermore, analysis of the marginal effects by appraiser race does not indicate a pattern pointing to a specific appraiser race as driving these results. For example, we find that 9% of Black appraisers have extremely low coefficients for black homeowners versus 5% for non-Black appraisers.[33] These extreme values are partly driven by appraisers that performed few appraisals. The takeaway from Figure 6 is that our findings are not the result of a few "bad" appraisers, but rather the tight distributions centered around the mean suggest that the appraisal-to-$\hat{V}$ gaps are a systematic characteristics of the appraisal process.

To gain further insight into the incidence of extreme racial disparities at the appraiser-level (conditional on our other controls), we plot in Figure 7 the cumulative distribution of the racial coefficients using the same data as Figure 6. In each panel, we list the number and share of appraisers with an extreme negative or positive coefficient ($\hat{\delta}_j < -0.3$ or $\hat{\delta}_j > 0.3$); that is, a 30 percentage point negative or positive difference. Panel A shows that for appraisers that complete appraisals for Asians and Whites, 34 appraisers, or 3%, have a large discount for Asian owners (<-0.3). In contrast, only 13 appraisers, or 1%, have a large positive app-to-$\hat{V}$ premium for Asian

[32] We exclude singleton observations that produce no variation as a result of a large number of control variables and zip code fixed effects used in the regressions.

[33] The results for Hispanic and Asian interactions are similar. We find that 4% of Asian appraisers having extremely low marginal effects (compared to 3% for non-Asian appraisers). In addition, we note that Hispanic and non-Hispanic appraisers account for 3% of the extremely low appraisal coefficients, respectively.

owners. Panel B repeats the same exercise for appraisers that completed appraisals for both Whites and Blacks. Twice as many appraisers have an extreme negative Black owner coefficient than have an extreme positive coefficient (235 extreme negative coefficients to 77 large positive). In Panel C, a similar pattern emerges in the Hispanic and White owner sample (121 extreme negative coefficients versus 74 large positive). Overall, Figure 7 shows that across all minority categories, it is much more common for an appraiser to have an extreme negative coefficient (lower valuation for minorities) than an extreme positive coefficient.

Finally, we ask whether an appraiser that discounts valuations for one minority group also discounts valuations for other minority groups. Intuitively, does an appraiser with a large Hispanic discount also have a large Black discount? Here again, we use the appraiser-level coefficient estimates from Equation (6). Figure 8 plots coefficient pairs for an individual appraiser. Panel A of Figure 8 plots the Asian and Black coefficients for the 634 appraisers that have both an Asian owner and Black owner coefficient. Panel B plots the appraiser-level Asian and Hispanic coefficients for the 738 appraisers with both an Asian and Hispanic coefficient, whereas Panel C includes 2,243 appraisers with both a Black and Hispanic coefficient. Across all three panels, there is clearly a positive relationship between the appraisers' coefficient pairs. The corresponding regression lines for the negative and positive coefficient pairs are plotted in red and blue, respectively, with the fitted equations and adjusted R^2 reported in the top right of each panel. In each case, the adjusted R^2 declines moving from the negative race coefficients ($X < 0$) to the positive race coefficients ($X > 0$). Figure 8 suggests that appraisers that discount valuations for one minority group do the same for other minority groups as well. But the regression lines also suggest that there is less correlation between race coefficients for appraisers that give favorable valuations to one minority group.

To summarize, the results in this section are not consistent with any one racial group driving the observed appraisal discount for minority homeowners. Thus, we view our findings as consistent with the application of standard appraisal rules and procedures followed by all appraisers, which results in minority homeowners tending to receive lower valuations on average, than individual appraisers specifically using race as a factor in determining the value of an individual property. However, we again note that regardless of whether the observed difference occurred due to disparate treatment or disparate impact, the implication is that minority homeowners, on average, had less access to their home equity than similar white homeowners.

5. Conclusion

Discrimination against racial minorities in the several stages of the home purchase process has resulted in lower homeownership rates for those groups. Attention in both the popular press and policy-making circles has recently centered on the appraisal process.

We use a large dataset of refinance loan applications which contains data on the property appraisal, the borrower and the appraiser to estimate models of appraisal bias. We find that appraisal-to-AVM gaps for property owned by Blacks are lower by 0.6 to 4.2 percentage points than comparable homes owned by Whites, depending on the comparison measure of home value. Hispanic and Asian households also receive lower valuations compared to White households. Interestingly, we find that these estimates do not decrease in magnitude when the appraiser shares the same race or ethnicity as the homeowner. These differences also do not vary greatly across neighborhood types or other demographic differences. Nor do we find large differences in appraisal fees.

Our examination of individual appraiser behavior suggests that the average appraisal bias is not simply caused by a few outliers but rather is more systematic. We find some evidence as well that appraisers who exhibit bias against one race will do so with other minority groups as well.

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6. Tables

Table 1. Appraisal Counts by Appraiser and Owner Race

Appraiser Race	Owner Race Asian	Black	Hispanic	White	Total
Asian	1,515	1,117	2,630	2,176	7,438
Black	149	2,032	1,068	2,038	5,287
Hispanic	609	2,354	8,015	4,743	15,721
White	6,285	36,462	35,765	98,956	177,468
Total	8,558	41,965	47,478	107,913	205,914

Note: This table reports the appraisal observation counts by appraiser and owner race. Appraiser race is inferred using the MAP BIFS algorithm.

Table 2. Descriptive Statistics for Main Refinance Sample

Panel A: Refinance Loans	Obs	Mean	Std. Dev.	Min	Max
Appraisal Value	222,269	\$277,987	\$171,488	\$35,000	\$2,600,000
AVM Value	222,269	\$270,685	\$176,949	\$17,000	\$3,600,000
App-to-AVM Ratio	222,269	1.09	0.29	0.30	3.00
App-to-$\hat{V}$	222,042	1.06	0.22	0.31	2.98
App-to-$\hat{V} < .8$	222,042	0.08	.	0	1
Appraisal Fee	78,065	\$345	\$94	\$75	\$1,200
Appraisal Fee $\geq$ \$600	78,065	0.02	.	0	1
Asian Owner	222,269	0.04	.	0	1
Black Owner	222,269	0.20	.	0	1
Hispanic Owner	222,269	0.23	.	0	1
White Owner	222,269	0.53	.	0	1
Second Home	222,269	0.01	.	0	1
Investment Property	222,269	0.06	.	0	1
Multi-unit	222,120	0.06	.	0	1
Condo	222,120	0.05	.	0	1
PUD	222,120	0.11	.	0	1

Panel B: Refinance Loans Mean By Owner Race	Asian	Black	Hispanic	White
Appraisal Value	\$399,165	\$242,604	\$290,485	\$276,786
AVM Value	\$397,187	\$234,196	\$285,987	\$268,276
App-to-AVM Ratio	1.05	1.12	1.07	1.09
App-to-$\hat{V}$	1.05	1.04	1.04	1.08
App-to-$\hat{V} < .8$	0.07	0.09	0.07	0.08
Appraisal Fee	\$388	\$341	\$353	\$339
Appraisal Fee $\geq$ \$600	0.06	0.02	0.03	0.02
Second Home	0.01	0.01	0.00	0.01
Investment Property	0.07	0.10	0.05	0.05
Multi-unit	0.05	0.09	0.09	0.03
Condo	0.11	0.04	0.05	0.05
PUD	0.14	0.10	0.09	0.11
Observations	9,127	45,263	50,901	116,978

Note: Panel A reports descriptive statistics for refinance applications that resulted in originated loans. Panel B reports the mean values of these variables by owner race. The standard deviation is not reported for binary variables.

Table 3. Appraised Value, AVM Estimates, and Owner Race

	(1) App to AVM	(2) App to AVM	(3) App to AVM	(4) App to AVM
Asian Owner	-0.003	-0.003	-0.004	-0.008**
	(0.003)	(0.003)	(0.003)	(0.003)
Black Owner	-0.009***	-0.009***	-0.009***	-0.006***
	(0.002)	(0.002)	(0.002)	(0.002)
Hispanic Owner	-0.007***	-0.007***	-0.008***	-0.002
	(0.002)	(0.002)	(0.002)	(0.002)
AVM Confidence		-0.001***	-0.001***	-0.001***
		(0.000)	(0.000)	(0.000)
Cash for Home Improvements			-0.011***	-0.008***
			(0.003)	(0.003)
Years at Residence			-0.001***	0.004**
			(0.000)	(0.001)
Ln(Total Assets)				0.026***
				(0.003)
Borrower Age				0.000***
				(0.000)
Ln(Income)				0.064***
				(0.002)
Dependents				0.001
				(0.002)
Years at Residence × Ln(Income)				-0.000**
				(0.000)
Years at Residence × Dependents				-0.000**
				(0.000)
Observations	195,158	195,158	195,158	195,158
Adjusted R-squared	0.184	0.185	0.185	0.195
Zip FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Property Type Controls	Y	Y	Y	Y
Appraiser FE	Y	Y	Y	Y
Missing Characteristics Dummies	N	Y	Y	Y
Missing Characteristics Interactions	N	N	N	Y

Note: This table presents estimates from regression models where the dependent variable is the appraisal-to-AVM ratio. Property type controls include indicators for whether the collateral is a second home, investment property, multi-unit property, condominium, or part of a planned unit development. Columns (2) - (4) include missing characteristics dummies for the for the additional controls reported in each column. For example, column (2) includes a dummy variable that takes a value of one if there is no AVM confidence score for the AVM estimate. *AVM Confidence* is set to 0 when the AVM confidence score is unavailable. Similar variable construction is used for the additional controls in column (4). The Missing Characteristics Interactions indicate that *Years at Residence* is interacted with the dummy variables for whether *Ln(Income)* or *Dependents* are missing. The sample includes refinance applications that resulted in originated loans from 2000 to 2007. Robust standard errors are reported in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.10$

Table 4. Appraisal Fees and Owner Race

	(1) Appraisal Fee	(2) Appraisal Fee > \$600
Asian Owner	2.974	0.001
	(2.411)	(0.005)
Black Owner	-1.653	-0.003
	(1.254)	(0.002)
Hispanic Owner	1.325	0.001
	(1.132)	(0.002)
Observations	63,662	63,662
Adjusted R-squared	0.349	0.153
Zip FE	Y	Y
Year FE	Y	Y
Property Type Controls	Y	Y
Appraiser FE	Y	Y
Missing Characteristics Dummies	Y	Y
Missing Characteristics Interactions	Y	Y
Other Controls	Y	Y

Note: This table presents estimates from regression models where the dependent variable in each column is listed in the column heading. The sample includes refinance applications that resulted in originated loans from 2000 to 2007. *Appraisal Fee* is the total cost the borrower paid for an appraisal, whereas *Appraisal Fee > \$600* is an indicator for whether the total appraisal fees exceed \$600. Property type controls include indicators for whether the collateral is a second home, investment property, multi-unit property, condominium, or part of a planned unit development. Other controls include *AVM Confidence*, *Cash for Home Improvements*, *Years at Residence*, *Ln(Total Assets)*, *Borrower Age*, *Ln(Income)*, *Dependents*, *Years at Residence* × *Ln(Income)*, and *Years at Residence* × *Dependents*. Missing characteristic dummies include indicators for whether a variable in the Other Controls list were set to zero when missing. Missing characteristics interactions include the interaction terms between the missing indicators for *Ln(Income)* and *Dependents* with the *Years at Residence* variable. Robust standard errors are reported in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.10$

Table 5. Appraised Value, Adjusted AVM Estimates, and Owner Race

	(1) Ln(Purch Price)	(2) App-to-$\hat{V}$	(3) App-to-$\hat{V} < .8$
Ln(AVM)	0.531***		
	(0.004)		
Asian Owner	0.019***	-0.019***	0.008**
	(0.002)	(0.003)	(0.003)
Black Owner	0.028***	-0.041***	0.019***
	(0.002)	(0.002)	(0.002)
Hispanic Owner	0.008***	-0.026***	0.015***
	(0.002)	(0.001)	(0.002)
Observations	134,272	195,085	195,085
Adjusted R-squared	0.906	0.214	0.115
Zip FE	Y	Y	Y
Year FE	Y	Y	Y
Property Type Controls	Y	Y	Y
Appraiser FE	N	Y	Y
Missing Characteristics Dummies	Y	Y	Y
Missing Characteristics Interactions	Y	Y	Y
Other Controls	Y	Y	Y
Sample	Purchases	Refinances	Refinances

Note: Column (1) presents estimates from regression model where the dependent variable is the the natural logarithm of the purchase price in our purchase sample. The model from column (1) is used to predict property values ($\hat{V}$) out-of-sample for applications in our refinance sample. The dependent variable in column (2) is the appraised value divided by $\hat{V}$ in the refinance sample. The dependent variable in column (3) is an indicator variable that takes a value of one if the appraised value is less than 80% of $\hat{V}$, and zero otherwise. Property type controls include indicators for whether the collateral is a second home, investment property, multi-unit property, condominium, or part of a planned unit development. Other controls include *AVM Confidence*, *Cash for Home Improvements*, *Years at Residence*, *Ln(Total Assets)*, *Borrower Age*, *Ln(Income)*, *Dependents*, *Years at Residence* $\times$ *Ln(Income)*, and *Years at Residence* $\times$ *Dependents*. Missing characteristic dummies include indicators for whether a variable in the Other Controls list were set to zero when missing. Missing characteristics interactions include the interaction terms between the missing indicators for *Ln(Income)* and *Dependents* with the *Years at Residence* variable. Robust standard errors are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.10

Table 6. Appraised Value, Adjusted AVM Estimates, Owner and Appraiser Race

	(1) App-to-$\hat{V}$	(2) App-to-$\hat{V}$	(3) App-to-$\hat{V}$
Asian Owner	-0.020***		
	(0.002)		
Black Owner	-0.042***		
	(0.002)		
Hispanic Owner	-0.025***		
	(0.001)		
Asian Appraiser		0.006*	
		(0.003)	
Black Appraiser		0.001	
		(0.004)	
Hispanic Appraiser		-0.002	
		(0.002)	
White Owner/Asian Appraiser			0.003
			(0.004)
White Owner/Black Appraiser			0.004
			(0.005)
White Owner/Hispanic Appraiser			-0.002
			(0.003)
Asian Owner/White Appraiser			-0.018***
			(0.003)
Asian Owner/Asian Appraiser			-0.029***
			(0.005)
Black Owner/White Appraiser			-0.042***
			(0.002)
Black Owner/Black Appraiser			-0.041***
			(0.005)
Hispanic Owner/White Appraiser			-0.024***
			(0.001)
Hispanic Owner/Hispanic Appraiser			-0.031***
			(0.003)
Observations	195,931	195,931	195,931
Adjusted R-squared	0.176	0.173	0.176
Zip FE	Y	Y	Y
Year FE	Y	Y	Y
Property Type Controls	Y	Y	Y
Appraiser FE	N	N	N
Missing Characteristics Dummies	Y	Y	Y
Missing Characteristics Interactions	Y	Y	Y
Other Controls	Y	Y	Y

Note: This table presents estimates from regression models where the dependent variable is the appraised value divided by $\hat{V}$ in the refinance sample. White Borrower/White Appraiser is the omitted category in column (3). Property type controls include indicators for whether the collateral is a second home, investment property, multi-unit property, condominium, or part of a planned unit development. Other controls include *AVM Confidence*, *Cash for Home Improvements*, *Years at Residence*, *Ln(Total Assets)*, *Borrower Age*, *Ln(Income)*, *Dependents*, *Years at Residence* $\times$ *Ln(Income)*, and *Years at Residence* $\times$ *Dependents*. Missing characteristic dummies include indicators for whether a variable in the Other Controls list were set to zero when missing. Missing characteristics interactions include the interaction terms between the missing indicators for *Ln(Income)* and *Dependents* with the *Years at Residence* variable. Robust standard errors are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.10

7. Figures

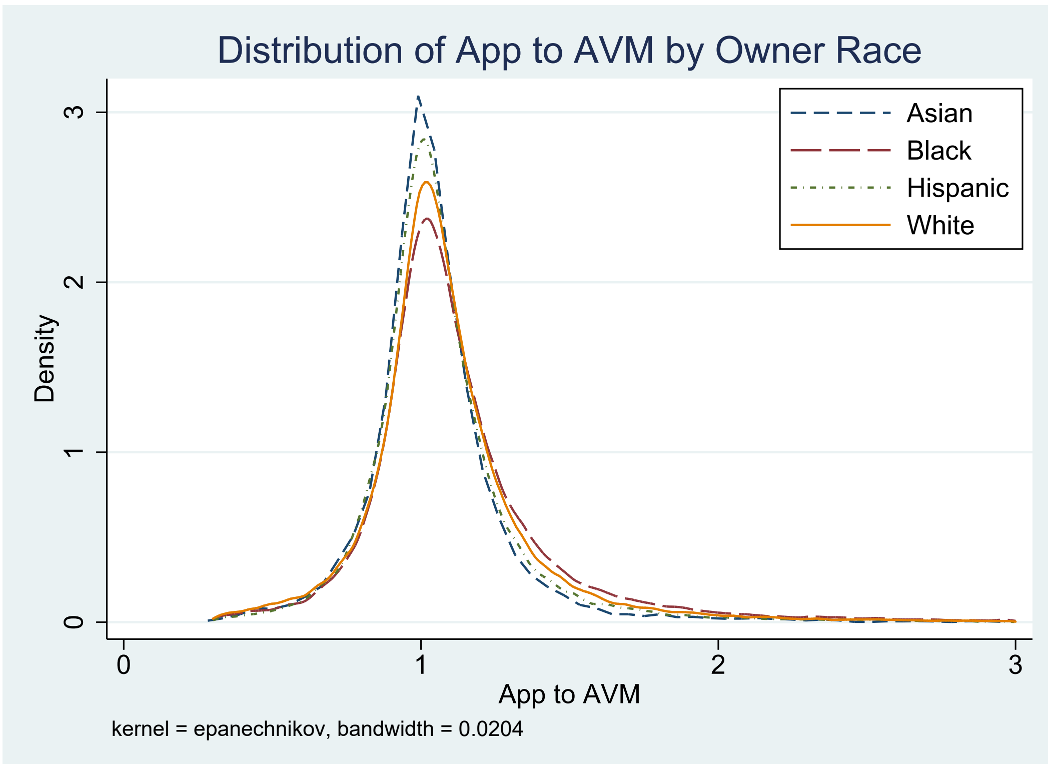


Figure 1. Distribution of App to AVM by Owner Race

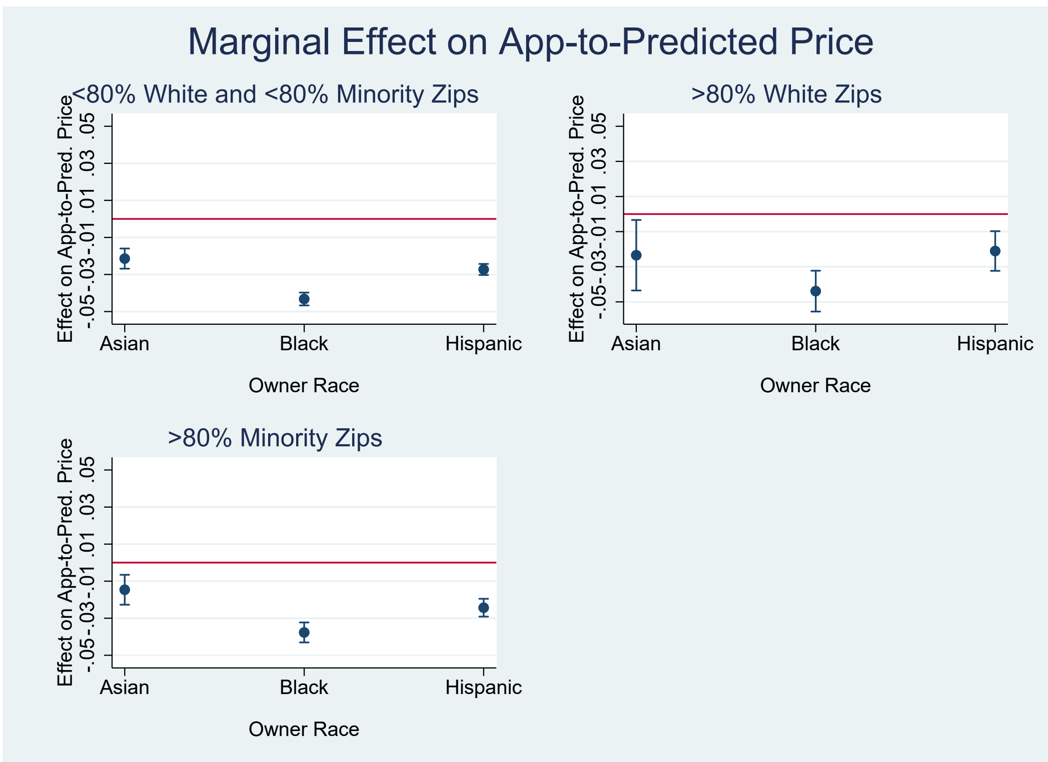


Figure 2. Marginal Effect of Owner Race on App-to-$\hat{V}$ by Zip Racial Composition

