Do Appraiser and Borrower Race Affect Valuation?

Brent W. Ambrose*, James N. Conklin†, N. Edward Coulson‡, Moussa Diop§, and Luis A. Lopez¶

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Abstract

Following concerns about undervaluation of minority-owned homes, we examine the incidence of racial appraisal bias using a nationwide sample of refinanced mortgages from 2000 to 2007. A unique feature of our data is that they allow us to observe the race of the both the homeowner and the appraiser. While we do observe systematic lower appraised values relative to automated valuation model (AVM) estimates for minority-owned homes, we do not find evidence that white and minority appriasers provide different valuations. That is, the appraiser's race and its interaction with the owner's race does not explain the lower minority valuations.

*Smeal College of Business, University Park, PA
†Terry College of Business, University of Georgia, Athens, GA
‡Paul Merage School of Business, University of California, Irvine, Irvine, CA
§Sol Price School of Public Policy, University of Southern California, Los Angeles, CA
¶College of Business Administration, University of Illinois at Chicago, Chicago, IL

1. Introduction

In the mortgage lending industry, lenders often rely on estimates of the values for the real properties (or real estate) that serve as collateral on loan contracts. Individual appraisers, trained in the practice of estimating asset values and licensed by state governments, provide these property value estimates. For many years, appraisers explicitly factored owner race and neighborhood race/ethnicity into their estimates of property values.[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 anecdotal evidence of continued discrimination in the appraisal process (see Haythorn, 2020; Kamin, 2020; Malagón, 2020). These articles echo findings of perceived racial bias in property valuations for minority homeowners documented in contemporary studies (Howell and Korver-Glenn, 2020; Perry, Rothwell, and Harshbarger, 2018).[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 ex-

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

[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

ample, a recent study by the American Enterprise Institute (AEI) finds no systematic evidence of appraisal discrimination (Pinto and Peter, 2021a). Furthermore, in a separate special briefing, the AEI suggests that Perry, Rothwell, and Harshbarger (2018) seriously overstate the impact of racial bias in property valuations (see Pinto and Peter, 2021b), putting into question whether policy efforts on 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 in recent years, we provide new insights into the incidence of racial bias in the appraisal process by using a novel dataset from an earlier period that provides us the opportunity to infer appraiser race and its interaction with owner race. Our data come from an administrative dataset on mortgages originated by New Century Financial Corporation (NCEN) during the housing boom prior to the Great Financial Crisis (GFC), a period when the appraisal industry faced less regulation and minorities played a larger role in the mortgage market.[5] This time period is often associated with expanding credit availability to minorities along with increasing minority homeownership rates as well as greater competition 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 individual actors in the mortgage origination process.[6] In contrast to previous studies, these data allows 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, allow-

(Boehm and Schlottmann, 2004; Bostic and Surette, 2001; Coulson and Dalton, 2010; Dawkins, 2005; Dietz and Haurin, 2003; Flippen, 2001, 2004; Gyourko, Linneman, and Wachter, 1999; