Do Appraiser and Borrower Race Affect Valuation?*

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Abstract

We examine the incidence of racial bias in property appraisals using a nationwide sample of refinanced mortgages from 2000 to 2007. Uniquely, our data allow us to observe the race of both the homeowner and the appraiser in a setting where the appraiser's valuation conveys critical information to the lender. We observe systematically lower appraised values relative to automated valuation model (AVM) estimates for minority-owned homes. However, we do not find evidence that minority valuation discounts vary with the race of the appraiser. After adjusting for potential bias in the AVM estimates, we find even larger minority valuation discounts.

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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 estimates. For many years, appraisers of residential property explicitly factored owner race and neighborhood race/ethnicity 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 the racial or ethnic composition of neighborhoods or the race/ethnicity of the property owner in estimating property values. And yet, 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).[2] 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. Because of these continuing reports, the Department of Housing and Urban Development (HUD) launched in June 2021 an inter-agency Property Appraisal Valuation Equity (PAVE) taskforce with the goal of examining the causes and consequences of undervaluation or misvaluation of minority-owned homes.[3]

While evidence of disparities in homeownership rates across race and ethnicity clearly exist, the reports suggesting widespread racial discrimination in appraisals are controversial.[4] For example,

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

[2] For instance, Perry, Rothwell, and Harshbarger (2018) compare the median home values between Black- and White-majority neighborhoods (i.e., census tracts) reported in the 2016 American Community Survey 5-year estimates; they find that Black neighborhoods are devalued by about 23% compared to White neighborhoods, once accounting for property and neighborhood characteristics.

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

[4] Numerous studies document significant disparities in homeownership experiences across racial and income groups (Coulson and Dalton, 2010; Krivo and Kaufman, 2004; Dawkins, 2005; Boehm and Schlottmann, 2004; Flippen, 2004;

a recent study by the American Enterprise Institute (AEI) finds no systematic evidence of appraisal discrimination (Pinto and Peter, 2021a). Furthermore, in a separate report, the AEI suggests that Perry, Rothwell, and Harshbarger (2018) seriously overstate the impact of racial differences in home prices (see Pinto and Peter, 2021b), putting into question whether policy efforts toward racial equity should focus on other components of the home buying or financing process to balance the homeownership experience of minorities.

Given the conflicting accounts of the magnitude of reported appraisal undervaluation of minority-owned properties, we provide new insights into the incidence of racial bias in the appraisal process by using a novel data set from an earlier period that provides us the opportunity to infer appraiser race and its interaction with owner race. We use an administrative data set on over 220,000 mortgages that were refinanced by New Century Financial Corporation (NCEN) between 2000 and 2007 (inclusive) and appraised by over 34,000 individual appraisers.[5] This period is often associated with expanding credit availability to minorities along with increasing minority homeownership rates, as well as greater competition and relatively loose regulation in the mortgage industry. To the best of our knowledge, this is the only publicly available dataset that provides researchers with the ability to infer the race and ethnicity of multiple individual actors in the mortgage origination process.[6] In contrast to previous studies, these data allow us to focus on the race of the homeowner that is recorded on the mortgage application rather than rely on demographic characteristics at the neighborhood level to infer a race effect. Most importantly for our purpose, the data contain the appraised value for the subject property, as well as the full name of the appraiser contracted by the mortgage broker, allowing us to use a race classification algorithm similar to

Dietz and Haurin, 2003; Flippen, 2001; Bostic and Surette, 2001; Gyourko, Linneman, and Wachter, 1999).

[5]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.

[6]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).

the one described by Ambrose, Conklin, and Lopez (2021) to infer the appraiser's race. Thus, we examine the question of whether racial bias in appraisals is sensitive to whether the homeowner and appraiser share the same race. To do so, we benchmark the appraised values to an independent property value estimate generated from an automated valuation model (AVM). Since the NCEN data set does not report an AVM estimate, we merge the NCEN data with data from ABSNet and HomeVal, which include AVM estimates.[7] This allows us to test whether appraiser race and its interaction with owner race is related to appraisal-to-AVM ratios after conditioning on property type, origination date, collateral location and appraiser fixed effects.

We focus on refinanced mortgages because most of the anecdotal evidence centers on these loans, and the incidence and magnitude of appraisal bias is likely to be more pronounced among refinanced mortgages than mortgages used to finance property purchases. For refinance mortgage applications, the appraisal is often the only estimate of value because there is no new purchase price, per se. The appraisal therefore plays a crucial role in the refinancing process of mortgages. In contrast, lenders generally underwrite purchase mortgages at the lesser of the purchase price or the appraised value. It is well documented that appraised values are rarely below, and often equal this contract price. This is consistent with the concept that appraisers target the contract price in property valuations (Agarwal, Song, and Yao, 2020; Cho and Megbolugbe, 1996; Calem et al., 2021; Conklin et al., 2020; Ding and Nakamura, 2016).[8] As a result, purchase price targeting leaves less room for appraiser racial bias than with a refinance mortgage application, where there is no definitive target for the valuation, and a low appraisal, in and of itself, does not necessarily preclude a loan from being funded.[9] In addition, appraisers are much more likely to observe the race of the applicant during an appraisal for a refinance than a purchase mortgage application since

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

[8]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.

[9]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.

the borrower (the current owner) usually occupies the property and interacts with the appraiser.[10] It also is worth noting that the 2000-2007 sample period is advantageous for our inquiry given that regulation of the appraisal process was much less pronounced than is the case now (under Dodd-Frank). Although our primary analysis focuses on appraisals used to refinance a property, we nevertheless extend our methodology to a sample of purchase mortgages.

We make five 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 Hispanic homeowners experienced appraisal-to-AVM (or app-to-AVM) gaps that are 0.9 and 0.7 percentage points lower, on average, than comparable White homeowners after conditioning on property controls, as well as location and time fixed effects.[11] 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. We confirm that these 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. To the best of our knowledge, we are the first to 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 receiv-

[10]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.

[11]In a previous version of the paper we focused solely on appraisals for White and Black owners where we inferred the race of the appraiser to also be either White or Black. We used a different appraiser race classification system in that version (MAP BIFSG) that likely resulted in too many appraisers being classified as minorities (including Asian, Black, and Hispanic). In this version, there are two key differences in our analysis: i) we use a different appraiser classification system (MAP BIFS); and ii) we do not focus solely on observations where the appraiser is inferred as White or Black. As a result, our findings have changed somewhat.

ing 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 relative to the AVM that were 0.8 percentage points lower from White appraisers and 0.6 percentage points lower from Black appraisers.[12] 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. Rather, our results point to an implicit bias against minority homeowners across all appraisers, regardless of race/ethnicity. In an extension to purchase mortgages, our results do not indicate systematic bias against minorities in appraisals on unfunded purchase mortgage applications or originated purchase loans.

Third, we explore whether the variation across race in the appraisal-to-AVM 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 -1 percentage point for Asian owners, -4 percentage points for Black owners, and -2 percentage points for Hispanic 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-AVM ratios by 30 percentage points or more) and 4% of appraisers give Blacks extremely low appraisals relative to Whites. 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, since our analysis of appraisal bias rests on the comparison of appraisals to value estimates obtained from an automated valuation model, we investigate whether these bias estimates

[12] We see a similar pattern for Hispanic owners of -0.6 percentage points and -0.7 percentage points valuation differences from White and Hispanic appraisers, respectively, relative to similar properties with White owners.

are impacted by lower value estimates from the AVMs themselves. While the AVM is admittedly a "black box", in theory it should produce race neutral valuation estimates since it is illegal for lenders to base lending decisions on valuation models that use information about the owner's race or ethnicity. However, for a subset of purchase transactions, where the purchase price is known and which should reflect the property's true value, we find evidence suggestive that the AVM undervalues properties of non-White owners. We therefore invoke a procedure to adjust AVM estimates to account for this undervaluation. Using this modified AVM valuation increases our estimate of appraisal bias to -3.6 percentage points for Black owners and -2 percentage points for Hispanic owners, although again this bias does not depend on the race of the appraiser.

Fifth, we also investigate whether there is a difference in the appraisal fees paid by minority and White owners. If the observed differences in appraisals by race were the result of systematic discrimination by appraisers, then we might also expect to see evidence of discriminatory pricing where appraisers charge minority owners higher fees. However, 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 actually paid no more than similar White owners.

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 disparate treatment 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.

Nonetheless, caution is required when interpreting the findings. First, the refinancing data consists of only funded loans. There is the slight possibility that appraisal bias is only observed in unfunded refinance applications, as we discuss below. Our purchase loan data can aid in the investigation of this issue. Although they introduce a new set of issues, which we discuss below, the purchase applications allow us to observe both funded and unfunded loan applications, using the actual purchase price as the anchor. We do not find large racial disparities in this alternative data set, although the interaction of race and appraisal value does seem to have implications for the probability of that the loan is funded. Lastly, we only observe the final appraisal on a property. Thus, we are unable to determine whether minority homeowners engaged with multiple appraisers before obtaining a value estimate that would support the mortgage application. However, if multiple appraisals are conducted, the owner would likely pay higher appraisal fees. We find no evidence that minorities are more likely to pay high (> $600) appraisal fees.

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 AMV 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. Moreover, there are approximately 45,000 separate mortgage brokerage firms that ordered appraisals from 61,000 unique appraisers in the New Century data, which reduces concerns that our findings are specific to one lender.[13] 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.[14] Second, the NCEN data contain the full name of the appraiser, which we use to infer the appraiser's race. 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 (AVM).

2.2. Automated Valuation Model Value Estimates

To obtain Automated Valuation Model property price estimates, we merge New Century funded loans with Lewtan's ABSNet Loan and HomeVal data sets. 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 come from a proprietary AVM developed by Collateral Analytics, an industry-leading provider of valuation solutions,

[13]There are approximately 35,000 unique appraisers in our final sample after merging with another mortgage data set 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.

[14]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" we then use the race codes/classifications in the data: "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, Black, Hispanic, and White. Our main analysis focuses on Asians, Blacks, Hispanics, and Whites.

which is currently owned by Black Knight.

We follow the matching procedure from Kruger and Maturana (2021), which merges the New Century and ABSNet/HomeVal data sets using the following variables: *ZIP Code*, *First Payment Date*, *Interest Rate Type* (fixed or adjustable rate), *Credit Score*, and *Loan Amount*.[15] 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. For precision, hereafter, we refer to these data as the ABSNet-NCEN matched sample.

Notice that the ABSNet-NCEN matched sample only includes applications that resulted in funded mortgages. Thus, we cannot speak directly to valuation differences across the borrower's and appraiser's race that occur prior to loan funding using this sample. To ensure that our results are not driven by this sample selection issue, we employ an alternate data set that includes purchase mortgage applications (both funded and unfunded) in the New Century data. We compare the appraised value to the purchase price in this analysis to determine whether race is related to the likelihood that an appraisal is below the sales contract price.

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

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

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*.[16] We then construct a discrete race categorization by applying a "maximum a posteriori" (MAP) classification scheme that sets the appraiser's race equal to the race associated with the highest Bayesian score.[17] 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 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 while 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 fig-

[16] 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.

[17] A more detailed discussion of our race classification algorithm is provided in Appendix A.1. Ambrose, Conklin, and Lopez (2021) use a similar method to examine disparities in mortgage pricing across borrower and broker race.

ures released by the Appraisal Foundation and the Appraisal Institute, reported in 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.[18]

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 momentarily.

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.[19] 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;

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

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

Kruger and Maturana, 2021). Although the average app-to-AVM value is greater than 1, it is not uncommon for appraised values to be below AVM values. In fact, 8% of the appraisals have an appraised value that is 20% below the AVM value (App-to-AVM$<$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.[20] 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), 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.

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-

[20]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.

owned properties are unconditionally similar in value, whereas the average Black-owned property is valued at an amount lower than that of the average White-owned property. For all races, the average appraised value is higher than the average AVM estimate. White-owned properties do not have the highest app-to-AVM ratio, which provides suggestive evidence that Whites are not receiving extremely favorable appraisal valuations. In fact, Whites are marginally more likely to receive low valuations (app-to-AVM$<$.8), but the difference in the low valuation likelihood with the other race categories is quite small. 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.

Descriptive statistics for NCEN purchase sample are reported in Panel A of Table A.2. There are 576,416 purchase mortgage applications in the NCEN purchase sample, 55% of which resulted in originated mortgages. Approximately 2% of the purchase applications 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 shows that applications from Black buyers are less likely to result in funded loans, but this does not necessarily imply racial disparities in loan approval rates because the NCEN data do not distinguish between rejected applications and applications that are approved but not accepted by the borrower. As is the case in our NCEN-ABSNet merge sample, 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 (2-3%), regardless of buyer race.

3. Racial Disparities in Appraisals on Refinance Loans

3.1. Individual appraiser analysis

Does an appraiser treat Whites and minorities differently? If appraisal racial bias exists, how common is it? To answer these questions, we compare many pairs of valuations by the same appraiser for homeowners of differing races. Using the app-to-AVM ratio as our valuation metric, we can examine the appraiser-level incidence of valuation differences across owner race because we can identify individual appraisers. To do so, we first define a measure of individual appraiser racial bias as follows:

$$\Phi_j = \left(\frac{1}{n_m}\sum\frac{Appraisal_{im}}{AVM_{im}}\right) - \left(\frac{1}{n_w}\sum\frac{Appraisal_{iw}}{AVM_{iw}}\right), \tag{1}$$

where n_m and n_w are the number of appraisals for minority and White owners, respectively, completed by appraiser j. $\frac{Appraisal_i}{AVM_i}$ is the app-to-AVM ratio on property i performed by appraiser j, with the w and m subscripts indicating owner race.[21] Thus, Φ_j is the mean difference in the app-to-AVM ratio across race for appraiser j. A negative value for Φ suggests that the appraiser gives higher valuation estimates for Whites, on average.

Exploiting within-appraiser variation comes at a cost, though, because many appraisers complete only a few appraisals for mortgages in the NCEN data. For example, 33% of the appraisers in our sample complete only one appraisal. To provide meaningful inference using Equation (1), we require that appraisers complete a minimum of two appraisals each for White and minority owners. There are 7,922 appraisers that meet this criterion, accounting for approximately 64% of the appraisals in our data.

Figure 2 shows the distribution of Φ. The distribution is centered around 0.01, and appears

[21] To save on notation, we use the term i to refer to either the property or the property owner.

symmetric, suggesting that the average appraiser is not biased against minorities. Although the plot is informative, it does not speak to whether the mean differences are statistically significant. To examine this question, we conduct a mean difference test for each appraiser. Under the null hypothesis of no mean difference, the test statistic is

$$T = \frac{\Phi_j}{(\frac{S_m^2}{n_m}) + (\frac{S_w^2}{n_w})} \tag{2}$$

where S_m^2 and S_w^2 are appraiser j's sample variances in the app-to-AVM ratios for minority and White owners, respectively. Assuming unequal variances, the test statistic is t-distributed with v degrees of freedom, where

$$v = \frac{(\frac{S_m^2}{n_m} + \frac{S_w^2}{n_w})^2}{\frac{\frac{S_m^2}{n_m}}{n_m - 1} + \frac{\frac{S_w^2}{n_w}}{n_w - 1}}. \tag{3}$$

For each appraiser we perform a one-sided t-test and reject the null hypothesis if $T < t_{\alpha,v}$, with $\alpha = 0.025$. A rejection implies that the appraiser may be biased against minority borrowers. Using this criterion, only 1.8% of appraisers appear biased against minorities, which is consistent with random chance alone given that $\alpha = 0.025$. To further put this figure in perspective, we also performed a one-sided t-test where we reject the null hypothesis if $T > t_{1-\alpha,v}$, which tests for more favorable valuations for minorities borrowers. Using this test, 2.4% of appraisers appear biased *in favor* of minorities, but again, this is about what would be expected from random chance alone. Taken together, these tests suggest that minority borrowers do not receive systematically lower valuations than Whites when using the same appraiser.

Still, the variation in Φ could be due to other sources of heterogeneity beyond the borrower's race. For instance, in the NCEN data, appraisals for Asians and Blacks are more likely to include investment properties than those for Hispanics or Whites, while multi-unit properties are more prevalent for Hispanic or Black owners than for Asians and Whites (see Panel B of Table 2). Asian owners are also more likely to have condos and properties located in a planned unit development

(PUD) than other racial groups. More generally, White owners are more likely to refinance an owner-occupied single family residence than other racial groups, which could be easier to appraise with less error than income producing properties.

3.2. Appraisals and Owner Race

To formally test whether appraisers treat White and minority borrowers differently, we estimate models of the following form:

$$Y_i = \delta_1 A_i + \delta_2 B_i + \delta_3 H_i + X_i\beta + \zeta_i + \gamma_i + \omega_j + \epsilon_i, \tag{4}$$

where Y_i represents the outcome of interest (the appraisal-to-AVM ratio or appraisal fees) for property i; A_i, B_i, and H_i are indicator variables denoting whether property owner i self-identifies in the HMDA disclosure fields as non-Hispanic Asian (A), non-Hispanic Black (B), or Hispanic (H), respectively, with White owners as the omitted group; X_i is a matrix of control variables for property type, including indicator variables for second homes, investment properties, multi-unit properties, condominiums, and PUDs; ζ_i and γ_i represent 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 lastly, ϵ_i is an error term. The δs are the parameters of interest.

The identifying assumption is that the owner race variables do not affect the property valuation if owner's race does not influence the appraiser. However, the principal threat to identification is that race may correlate with unobservable confounding factors. To address this concern, besides using a rich set of control variables, we include appraiser fixed effects in Equation (4). Note that this precludes the direct investigation of the role of appraiser race but controls for a variety of unobservable factors in the appraisal. In Section 3.3, we consider heterogeneous owner-race effects with respect to time and the demographic composition or house price level of neighborhoods. In the appendix, we also test our specifications using combinations of various control variables.

Table 3 presents the ordinary least squares (OLS) coefficient estimates of the effect of the property owner's race on four different outcomes using Equation (4). The omitted category in all columns is White owner. The dependent variable is set to the app-to-AVM ratio in column (1) and the appraiser fees in column (3). In columns (2) and (4), we examine the extremities of these two dependent variables. Specifically, in column (2), we use an indicator variable ($1[\textit{App-to-AVM} < .8]$) that takes a value of one if the appraised value is less than 80% of the AVM valuation, which is equivalent to one-standard-deviation below the average app-to-AVM ratio; and zero if otherwise.[22] Similarly, in column (4), we use an indicator variable ($1[\text{Appraisal Fee} > \$600]$) that takes a value of one if the appraisal fee is greater than or equal to $600; it is zero if otherwise.[23]

We stress that all four columns include individual appraiser fixed effects. This approach has the advantage of controlling for appraiser heterogeneity and approximates the identification strategy in experimental paired-audit studies (e.g., Ayers and Siegelman (1995)). Most appraisals (85%) in our data are from appraisers that completed at least one appraisal for a White owner and one appraisal for a minority owner. The race coefficients in each column in Table 3 rely on valuation and race variation within this subset of appraisers.

We find that the app-to-AVM of Black and Hispanic owned homes are about 0.9 and 0.7 percentage points lower than that of White owned homes, respectively. These marginal differences are statistically significant at the 1% level. To put these numbers in perspective, a property that is owned by a White household and appraised at the average value of $278,000 would have been appraised at about $275,700 if owned instead by a Black household. The resulting capacity for a cash-out refinance would be reduced (assuming a loan-to-value ratio of 78%) by almost $1,800.[24] In contrast, we do not observe a statistically significant difference in the average app-to-AVM ra-

[22]Eight percent of the app-to-AVMs are below 0.80.

[23]$600 is approximately twice the average appraisal fee observed in the data and thus would likely represent multiple appraisals.

[24]Most of the loans (85%) are cash-out, as opposed to rate term, refinances. The average loan-to-value ratio in our sample is 78%.

tio between White and Asian owned homes, once accounting for appraiser fixed effects and other factors. This suggests that during our sample period, racial valuation disparities were visible, but smaller than the figures ($\approx 25\%$ discount for Black owners) reported in recent anecdotal accounts in the popular press (Kamin, 2020; Malagón, 2020; Haythorn, 2020).[25]

We now investigate the possibility that certain groups may be more likely to get extremely low valuations, which would be consistent with some of the anecdotal evidence in the press. Column (2) reports a coefficient of 0.008 on the indicator for Hispanic Owner, which is statistically significant at the 1% level.[26] The other coefficients are also positive but smaller, and not statistically significant at conventional levels. The results imply that homes owned by Hispanics are about 10% more likely than White-owned homes to be appraised one or more standard deviations below the average app-to-AVM value, but less evidence is available for this occurrence in Asian and Black households.[27]

Perhaps a minority owner requires multiple appraisals on the property to get a fair value. 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. Alternatively, an average (or low) appraisal fee does not necessarily rule out the possibility of multiple appraisals. But high appraisal fees should serve as a reasonable proxy for the use of multiple appraisals. Column (3) suggests that the average Asian owner pays

[25] Table A.3 in the appendix shows that our results hold using alternative combinations of control variables once calibrating the model for location.

[26] We find similar results using an app-to-AVM threshold of 0.9 instead of 0.8 for the dependent variable in the linear probability model.

[27] $10\% = 0.008/0.08$.

about \$3.60 more than White owners for an appraisal (which is statistically significant at the 10% level), whereas the average difference in appraiser fees between White and Hispanic or Black owners is not statistically significant. However, in column (4), the coefficients are almost trivially small and statistically insignificant suggesting that very high appraisal fees are not a feature of minority home appraisals.

In sum, we find little evidence of systematic racial disparities in appraisal fees.[28] 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. Therefore, we focus on the app-to-AVM ratio for the rest of the analysis.

3.3. Do the App-to-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. To investigate this possibility, 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 (4) 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).[29]

Figure 3 plots coefficient estimates from the app-to-AVM regressions.[30] In the top left panel

[28]We draw similar conclusions about appraiser fee differences using alternative combinations of controls (see Table A.4 in the appendix).

[29]Approximately 56%, 19%, and 25% of the appraisals are in mixed ZIPs, high White population share ZIPs, and high minority population share ZIPs, respectively.

[30]The estimates are also reported in Appendix Table A.5. 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.

(mixed race ZIPs), all the coefficient estimates are negative, but the absolute magnitudes are as before (<1 percentage point). In primarily White ZIPs (top right panel), the magnitude of the discounts increases, consistent with the hypothesis that minorities face larger racial valuation bias in White neighborhoods. Note, though, that the confidence intervals are somewhat wider in this sample, and the differences remain statistically similar to prior estimates. For example, valuations on Black-owned properties are 1.6 percentage points lower than those on White-owned properties in primarily White ZIP codes. In high minority share ZIP codes, the Black and Hispanic coefficients remain negative and small, whereas the Asian coefficient is now slightly positive (albeit not statistically distinguishable from zero). Although the race coefficients vary somewhat with ZIP racial composition, it is important to note that the individual race coefficients are not significantly different, in a statistical sense, across the different ZIP types.[31]

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. We create house price level quintiles based on this data, and 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.[32] We then estimate the regressions separately for the three different house price level categories and plot the coefficients in Figure 4.[33] The only minority coefficient that is positive corresponds to Asian owners in low price ZIPs, however, the confidence intervals are quite wide because there are very few Asian owners located in the low price ZIPs. Otherwise, the results are quite similar across ZIP code house price levels. Minority owners generally receive modestly lower appraisal values relative to AVM values.

[31]Each of the panels in Figure 3 is based on a separate regression. When we estimate a single regression with indicators for high White share ZIP codes and high minority share ZIP codes, along with their interactions with the race categories, the interaction terms are not statistically significant.

[32]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.

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

Lastly, we examine whether the appraisal racial disparities vary over time. We first estimate the app-to-AVM regressions separately for each application year.[34] Figure 5 shows the coefficient estimates across years (see also Table A.7 in the appendix). The most important cross-year differences are for Black and Hispanic owners. The Black coefficient is largest in absolute magnitude in 2006. Note, though, that this coefficient is not statistically different from the Black owner coefficient in the other three years. While the Black owner disparity is largest in 2006, the Hispanic owner coefficient starts at -0.018 in 2003 but moves monotonically over time towards zero. Moreover, the Hispanic coefficient in 2003 is statistically different from the coefficient in 2005 and 2006. Even though the coefficients vary somewhat over time, app-to-AVM disparities across race remain much the same.

3.4. Appraiser Race

In this section, we investigate the effect of the interaction of the borrower's and appraiser's race on valuation. Specifically, we expand the regression specification as follows:

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

where W_i is 1 if the owner is White, and 0 if otherwise; 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

[34] 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.

a Black owner and a White appraiser. The specification also includes interactions 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 $W_i \times P_i^W$. Thus, each δ can be interpreted as the marginal difference in valuation relative to White owned homes appraised by White appraisers.[35] 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 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).

We use Equation (5) to test whether appraiser race and its interaction with owner race is related to the app-to-AVM ratio. Table 4 presents the estimated coefficients for the OLS regressions of the app-to-AVM on indicators for owner and appraiser race. All columns include ZIP code and year fixed effects, as well as property type controls. Column (1) includes owner race coefficients, and thus the results are very similar to those in column (1) of Table 3. Column (2) removes the owner race indicators and adds appraiser race indicators. The Asian and Hispanic appraiser coefficients are essentially zero, however, Black appraisers have app-to-AMV ratios that are slightly higher than White appraisers (0.9 percentage points).

Next, we include the aforementioned indicators for the owner-appraiser race pairs. The omitted category in the regression, as noted, is a White owner matched to a White appraiser. Thus, all regression coefficients in column (3) can be interpreted as the marginal difference in the app-to-AVM ratio relative to White owners using White appraisers. To ease interpretation, we plot the coefficients from column (3) in Figure 6. White owners matched with Asian or Hispanic appraisers receive app-to-AVMs that are no different from White owners using White appraisers.

[35]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.

Somewhat surprisingly, White owners receive higher app-to-AVMs (1.7 percentage points) with Black appraisers. Thus, there is no evidence that White owners receive more favorable treatment with White appraisers.

All the minority owner coefficients, regardless of appraiser race, are negative, and similar in magnitude to our previous estimates, which suggests minorities receive slightly lower valuations. However, for each minority group, the app-to-AVM discount varies little with appraiser race. For example, a White appraiser discounts a Black owner's valuation by 0.8 percentage points while a Black appraiser discounts by 0.6 percentage points. White and Hispanic appraisers of Hispanic property provide nearly identical discounts (0.6 and 0.7 percentage points, respectively). And while Asian homeowners receive a 1.2 percentage point discount from Asian appraisers, this discount is 0.4 percentage points from White appraisers. None of these differences is statistically significant: a Wald test for equality of the Asian Owner/White Appraiser (A/W) and the Asian Owner/Asian Appraiser (A/A) coefficients has a p-value of 0.36. Similarly, B/W is not significantly different from B/B (with a p-value of 0.75), nor is H/W different from H/H (where the p-value is 0.74).

To summarize, minority owners do receive somewhat lower app-to-AVMs, on average. However, this disparity is not appreciably reduced by working with an appraiser of the same race.

3.5. Adjusting AVM to Account for Race

Bartlett et al. (2022) has noted that AVMs can undervalue homes with minority owners. If this is the case, then our estimates of the δ parameters may understate racial appraisal bias by using AVMs as the comparison valuation for appraisals. We take advantage of 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 owner race. The projection of this model provides an adjustment that punitively corrects the AVM for any differences in owner ethnicity. Specifically, 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:

$$\ln(P_i) = \rho \ln(AVM_i) + \delta_1 A_i + \delta_2 B_i + \delta_3 H_i + X_i \beta + \zeta_i + \gamma_i + \varepsilon_i \tag{6}$$

where $\ln(AVM_i)$ is the natural log of the AVM, the parameter ρ is the conditional price elasticity of the AVM, and ε_i is an error term. The other variables on the right-hand-side are the same as in Equation (4), except for the exclusion of appraiser fixed effects. The market value in levels can be estimated as:

$$\hat{V} = \hat{P} = \exp\{\widehat{ln(P_i)} + \hat{\sigma}^2/2\} \tag{7}$$

where $\hat{\sigma}^2$ is the standard error of the regression (Equation (6)).

To implement this procedure, we first estimate Equation (6) using a sample of purchase mortgage applications, which report the purchase price. Importantly, we include binary variables that specify the ethnic category of the purchaser/borrower. This allows the projection of purchase price onto AVM value, and other controls including the borrower's ethnicity. If the AVM undervalues the purchase price for a particular race, then the fitted values from this regression adjust accordingly. Second, we use the estimated coefficients to predict the market value of the properties in the refinance mortgage sample using Equation (7). Finally, we estimate our baseline regressions, models (4) and (5), using the refinanced mortgages but with the "corrected" AVM values in the dependent variable as follows:

$$\frac{AppraisedValue_i}{\hat{P}_i}. \tag{8}$$

In Table 5 we report the results from correcting the AVM for racial differences in home prices. The first column shows the coefficient point estimates of Equation (6) using the purchase sample. The R^2 is high, indicating a strong goodness of fit. The AVMs, when applied to homes purchased by Black and Asian owners, provide valuations that are about 2% lower than the purchase price, while those for Hispanic purchasers are, on average, slightly higher than the purchase price. Column (2) reports the coefficient estimates of Equation (4) using the sample of refinanced mortgages and the corrected app-to-AVM measure. Compared to the corresponding estimates in column (1) of Table 4, these estimates of appraisal bias relative to 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 that of White homeowners. These latter parameter estimates suggest that appraisers have underestimated the estimated purchase price by about 1 percentage points for Asian owners, 3.6 percentage points for Black owners, and 2 percentage points for Hispanic owners when compared to the average valuation of White-owned homes. These differences are statistically significant at the 1% significance level. Hence, our prior point estimates for racial appraisal bias are conservative.

As before, we examine whether the bias varies with the race of the appraiser. In column (3), we interact indicators for the owner's race with indicators for the appraiser's race as in Equation (5) using the corrected app-to-AVM measure as the dependent variable. Figure 7 plots the effect of the owner's and appraiser's race on the modified app-to-AVM ratio with 95% confidence intervals for each race, setting the interaction of a White appraiser and White owner as the reference benchmark. Although racial appraisal bias appears to be statistically significant for each cross-race interaction, the appraisal bias for each minority owner race again does not vary appreciably with the race of the appraiser. Black homeowners experience a 3.8 percentage point decline in appraised value with a White appraiser, and a 3.4 percentage point decline with a Black appraiser. The corresponding estimates for Hispanic borrowers are 1.9 and 2.3 percentage point declines from White and Hispanic appraisers, while Asian homeowners see a 0.9 and 1.3 percentage point drop from White and Asian appraisers. None of these differences between White and minority appraisers are statistically significant.

In the online appendix, we examine alternative specifications for the market value (Equation (6)). First, we allow the relationship between AVM and price to vary with the race of the owner by interacting owner race indicators with the $ln(AVM)$ variable. Second, we examine another specification of the market value that includes the homeowner's income in the natural log form to proxy for unobservable characteristics of the property that may correlate with the owner's income. Appendix Table A.8 reports the results using these alternative specifications to estimate $\hat{P}_i$. Although the magnitude of the owner race coefficients in the appraisal to predicted price change slightly relative to column (2) in Table 5, we draw the same conclusion: racial disparities in valuation are larger when we account for differences in AVM values across race.

3.6. 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. We provided preliminary evidence along these lines in Section 3.1 by examining appraiser-level *unconditional* mean-differences in valuation for minorities and Whites. We now estimate appraiser-level racial disparities conditional on a host of control variables. More specifically, we estimate a slightly modified version of Equation (4) that takes the following form:

$$Y_i = \alpha M_i + \lambda_j \omega_j + \sum_j \delta_j \cdot (\omega_j \times M_i) + X_i \beta + \zeta_i + \gamma_i + \epsilon_i, \tag{9}$$

where Y_i is the appraisal-to-predicted price ratio for property i, as calculated in Section 3.5. 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. One key distinction is that the fixed effect for each appraiser j is interacted with the minority owner indicator. As a result, this specification allows the minority effect on the app-to-AVM ratio to vary uniquely for each appraiser who has appraised White and minority owned homes. Put differently, the gap in the app-to-AVM ratio that a minority homeowner encounters relative to a white homeowner depends on who appraises the property; this appraiser-specific gap is defined by $\hat{\alpha} + \hat{\delta}_j$.[36]

We estimate Equation (9) 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 8. Panel A illustrates the distribution of the individual appraiser race effects from a regression where only White- and Asian- owned homes, appraised by 1,029 appraisers, are included in the sample.[37] 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. The average appraiser-level race coefficients imply an appraisal bias of approximately -1 percentage point 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). These extreme values are partly driven by appraisers that performed few appraisals. For example, in the Asian-White sample, appraisers with coefficients in the bottom decile or top decile of this distri-

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

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

bution appraised an average of 12 homes, whereas appraisers with coefficients in the middle 80% of the distribution appraised an average of 25 homes. We observe similar statistics for the Black-White and Hispanic-White samples. In general, the more homes an appraiser appraises, the less noisy is the appraiser-specific minority effect.

The results in Figure 8 provide some suggestive evidence that the magnitude of the average conditional racial disparities documented in Section 3.1 are not driven by large disparities within just a few appraisers, but rather small racial disparities for many appraisers. Nevertheless, we further examine the incidence of extreme racial disparities at the appraiser-level (conditional on our other controls). Figure 9 plots the cumulative distribution of the racial coefficients using the same data as Figure 8. 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, 28 appraisers, or 3%, have a large discount for Asian owners (<-0.3). In contrast, only 12 appraisers, or 1%, have a large positive app-to-AVM premium for Asian 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 (208 extreme negative coefficients to 104 large positive). In Panel C, a similar pattern emerges in the Hispanic and White owner sample (136 extreme negative coefficients versus 95 large positive). Overall, Figure 9 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.

Next, 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 (9). Figure 10 plots coefficient pairs for an individual appraiser. Panel A of Figure 10 plots the Asian and Black coefficients for the 634 appraisers that 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 from the negative race coefficients ($X < 0$) to the positive race coefficients ($X > 0$). Figure 10 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.

4. Racial Differences in Valuations on Purchase Applications

A limitation of the above analysis is that the AVM estimate is only available for originated loans. If large racial disparities in valuation exist, but are *only* reflected in unfunded applications, our app-to-AVM analysis would not detect this. But this seems highly improbable. In refinance loans, a low appraisal seems unlikely to materially affect either the lender's decision to approve the loan, or a borrower's willingness to refinance. It only affects the amount of cash to be taken out of the owner's equity at the time of the refinance, particularly in our sample period. However, in marginal cases, parties to the loan may indeed turn away if there is disappointment either in the collateral value or in the amount of the cash out.

To examine this issue, we utilize a different sample of mortgage applications from New Century. This sample, which we term the NCEN purchase sample, is comprised of appraisals associated with both unfunded and funded (originated) purchase applications. Instead of comparing the appraised value to an AVM estimate, we first compare it to the sales contract price. We can then test whether the likelihood of a below contract price appraisal is related to the property buyer's race. The advantage of this approach is that we observe the appraised value and the contract price for both funded and unfunded purchase applications. However, there are two disadvantages in using these data. First, as others have documented, below-contract price appraisals are uncommon. Ninety eight percent of appraisals in our purchase sample are at or above the sales contract price, which means that there is relatively little variation in the dependent variable of interest.[38] Second, an appraiser is less likely to deal directly with the mortgage applicant on a purchase transaction, and thus is less likely to observe the applicant's race. However, the appraiser generally receives a copy of the sales contract, which contains the buyer's name, so even when not dealing directly with the applicant, race can be inferred. With these limitations in mind, we proceed with our analysis on purchase applications.

Columns (1) and (2) in Table 6 present linear probability models (OLS) using Equation (4) but setting the dependent variable to indicate whether the appraised value is below the contract purchase price. The main variables (A_i, B_i, an H_i) denote the race of the buyer (or "the owner to be"). The omitted racial category in all columns is White buyer. Among unfunded applications (column (1)), the Asian, Black, and Hispanic buyer coefficients are not statistically significant and are essentially zero, which does not support the hypothesis that large racial valuation bias exists on unfunded loan applications. Column (2) limits the sample to appraisals associated with purchase applications that resulted in funded loans. Here we see that appraisals for Black and Hispanic buyers are actually less likely to come in below the contract price. In other words, there is little evidence that large racial appraisal bias against minorities exists in home purchase appraisals. This stands in contrast to the findings of Freddie Mac (2021), who examine the same question over a different time and find large racial disparities.

Column (3) in Table 6 presents the estimation results for the linear probability model (OLS)

[38] Studies using more recent data find higher shares of below-contract appraisals, $\approx 8\%$ (Fout, Mota, and Rosenblatt, 2021; Freddie Mac, 2021), likely as a result of greater appraisal scrutiny and increased appraiser oversight after the global financial crisis.

using a version of Equation (4). The dependent variable indicates whether the application results in an originated loan and the controls include interactions of the race variables with a dummy variable for whether the appraised price is below the purchase contract price. All minority groups are less likely to have an application result in a funded loan. However, the relationship between a below-contract appraisal and the likelihood that an application results in an originated loan varies considerably with buyer race. For example, a below-contract appraisal reduces the likelihood that an application for a White buyer results in a funded loan by 13.2 percentage points. For Blacks and Hispanics the origination likelihood further decreases by 8.1 percentage points and 0.9 percentage points, respectively. In contrast, a below contract appraisal has less of an impact (5.2 percentage point decrease) on the likelihood of origination for Asian buyers.

Column (4) in Table 6 presents OLS estimates of Equation (4) using the app-to-AVM ratio as the dependent variable and the sample of originated purchase applications. For Black buyers, the appraised value is 1.3 percentage points higher relative to the AVM than for White buyers. The difference is statistically significant at the 1% level. In contrast, we do not observe any statistically significant differences in the purchase app-to-AVM between White and Hispanic or Asian buyers. The results are in direct contrast to those reported in Column (1) of Table 3 but consistent with the findings in columns (1)-(3) of Table 6. One reason is that the appraiser's incentives differ between purchase applications and refinance applications. Prior literature has shown an abundance of evidence of the pressure that appraisers were under during the housing boom to overvalue properties in order that they meet or exceed the purchase price (Kruger and Maturana, 2021). By contrast, refinance applications do not produce a hurdle price that appraisals must meet to allow the transaction to occur. Thus, appraisers have more flexibility to express their own beliefs about the value of the property in refinance than purchase appraisals.

Taken together, the results in Table 6 do not show large, systematic racial bias in appraisals on unfunded purchase mortgage applications or originated purchase loans during the buildup of the subprime mortgage crisis from 2000 to 2007. However, the relationship between a below-contract appraisal and the likelihood of loan funding does vary significantly by buyer race.

5. Conclusion

The disparate treatment of 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 data set 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 3.8 percentage points than comparable homes owned by Whites, depending on the comparison measure of home value. Hispanic households also receive lower valuations compared to White households. Interestingly, we find that these estimates do not vary greatly with the ethnicity of the appraiser. These differences also do not vary greatly across neighborhood type or other demographic differences. We do not find large differences in appraisal fees. Our extension to purchase mortgages suggests less evidence of discrimination for these loans, which is presumably due to price targeting by appraisers, although when a below contract price appraisal occurs, minority borrowers are more likely to turned down.

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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. To ease interpretation of our regression results, we exclude a small share of observations (4%) where both the appraiser and the owner are minorities, but not of the same race.

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-AVM $< .8$	222,269	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-AVM $< .8$	0.08	0.08	0.08	0.09
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 $<$ .8	(3) Appraisal Fee	(4) Appraisal Fee $>$ \$600
Asian Owner	-0.003	0.005	3.594*	0.002
	(0.004)	(0.004)	(2.051)	(0.004)
Black Owner	-0.009***	0.001	-1.907	-0.003
	(0.002)	(0.002)	(1.216)	(0.002)
Hispanic Owner	-0.007***	0.008***	0.937	0.000
	(0.002)	(0.002)	(1.087)	(0.002)
Observations	195,158	195,158	63,662	63,662
Adjusted R^2	0.184	0.056	0.348	0.151
Property Type Controls	Y	Y	Y	Y
ZIP FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Appraiser FE	Y	Y	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. *** p<0.01, ** p<0.05, * p<0.10

Table 4. Appraised Value, AVM Estimates, Owner and Appraiser Race

	(1) App to AVM	(2) App to AVM	(3) App to AVM
Asian Owner	-0.006		
	(0.004)		
Black Owner	-0.008***		
	(0.002)		
Hispanic Owner	-0.006***		
	(0.002)		
Asian Appraiser		-0.001	
		(0.005)	
Black Appraiser		0.009**	
		(0.004)	
Hispanic Appraiser		-0.001	
		(0.003)	
Asian Owner/White Appraiser			-0.004
			(0.004)
Asian Owner/Asian Appraiser			-0.012
			(0.008)
Black Owner/White Appraiser			-0.008***
			(0.002)
Black Owner/Black Appraiser			-0.006
			(0.006)
Hispanic Owner/White Appraiser			-0.006***
			(0.002)
Hispanic Owner/Hispanic Appraiser			-0.007*
			(0.004)
White Owner/Asian Appraiser			0.000
			(0.006)
White Owner/Black Appraiser			0.017***
			(0.006)
White Owner/Hispanic Appraiser			-0.001
			(0.004)
Observations	196,002	196,002	196,002
Adjusted R^2	0.159	0.159	0.159
Property Type Controls	Y	Y	Y
ZIP FE	Y	Y	Y
Year FE	Y	Y	Y

Note: This table presents estimates from regression models where the dependent variable is the appraised value divided by the AVM value. White Borrower/White Appraiser is the omitted category in column (3). *** 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-$\hat{P}$	(3) App-to-$\hat{P}$
Ln(AVM)	0.626***		
	(0.002)		
Asian Owner	0.019***	-0.010***	
	(0.003)	(0.003)	
Black Owner	0.020***	-0.036***	
	(0.002)	(0.002)	
Hispanic Owner	-0.005***	-0.020***	
	(0.002)	(0.002)	
Asian Owner/White Appraiser			-0.009***
			(0.003)
Asian Owner/Asian Appraiser			-0.013**
			(0.006)
Black Owner/White Appraiser			-0.038***
			(0.002)
Black Owner/Black Appraiser			-0.034***
			(0.005)
Hispanic Owner/White Appraiser			-0.019***
			(0.002)
Hispanic Owner/Hispanic Appraiser			-0.023***
			(0.003)
White Owner/Asian Appraiser			-0.000
			(0.005)
White Owner/Black Appraiser			0.008
			(0.005)
White Owner/Hispanic Appraiser			-0.002
			(0.003)
Observations	136,916	195,044	195,889
Adjusted R^2	0.891	0.215	0.177
Property Type Controls	Y	Y	Y
ZIP FE	Y	Y	Y
Year FE	Y	Y	Y
Appraiser FE	N	Y	N
Sample	Purchases	Refinances	Refinances

Note: Column (1) presents estimates from regression models 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 ($\hat{P}$) out-of-sample for applications in our refinance sample. The dependent variable in columns (2) and (3) is the appraised value divided by $\hat{P}$ in the refinance sample. *** p<0.01, ** p<0.05, * p<0.10

Table 6. Appraisals and Borrower Race on Purchase Applications

	(1)	(2)	(3)	(4)
	Unfunded Applications Below Contract	Originated Loans Below Contract	Pr(Originated)	App to AVM
Asian Buyer	0.002	0.002	-0.017***	-0.004
	(0.003)	(0.001)	(0.004)	(0.003)
Black Buyer	0.002	-0.003**	-0.028***	0.013***
	(0.002)	(0.001)	(0.003)	(0.003)
Hispanic Buyer	-0.002	-0.003***	-0.016***	0.001
	(0.002)	(0.001)	(0.002)	(0.002)
Below Contract			-0.132***	
			(0.009)	
Asian Buyer × Below Contract			0.080***	
			(0.019)	
Black Buyer × Below Contract			-0.081***	
			(0.014)	
Hispanic Buyer × Below Contract			-0.009	
			(0.013)	
Observations	102,024	239,062	359,011	112,761
Adjusted R^2	-0.004	0.003	0.082	0.165
Property Type Controls	Y	Y	Y	Y
ZIP FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Appraiser FE	Y	Y	Y	Y

Note: This table presents estimates from regression models where the dependent variable in columns (1) and (2) is an indicator variable that takes a value of one of the appraised value is below the sales contract price, and zero otherwise. In column (3) the dependent variable is a binary variable that takes a value of one if the application results in a funded loan, and zero otherwise. The dependent variable in column (4) is the appraised value divided by the AVM value. The samples in columns (1) and (2) include unfunded purchase applications and originated purchase loans, respectively. The sample in column (3) includes both unfunded purchase applications and originated purchase loans. The sample in column (4) includes purchase applications that resulted in funded loans that are matched to the ABSNet data. *** p<0.01, ** p<0.05, * p<0.10

7. Figures

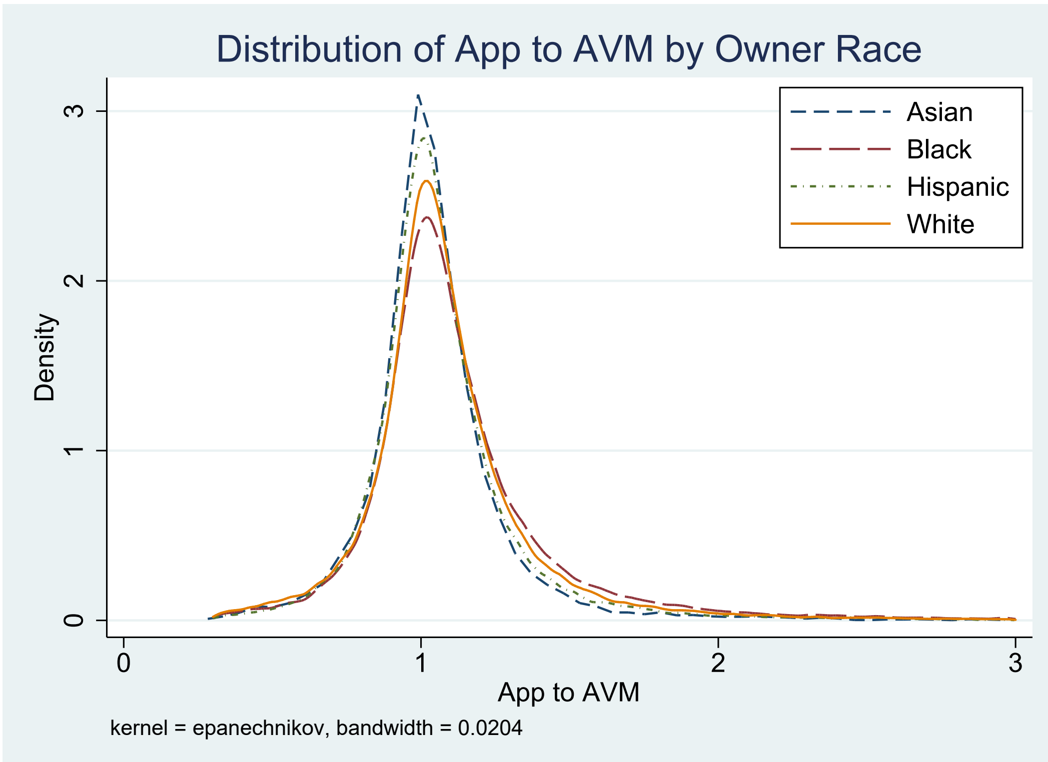


Figure 1. Distribution of App to AVM by Owner Race

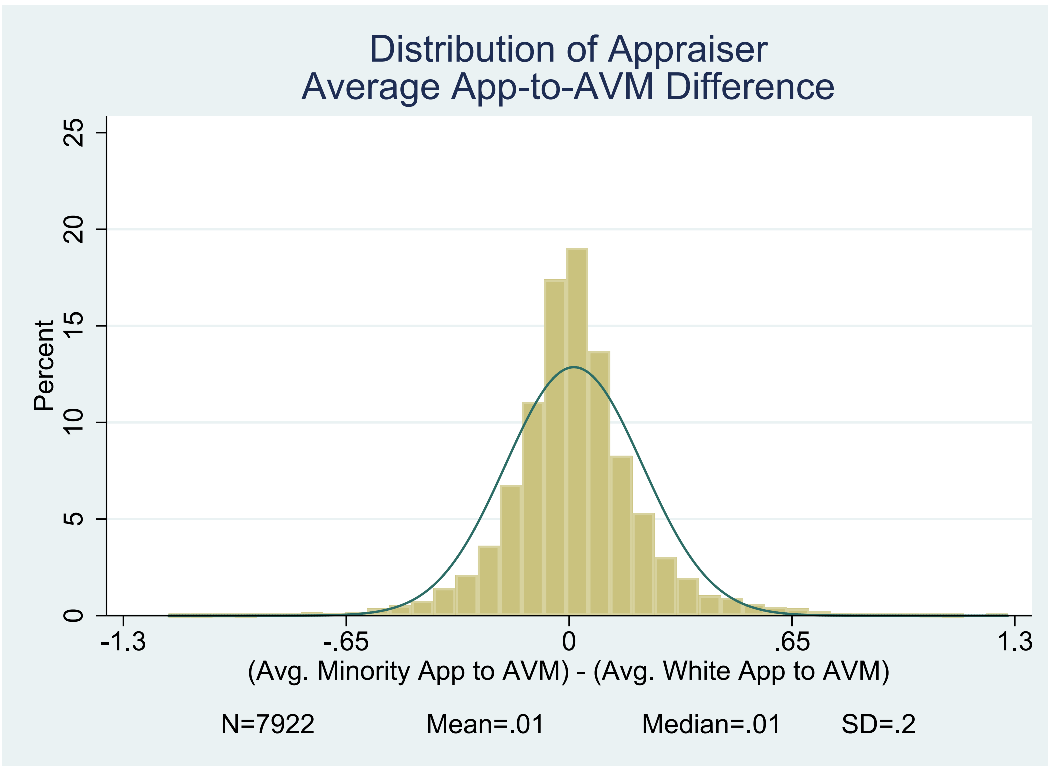


Figure 2. Distribution of Appraiser Level Mean Difference between Minority App-to-AVMs and White App-to-AVMs.

Note: Sample includes appraisers that had at least two appraisals for White owners and two appraisals for minority owners.

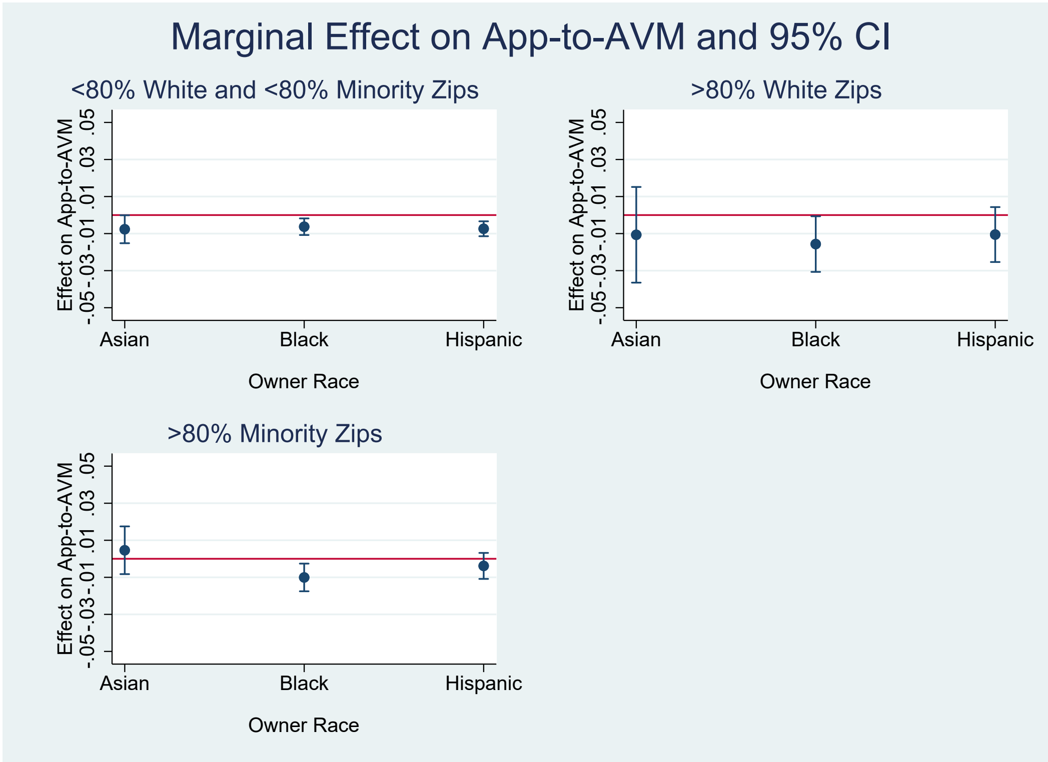


Figure 3. Marginal Effect of Owner Race on app-to-AVM by Zip Racial Composition

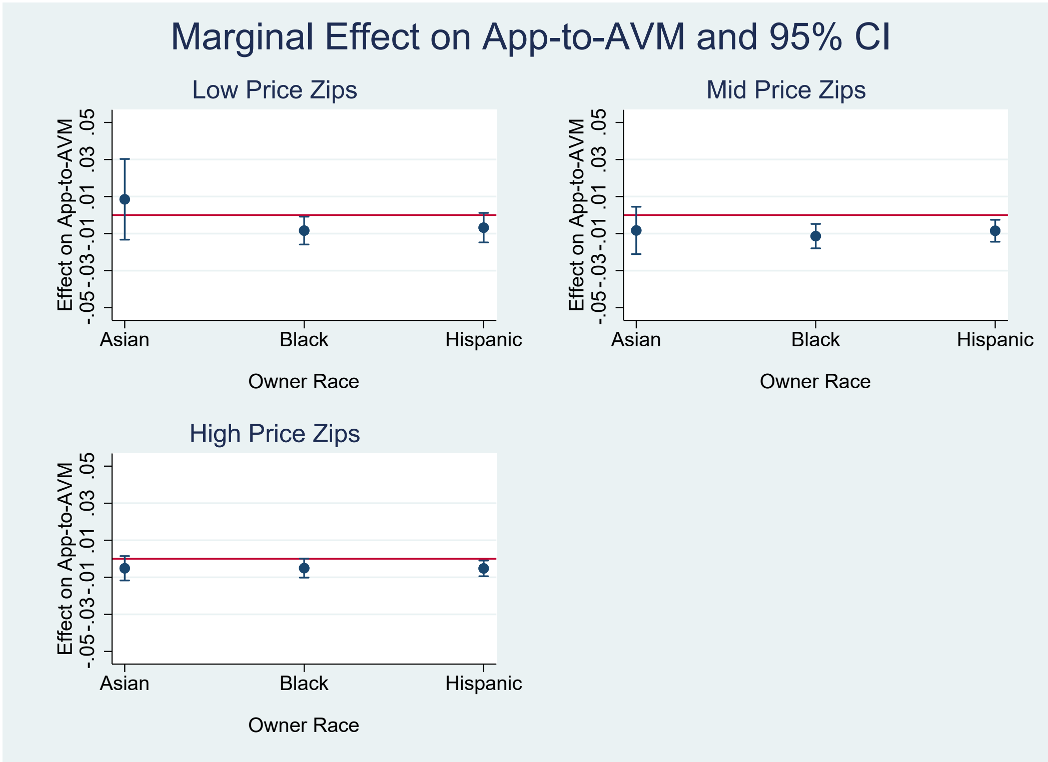


Figure 4. Marginal Effect of Owner Race on app-to-AVM by Zip House Price Level

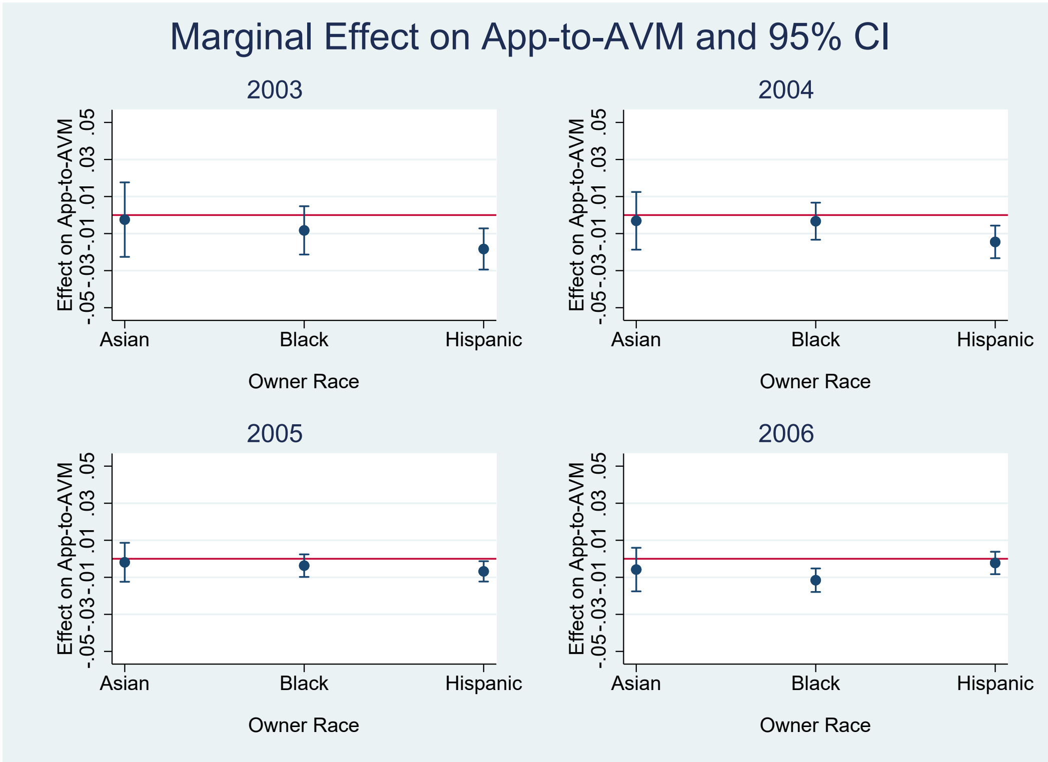


Figure 5. Marginal Effect of Owner Race on app-to-AVM by Year

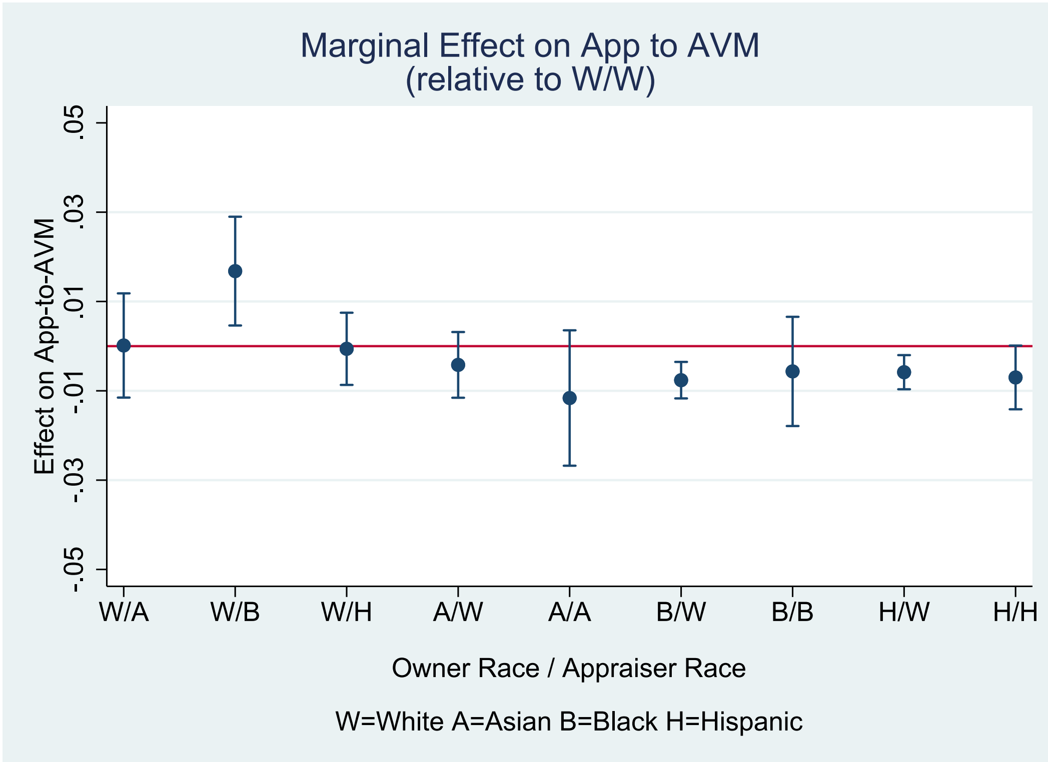


Figure 6. Marginal Effect of Owner and Appraiser Race on App-to-AVM

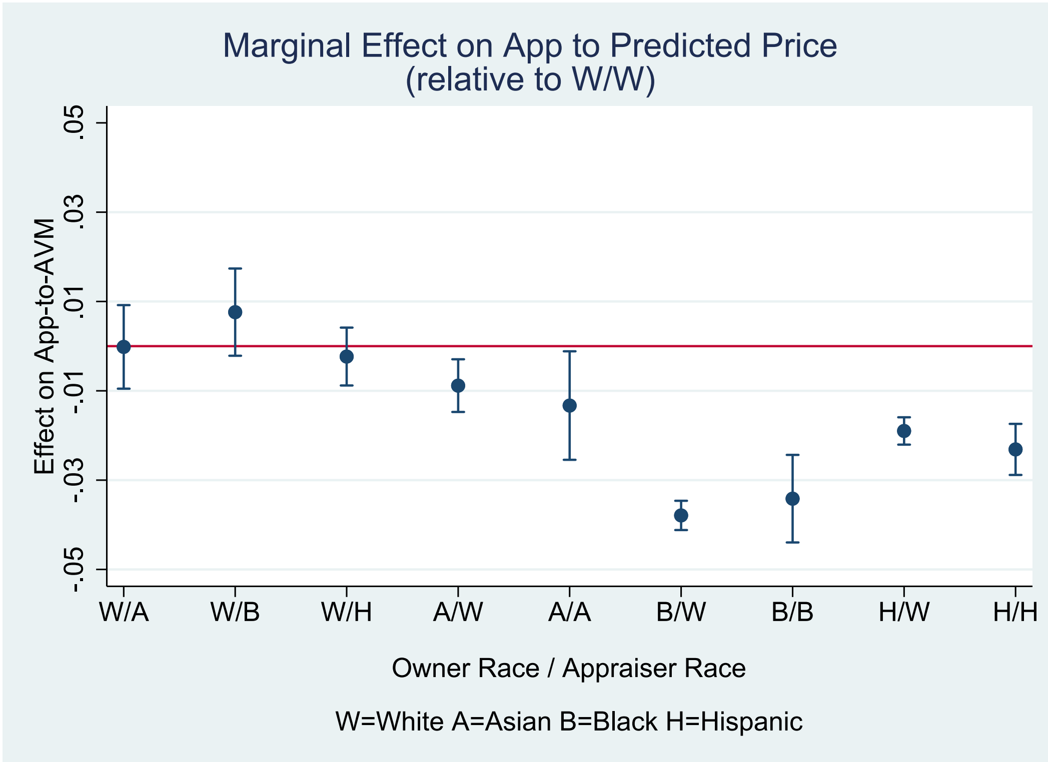
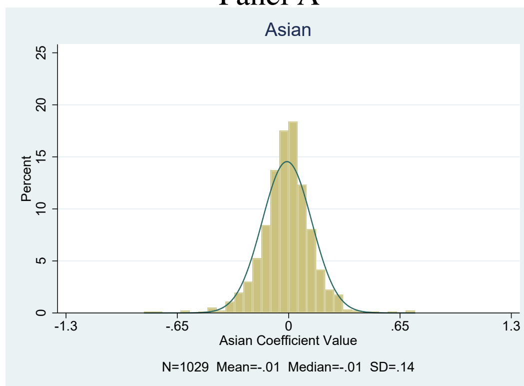
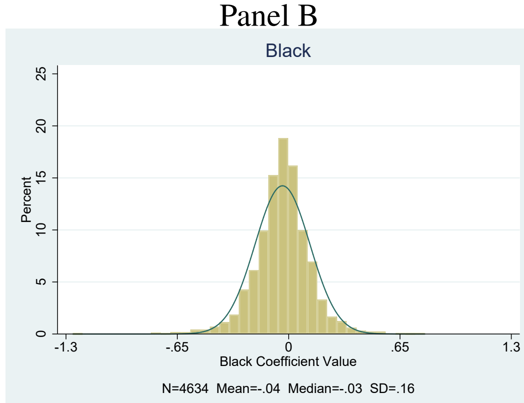


Figure 7. Marginal Effect of Owner and Appraiser Race on App-to-$\hat{P}$

Panel A



Panel B



Panel C

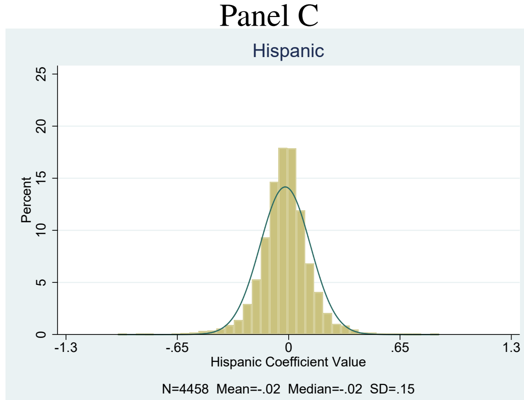
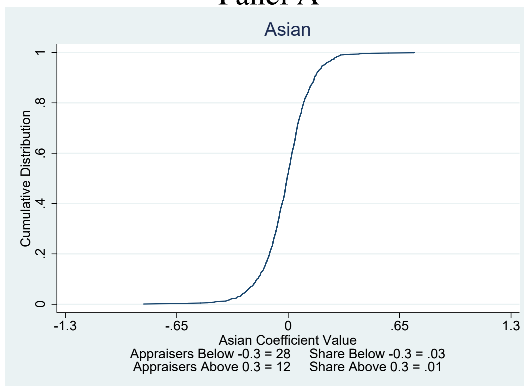
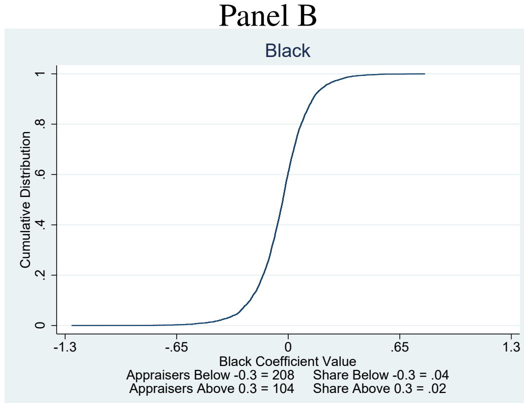


Figure 8. Distribution of individual appraiser race coefficients.

Panel A



Panel B



Panel C

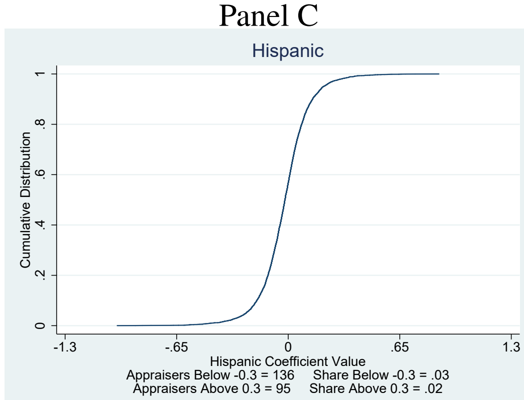
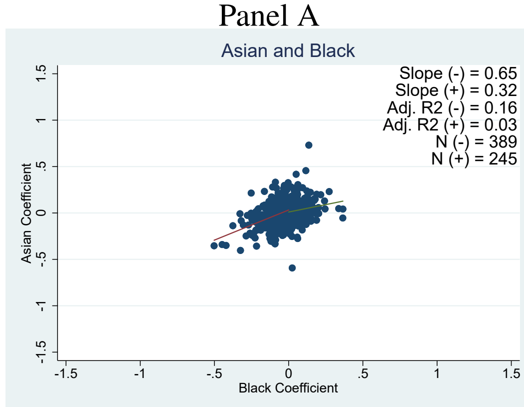
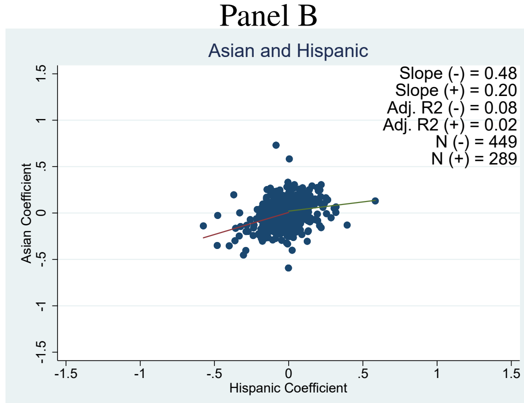


Figure 9. Cumulative distribution of individual appraiser race coefficients.

Panel A



Panel B



Panel C

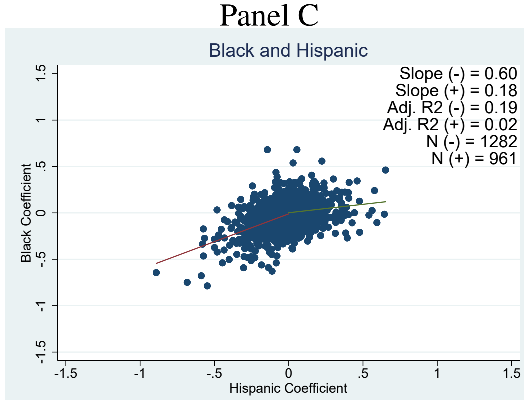


Figure 10. Correlation between individual appraisers race coefficients.
Note: Each point represents an individual appraiser and the individual appraiser race coefficients associated with that appraiser. Two separate linear fit lines are plotted for X<0 (-) and X≥0 (+).

INTERNET APPENDIX

A.1. 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.[1] 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).[2]

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.[3] 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 name.[4] For each appraiser, we now have the likelihood (BIFS score) that the appraiser falls into

[1]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.

[2]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.

[3]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,

[4]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).

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 includes 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.

A.2. Additional Tables

Table A.1. Racial Distribution of Appraisers

Appraiser Race	NCEN-ABSNet Freq.	NCEN-ABSNet Share	Appraisal Foundation Share	Appraisal Institute 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: Purchase Applications

	Obs	Mean	Std. Dev.	Min	Max
Funded (originated)	576,416	0.55	.	0	1
Appraisal Value	576,416	$254,293	$176,461	$30,000	$4,000,000
Purchase Price	576,416	$249,989	$174,042	$30,000	$4,000,000
Below Contract	576,416	0.02	.	0	1
App-to-AVM Ratio	135,078	1.07	0.23	0.30	3
Price to AVM	135,152	1.05	0.23	0.30	3
Asian Owner	576,416	0.06	.	0	1
Black Owner	576,416	0.20	.	0	1
Hispanic Owner	576,416	0.25	.	0	1
White Owner	576,416	0.49	.	0	1
Second Home	576,416	0.03	.	0	1
Investment Property	576,416	0.13	.	0	1
Multi-unit	576,416	0.07	.	0	1
Condo	576,416	0.09	.	0	1
PUD	576,416	0.12	.	0	1

Panel B: Purchase Applications

Mean by Race	Asian	Black	Hispanic	White
Funded (originated)	0.57	0.48	0.55	0.57
Appraisal Value	$373,147	$214,967	$293,553	$235,261
Purchase Price	$371,247	$210,697	$292,567	$231,984
Below Contract	0.03	0.02	0.02	0.02
App-to-AVM Ratio	1.04	1.11	1.06	1.06
Price to AVM	1.03	1.09	1.04	1.04
Second Home	0.05	0.03	0.03	0.04
Investment Property	0.11	0.17	0.09	0.13
Multi-unit	0.07	0.10	0.09	0.05
Condo	0.16	0.06	0.09	0.09
PUD	0.17	0.11	0.11	0.12
Observations	35,328	118,502	143,410	283,472

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. Appraised Value, AVM Estimates, and Owner Race

	(1) App to AVM	(2) App to AVM	(3) App to AVM	(4) App to AVM	(5) App to AVM
Asian Owner	-0.044***	-0.004	-0.004	-0.005	-0.003
	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)
Black Owner	0.033***	-0.008***	-0.008***	-0.008***	-0.009***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Hispanic Owner	-0.021***	-0.005***	-0.005***	-0.007***	-0.007***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Observations	222,269	220,451	220,451	220,306	195,158
Adjusted R^2	0.004	0.152	0.157	0.158	0.184
Property Type Controls	N	N	N	Y	Y
ZIP FE	N	Y	Y	Y	Y
Year FE	N	N	Y	Y	Y
Appraiser FE	N	N	N	N	Y

Note: This table presents estimates from regression models where the dependent variable is the appraised value divided by the AVM value in columns (1) - (5). The sample includes refinance applications that resulted in originated loans. *** p<0.01, ** p<0.05, * p<0.10

Table A.4. Appraisal Fee and Owner Race

	(1) Appraisal Fee	(2) Appraisal Fee	(3) Appraisal Fee	(4) Appraisal Fee	(5) Appraisal Fee
Asian Owner	49.126***	1.055	0.643	-0.389	3.594*
	(1.646)	(1.805)	(1.801)	(1.694)	(2.051)
Black Owner	1.965**	0.738	0.298	-0.216	-1.907
	(0.866)	(1.083)	(1.081)	(1.017)	(1.216)
Hispanic Owner	13.875***	4.102***	3.809***	-0.131	0.937
	(0.831)	(0.983)	(0.981)	(0.924)	(1.087)
Observations	78,065	75,907	75,907	75,874	63,662
Adjusted R^2	0.014	0.174	0.178	0.273	0.348
Property Type Controls	N	N	N	Y	Y
ZIP FE	N	Y	Y	Y	Y
Year FE	N	N	Y	Y	Y
Appraiser FE	N	N	N	N	Y

Note: This table presents estimates from regression models where the dependent variable is appraisal fee in columns (1) - (5). The sample includes refinance applications where the appraisal fee is available. *** p<0.01, ** p<0.05, * p<0.10

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

	(1) Mixed Zips App to AVM	(2) White Zips App to AVM	(3) Minority Zips App to AVM
Asian Owner	-0.008**	-0.011	0.005
	(0.004)	(0.013)	(0.007)
Black Owner	-0.006***	-0.016**	-0.010***
	(0.002)	(0.008)	(0.004)
Hispanic Owner	-0.007***	-0.011	-0.004
	(0.002)	(0.008)	(0.004)
Observations	123,111	41,447	55,313
Adjusted R^2	0.138	0.110	0.227
Property Type Controls	Y	Y	Y
ZIP FE	Y	Y	Y
Year FE	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 where at least 80% of the population is White. The sample in column (2) includes refinance applications that resulted in originated loans in ZIP codes where at least 80% of the population are minorities. *** p<0.01, ** p<0.05, * p<0.10

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

	(1) Low Price Zips App to AVM	(2) Mid Price Zips App to AVM	(3) High Price Zips App to AVM
Asian Owner	0.008	-0.008	-0.005
	(0.011)	(0.007)	(0.003)
Black Owner	-0.008**	-0.011***	-0.005*
	(0.004)	(0.003)	(0.003)
Hispanic Owner	-0.007*	-0.008***	-0.005**
	(0.004)	(0.003)	(0.002)
Observations	70,312	63,263	82,524
Adjusted R^2	0.160	0.076	0.069
Property Type Controls	Y	Y	Y
ZIP FE	Y	Y	Y
Year FE	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 *** p<0.01, ** p<0.05, * p<0.10

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

	(1) 2003 App to AVM	(2) 2004 App to AVM	(3) 2005 App to AVM	(4) 2006 App to AVM
Asian Owner	-0.002	-0.003	-0.002	-0.006
	(0.010)	(0.008)	(0.005)	(0.006)
Black Owner	-0.008	-0.003	-0.004	-0.012***
	(0.007)	(0.005)	(0.003)	(0.003)
Hispanic Owner	-0.018***	-0.014***	-0.007**	-0.002
	(0.006)	(0.004)	(0.003)	(0.003)
Observations	19,600	32,037	76,986	69,287
Adjusted R^2	0.305	0.300	0.174	0.157
Property Type Controls	Y	Y	Y	Y
ZIP FE	Y	Y	Y	Y
Year FE	N	N	N	N

Note: This table presents estimates from regression models where the dependent variable is the appraised value divided by the AVM value. The sample includes refinance applications that resulted in originated loans. The sample in each column includes on applications from the year indicated in the column header. *** p<0.01, ** p<0.05, * p<0.10

Table A.8. Appraised Value, Adjusted AVM Estimates, and Owner Race

	(1) Ln(Purch Price)	(2) App-to-$\hat{P}$	(3) Ln(Purch Price)	(4) App-to-$\hat{P}$
Ln(AVM)	0.646***		0.540***	
	(0.002)		(0.002)	
Asian	-0.086	-0.009***	0.021***	-0.021***
	(0.054)	(0.003)	(0.002)	(0.003)
Black	0.795***	-0.032***	0.029***	-0.039***
	(0.031)	(0.002)	(0.002)	(0.002)
Hispanic	0.210***	-0.018***	0.008***	-0.026***
	(0.031)	(0.002)	(0.002)	(0.001)
Ln(AVM) × Asian	0.008*			
	(0.004)			
Ln(AVM) × Black	-0.064***			
	(0.003)			
Ln(AVM) × Hispanic	-0.018***			
	(0.003)			
Ln(Income)			0.177***	
			(0.001)	
Observations	136,916	195,049	136,621	194,777
Adjusted R-squared	0.616	0.214	0.663	0.201
Property Type Controls	Y	Y	Y	Y
ZIP FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Appraiser FE	N	Y	N	Y

Note: Columns (1) and (3) presents estimates from regression models where the dependent variable is the the natural logarithm of the purchase price in our purchase sample. The models from column (1) and (3) are used to predict property values ($\hat{P}$) out-of-sample for applications in our refinance sample. The dependent variables in columns (2) and (4) are the appraised value divided by $\hat{P}$ (from columns (1) and (3), respectively) in the refinance sample. *** p<0.01, ** p<0.05, * p<0.10