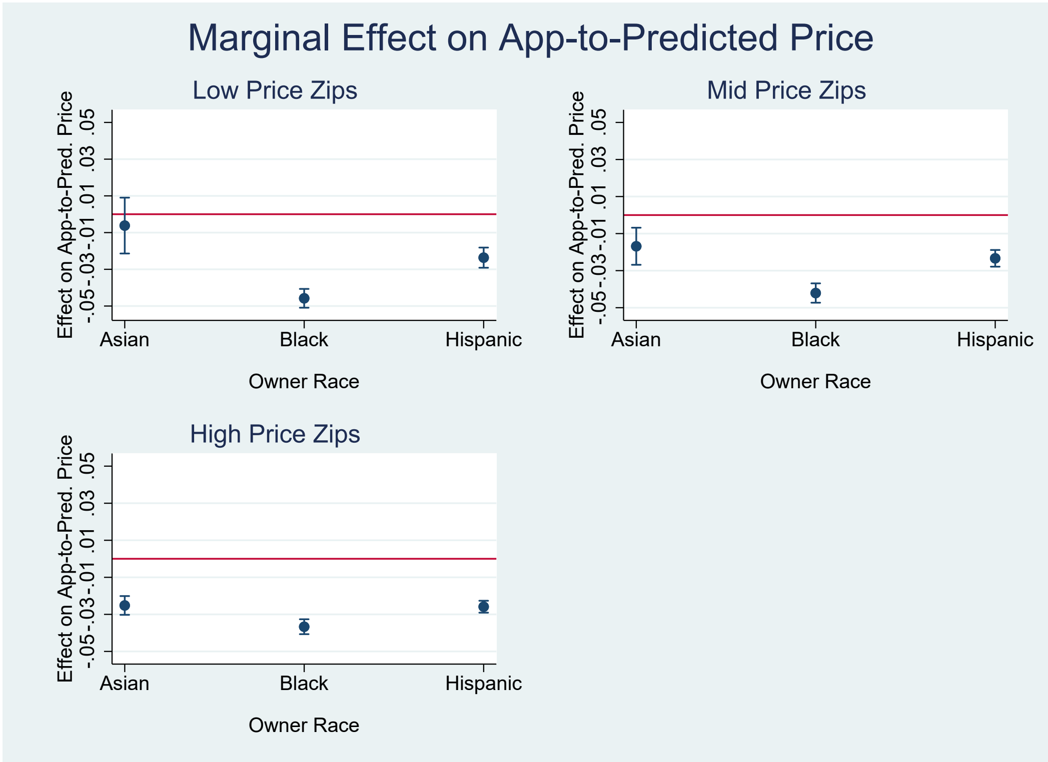


Figure 3. Marginal Effect of Owner Race on App-to-$\hat{V}$ by Zip House Price Level

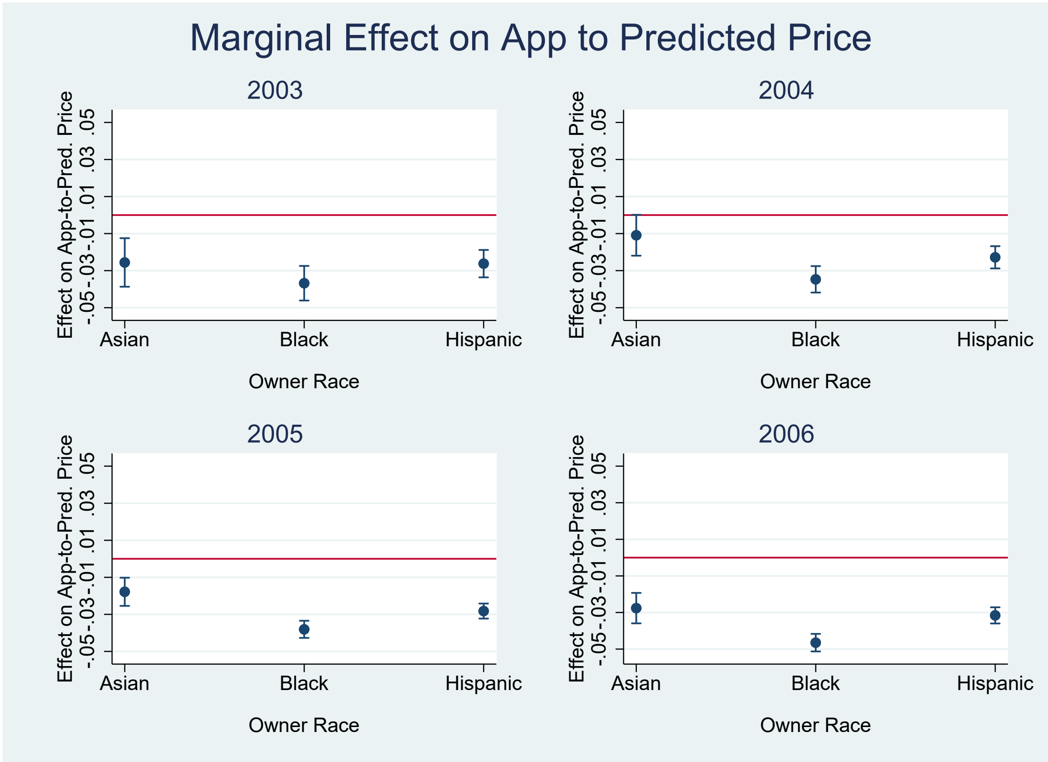


Figure 4. Marginal Effect of Owner Race on App-to-$\hat{V}$ by Year

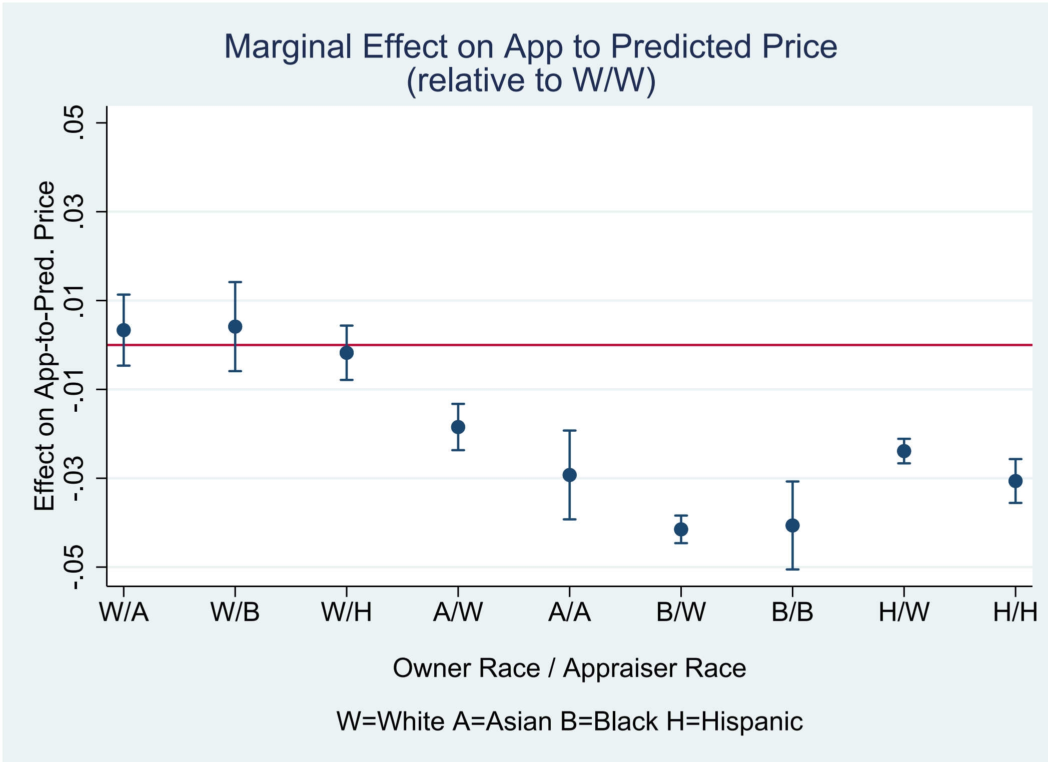
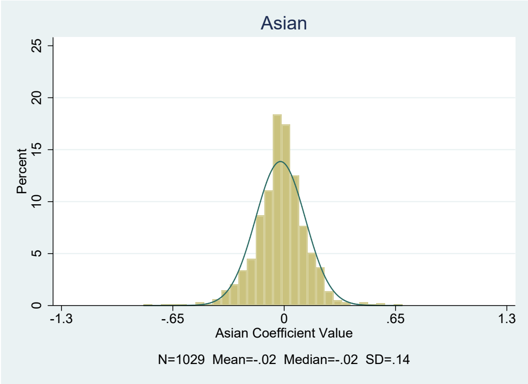
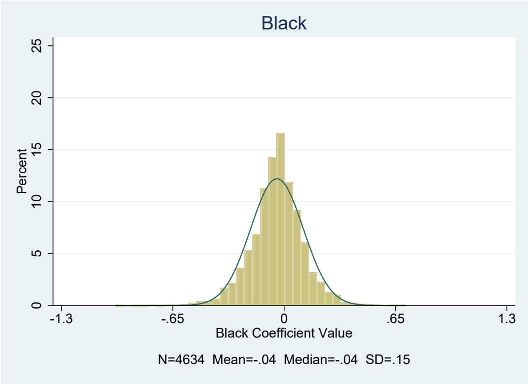


Figure 5. Marginal Effect of Owner and Appraiser Race on App-to-$\hat{V}$

Panel A



Panel B



Panel C

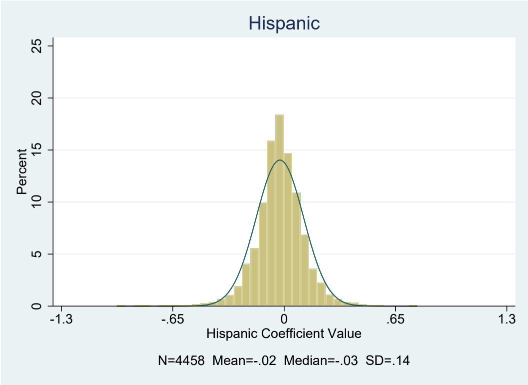
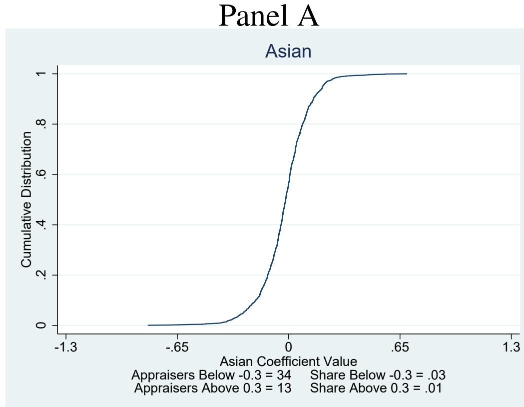
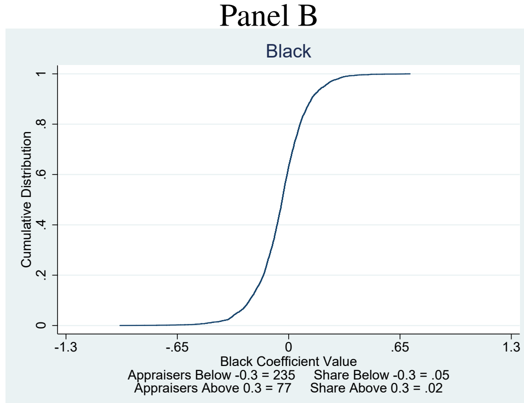


Figure 6. Distribution of individual appraiser race coefficients.

Panel A



Panel B



Panel C

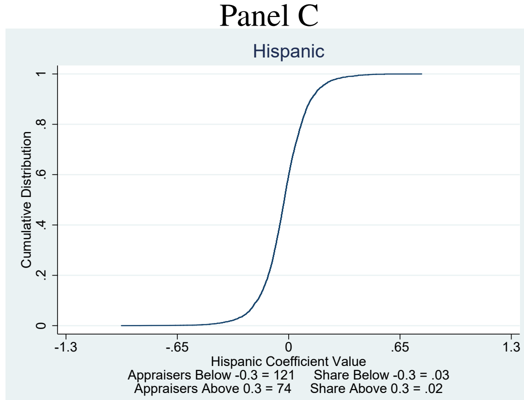
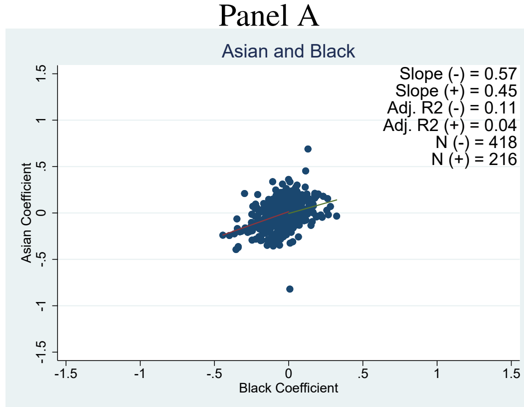
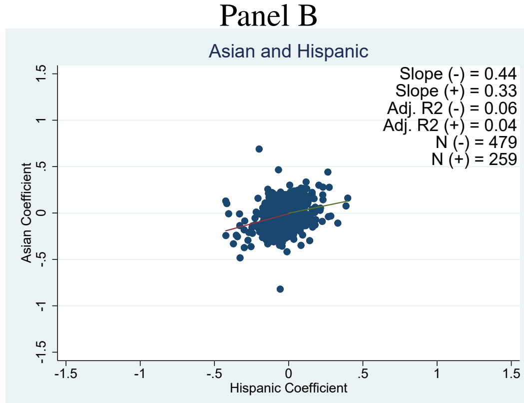


Figure 7. Cumulative distribution of individual appraiser race coefficients.

Panel A



Panel B



Panel C

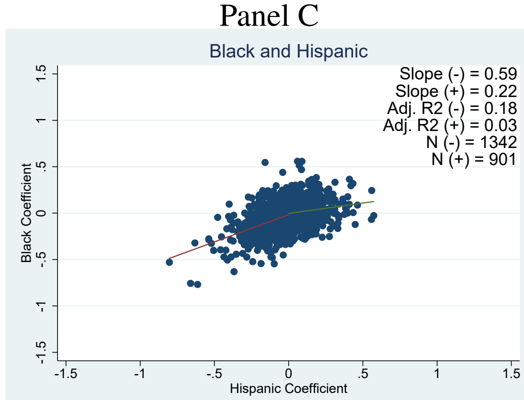


Figure 8. Correlation between individual appraisers race coefficients.
Note: Each point represents an individual appraiser and the individual appraiser race coefficients associated with that appraiser. Two separate linear fit lines are plotted for X<0 (-) and X≥0 (+).

INTERNET APPENDIX

A.1. AVM Background

In this study, we use Collateral Analytics' Automatic Valuation Model (CA AVM), which was designed by the founder after creating two valuation-related patents: Value Your Home (2002) and System and Method for Evaluating Future Collateral Risk Quality of Real Estate (2003).[1] The market for CA AVM gained traction following the Great Financial Crisis (GFC) in 2007-2009, when Lewtan Technologies, a major data provider for residential mortgage-backed security issuers, launched the ABSnet Loan HomeVal product.[2] This product used CA AVM to match securitized loans in MBS pools to individual properties, providing investors with independent valuations on the underlying collateral, whereas beforehand investors did not have access to such estimates.

The AVM builds valuations using hedonic approaches based on publicly available property characteristics commonly found in assessor records, which may be complemented with variables and records from local multiple listing service data providers. As the exact model is unknown and proprietary, reverse engineering the AVM is difficult because key location attributes about the property are only accessible to Collateral Analytics. However, Jensen and Reifler (2010) provide evidence that the AVM outperforms alternative valuation metrics including repeat sales and transaction-based home price indices. Furthermore, the AVM confidence scores that accompany AVM estimates suggest that the average accuracy is approximately 80 to 85% (see Table A.3).

In 2014, the US Securities and Exchange Commission's (SEC) revised Regulation AB (79 FR 57183) requiring issuers to provide asset-level disclosures, including the geo-location of the property, property valuation, and loan-to-value (LTV) ratios. The change in disclosure requirements

[1]See `https://patents.google.com/patent/US20020087389A1/en` and `https://patents.google.com/patent/US20040153330A1/en`.

[2]See https://asreport.americanbanker.com/news/lewtan-technologies-to-launch-absnet-loan-homeval-153-product.

led to an increase in the popularity of CA AVM as a viable valuation product.

Additionally, U.S. courts have ruled that lenders may use AVMs to determine the value of a property (Neng-Guin Chen v. Citibank, 2011), and have accepted AVM estimates as evidence of fraudulent valuations by appraisers in court cases related to MBS (see FHFA v. UBS Ams., Inc., 2012; Nomura Asset Acceptance Corp. Alt. Loan Tr. v. Nomura Credit & Capital, Inc., 2018). In fact, studies by Griffin and Maturana (2016) and Kruger and Maturana (2021) use CA AVM to detect fraudulent practices in MBS subprime markets, as they point out that CA AVM is among the top industry performers in competitions for AVM accuracy. Subsequently, Black Knight, Inc., a leading data provider in the real estate industry, purchased Collateral Analytics in 2020, obtaining ownership of the CA AVM product.[3]

A.2. Maximum a Posteriori (MAP) Bayesian Improved First Name Surname (BIFS) Race Classification.

The appraiser's full name is recorded in the NCEN data, which we use to infer race with a Bayesian based classifier approach.[4] Specifically, we use a Bayesian Improved First Name Surname (BIFS) method similar in spirit to the commonly used Bayesian Improved Surname Geocoding (BISG) method developed by the RAND Corporation. In contrast with the BISG approach that uses location to help infer race, we do not observe where the appraiser lives, so we instead use first name racial distribution information to improve race classification. The assumptions underlying a Bayesian Improved classifier, such as the BIFS or BISG are discussed in detail in Voicu (2018).[5]

[3] See https://www.prnewswire.com/news-releases/black-knight-announces-acquisition-of-collateral-analytics-a-leading-provider-of-analytic-technology-for-the-mortgage-capital-markets-and-real-estate-markets-301015678.html.

[4] Our sample includes applications from 2000 thru 2007 because the appraiser-name field is sparsely populated prior to 2000. In 2000, 30% of funded loans recorded an appraiser's name. From 2001-2007, 87% of funded loans recorded an appraiser's name. The appraiser-name field is much less likely to be reported for applications that did not result in funded loans, most likely because many of these applications never made it to the appraisal stage.

[5] Our method is also closely related to the BIFSG approach developed in Voicu (2018) and used in Ambrose, Conklin, and Lopez (2021) to examine racial disparities in mortgage pricing.

The BIFS approach proceeds in three steps. First, we match the appraiser's last name to a list of frequently occurring surnames from the 2000 U.S. Census that has the racial distribution associated with each of those names. This gives us the likelihood that an individual falls into each race category, conditional on last name alone.[6] Second, we match the appraiser's first name to the database from Tzioumis (2018) which contains race distributions associated with first names. Updated probabilities for the appraiser are then calculated, now conditional on both last and first names.[7] For each appraiser, we now have the likelihood (BIFS score) that the appraiser falls into each race category, conditional on last name and first name. In other words, each appraiser has six BIFS scores – one for each of the six race categories. Finally, we use the maximum a posteriori (MAP) classification scheme, which assigns the appraiser to the race for which he has the highest BIFS score.

To examine the accuracy of the MAP BIFS methodology, we use publicly available voter registration data from the state of Florida. These data include 13.3 million voter records, covering nearly 63% of Florida's population. For each voter, we observe the surname, first name, and self-reported race/ethnicity. Thus, we can infer voter race using MAP BIFS and compare it to the actual race disclosed by the voter. For each of the racial groups used in our study (Asians, Hispanics, Blacks, and Whites), we calculate the MAP BIFS accuracy rate as the number of voters in that group classified correctly divided by the total number of voters classified into that group. The accuracy rate is 79% for both White and Hispanic voters. For Blacks and Asians, the accuracy rate is 65% and 61%, respectively. Although we cannot directly test the accuracy of the MAP BIFS approach in our appraiser data, accuracy rates in voter data should provide a reasonable proxy for accuracy rates in the NCEN data.

[6] We use the following groups to be consistent with classification standards of federal data on race and ethnicity (62 Fed. Reg. 131, July 9, 1997): American Indian or Alaskan Native, Asian or Pacific Islander, Black, Hispanic, White, and two or more races,

[7] Calculating these Bayesian improved updated probabilities relies on conditional independence assumptions as discussed in Voicu (2018), Consumer Financial Protection Bureau (2014), and Elliott et al. (2009).

A.3. Descriptive Statistics for Home Purchase Sample

Descriptive statistics for NCEN purchase sample are reported in Panel A of Table A.2. There are 136,916 home purchase mortgages in the ABSNet-NCEN merged purchase sample. Approximately 2% of the purchase loans had an appraised value for the collateral below the contract price, which is consistent with data from Calem et al. (2021) on appraisals for GSE mortgages originated between 2003 and 2009. Hence, our data appear to be representative of the mortgage market during the early 2000s. Panel B reports descriptive statistics by race. As is the case in our NCEN-ABSNet merge sample of refinances, property values are highest for Asians and lowest for Blacks. Panel B also shows that the share of appraisals that come in below the purchase contract price is low (1-3%), regardless of buyer race.

A.4. Additional Tables

Table A.1. Racial Distribution of Appraisers

	NCEN-ABSNet		Appraisal Foundation	Appraisal Institute
Appraiser Race	Freq.	Share	Share	Share
Asian	759	2%	2%	1%
Black	943	3%	5%	1%
Hispanic	1,555	4%	4%	5%
White	31,674	91%	89%	93%
Total	34,931	100%	100%	100%

Note: The first column reports the number of individual appraisers in the NCEN-ABSNet merged sample that MAP BISF classifies into each race. The second column reports the share of appraisers in the NCEN-ABSNet merged sample that MAP BISF classifies into each race. The third and fourth columns report the share of appraisers in each racial category according to a recent reports by the Appraisal Foundation and the Appraisal Institute, respectively. The shares in all columns are calculated conditional on the reported race falling into one of these four categories.

Table A.2. Descriptive Statistics for Purchase Sample

Panel A: Home Purchases	Obs	Mean	Std. Dev.	Min	Max
Appraisal Value	136,916	$275,769	$171,752	$38,495	$3,800,000
Purchase Price	136,916	$270,683	$168,968	$37,000	$2,600,000
Below Contract	136,916	0.02			
AVM Value	136,916	$265,499	$175,691	$10,000	$7,900,000
App-to-AVM Ratio	135,078	1.07	0.23	0.30	3
Appraisal Fee	70,594	$357			
Appraisal Fee ¿= $600	70,594	0.03			
Asian Owner	136,916	0.07			
Black Owner	136,916	0.20			
Hispanic Owner	136,916	0.29			
White Owner	136,916	0.44			
Second Home	136,916	0.04			
Investment Property	136,916	0.09			
Multi-unit	136,916	0.07			
Condo	136,916	0.10			
PUD	136,916	0.16			

Panel B: Home Purchases Mean by Race	Asian	Black	Hispanic	White
Appraisal Value	$387,130	$233,248	$314,559	$252,289
Purchase Price	$381,082	$228,308	$309,997	$246,942
Below Contract	0.03	0.01	0.02	0.02
avm	377,320	$219,224	$304,410	$243,540
App-to-AVM Ratio	1.04	1.11	1.06	1.06
Appraisal Fee	$394	$347	$364	$351
Appraisal Fee ¿= $600	0.05	0.02	0.03	0.02
Second Home	0.06	0.04	0.04	0.04
Investment Property	0.09	0.13	0.07	0.09
Multi-unit	0.07	0.10	0.09	0.05
Condo	0.18	0.07	0.09	0.10
PUD	0.20	0.17	0.13	0.16
Observations	9,289	$27,029	39,776	60,822

Note: Panel A reports descriptive statistics for unfunded purchase applications and originated purchase loans. Panel B reports the mean values of these variables by owner race. Variables with missing standard deviation, minimum, and maximum in Panel A are binary.

Table A.3. Descriptive Statistics for Additional Property and Owner Characteristics

Panel A: Share Missing in Full Sample	Asian	Black	Hispanic	White
Missing AVM Confidence	0.68	0.62	0.64	0.66
Missing Years Residence	0.01	0.01	0.01	0.01
Missing Ln(Total Assets)	0.68	0.72	0.70	0.70
Missing Borrower Age	0.02	0.01	0.01	0.01
Missing Ln(Income)	0.02	0.01	0.01	0.01
Missing Dependants	0.70	0.76	0.72	0.73

Panel B: Mean for Non-Missing	Asian	Black	Hispanic	White
AVM Confidence	84.88	79.25	83.35	83.37
Cash for Home Improvement	0.05	0.04	0.06	0.04
Years at Residence	6.65	8.86	6.46	7.77
Ln(Total Assets)	12.71	12.18	12.29	12.34
Borrower Age	44.82	47.31	42.84	45.16
Ln(Income)	8.84	8.48	8.54	8.60
Dependants	1.34	1.28	1.47	1.33

Note: Panel A reports the share of observations with missing information for the characteristics by race in the refinance sample. Panel B reports the mean values of these characteristics by owner race for the observations where the characteristics are not missing.

Table A.4. Appraised Value, Different Adjusted AVM Estimates, and Owner Race

	(1) App-to-$\hat{V}$	(2) App-to-$\hat{V}$	(3) App-to-$\hat{V}$
Asian Owner	-0.018***	-0.022***	-0.009***
	(0.003)	(0.003)	(0.003)
Black Owner	-0.037***	-0.039***	-0.027***
	(0.002)	(0.002)	(0.002)
Hispanic Owner	-0.024***	-0.027***	-0.014***
	(0.001)	(0.001)	(0.002)
Observations	195,083	195,100	195,088
Adjusted R-squared	0.214	0.216	0.197
Zip FE	Y	Y	Y
Year FE	Y	Y	Y
Property Type Controls	Y	Y	Y
Appraiser FE	Y	Y	Y
Missing Characteristics Dummies	Y	Y	Y
Missing Characteristics Interactions	Y	Y	Y
Other Controls	Y	Y	Y

Note: This table presents estimates from regression models where the dependent variable is the appraised value divided by $\hat{V}$. The model used to estimate $\hat{V}$ varies across columns. In column (1) the model for $\hat{V}$ is the same as column (1) of 5 except that we interact Ln(AVM) with owner race. In column (2) we interact Ln(AVM) and owner race with all other controls. In column (3) we estimate separate models for $\hat{V}$ for each race. The sample in all columns includes refinance applications that resulted in originated loans from 2000 to 2007. Property type controls include indicators for whether the collateral is a second home, investment property, multi-unit property, condominium, or part of a planned unit development. Other controls include *AVM Confidence*, *Cash for Home Improvements*, *Years at Residence*, *Ln(Total Assets)*, *Borrower Age*, *Ln(Income)*, *Dependents*, *Years at Residence* $\times$ *Ln(Income)*, and *Years at Residence* $\times$ *Dependents*. Missing characteristic dummies include indicators for whether a variable in the Other Controls list were set to zero when missing. Missing characteristics interactions include the interaction terms between the missing indicators for *Ln(Income)* and *Dependents* with the *Years at Residence* variable. Robust standard errors are reported in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.10$

Table A.5. Appraised Value, Adjusted AVM Estimates, and Owner Race by Zip Racial Composition

	(1) Mixed Zips App-to-$\hat{V}$	(2) White Zips App-to-$\hat{V}$	(3) Minority Zips App-to-$\hat{V}$
Asian Owner	-0.021***	-0.023**	-0.015***
	(0.003)	(0.010)	(0.004)
Black Owner	-0.043***	-0.044***	-0.038***
	(0.002)	(0.006)	(0.003)
Hispanic Owner	-0.027***	-0.021***	-0.024***
	(0.002)	(0.006)	(0.002)
Observations	123,087	41,396	55,311
Adjusted R-squared	0.149	0.255	0.159
Zip FE	Y	Y	Y
Year FE	Y	Y	Y
Property Type Controls	Y	Y	Y
Appraiser FE	N	N	N
Missing Characteristics Dummies	Y	Y	Y
Missing Characteristics Interactions	Y	Y	Y
Other Controls	Y	Y	Y

Note: This table presents estimates from regression models where the dependent variable is the appraised value divided by $\hat{V}$. The sample in column (1) includes refinance applications that resulted in originated loans in ZIP codes where less than 80% of the population is White and less than 80% of the population are minorities. The sample in column (2) includes refinance applications that resulted in originated loans in ZIP codes where at least 80% of the population is White. The sample in column (3) includes refinance applications that resulted in originated loans in ZIP codes where at least 80% of the population are minorities. Property type controls include indicators for whether the collateral is a second home, investment property, multi-unit property, condominium, or part of a planned unit development. Other controls include *AVM Confidence*, *Cash for Home Improvements*, *Years at Residence*, *Ln(Total Assets)*, *Borrower Age*, *Ln(Income)*, *Dependents*, *Years at Residence* $\times$ *Ln(Income)*, and *Years at Residence* $\times$ *Dependents*. Missing characteristic dummies include indicators for whether a variable in the Other Controls list were set to zero when missing. Missing characteristics interactions include the interaction terms between the missing indicators for *Ln(Income)* and *Dependents* with the *Years at Residence* variable. Robust standard errors are reported in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.10$

Table A.6. Appraised Value, Adjusted AVM Estimates, and Owner Race by Zip House Price Level

	(1) Low Price Zips App-to-$\hat{V}$	(2) Mid Price Zips App-to-$\hat{V}$	(3) High Price Zips App-to-$\hat{V}$
Asian Owner	-0.006	-0.017***	-0.025***
	(0.008)	(0.005)	(0.003)
Black Owner	-0.046***	-0.042***	-0.037***
	(0.003)	(0.003)	(0.002)
Hispanic Owner	-0.024***	-0.023***	-0.026***
	(0.003)	(0.002)	(0.002)
Observations	70,288	63,233	82,503
Adjusted R-squared	0.200	0.191	0.217
Zip FE	Y	Y	Y
Year FE	Y	Y	Y
Property Type Controls	Y	Y	Y
Appraiser FE	N	N	N
Missing Characteristics Dummies	Y	Y	Y
Missing Characteristics Interactions	Y	Y	Y
Other Controls	Y	Y	Y

Note: This table presents estimates from regression models where the dependent variable is the appraised value divided by the AVM value. The sample in column (1) includes refinance applications that resulted in originated loans in ZIP codes in quintiles 1-3 of 2005 zip house price levels. Columns (2) and (3) include refinance applications that resulted in originated loans in ZIP codes in quintiles 4 and 5, respectively, of 2005 zip house price levels. Property type controls include indicators for whether the collateral is a second home, investment property, multi-unit property, condominium, or part of a planned unit development. Other controls include *AVM Confidence*, *Cash for Home Improvements*, *Years at Residence*, *Ln(Total Assets)*, *Borrower Age*, *Ln(Income)*, *Dependents*, *Years at Residence* $\times$ *Ln(Income)*, and *Years at Residence* $\times$ *Dependents*. Missing characteristic dummies include indicators for whether a variable in the Other Controls list were set to zero when missing. Missing characteristics interactions include the interaction terms between the missing indicators for *Ln(Income)* and *Dependents* with the *Years at Residence* variable. Robust standard errors are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.10

Table A.7. Appraised Value, Adjusted AVM Estimates, and Owner Race by Year

	(1) 2003 App-to-$\hat{V}$	(2) 2004 App to $\hat{V}$	(3) 2005 App to $\hat{V}$	(4) 2006 App to $\hat{V}$
Asian Owner	-0.026***	-0.011*	-0.018***	-0.028***
	(0.007)	(0.006)	(0.004)	(0.004)
Black Owner	-0.037***	-0.035***	-0.038***	-0.046***
	(0.005)	(0.004)	(0.002)	(0.002)
Hispanic Owner	-0.026***	-0.023***	-0.028***	-0.032***
	(0.004)	(0.003)	(0.002)	(0.002)
Observations	19,596	32,026	76,964	69,265
Adjusted R-squared	0.366	0.301	0.187	0.202
Zip FE	Y	Y	Y	Y
Year FE	N	N	N	N
Property Type Controls	Y	Y	Y	Y
Appraiser FE	N	N	N	N
Missing Characteristics Dummies	Y	Y	Y	Y
Missing Characteristics Interactions	Y	Y	Y	Y
Other Controls	Y	Y	Y	Y

Note: This table presents estimates from regression models where the dependent variable is the appraised value divided by $\hat{V}$. The sample includes refinance applications that resulted in originated loans. The sample in each column includes applications from the year indicated in the column header. Property type controls include indicators for whether the collateral is a second home, investment property, multi-unit property, condominium, or part of a planned unit development. Other controls include *AVM Confidence*, *Cash for Home Improvements*, *Years at Residence*, *Ln(Total Assets)*, *Borrower Age*, *Ln(Income)*, *Dependents*, *Years at Residence* $\times$ *Ln(Income)*, and *Years at Residence* $\times$ *Dependents*. Missing characteristic dummies include indicators for whether a variable in the Other Controls list were set to zero when missing. Missing characteristics interactions include the interaction terms between the missing indicators for *Ln(Income)* and *Dependents* with the *Years at Residence* variable. Robust standard errors are reported in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.10$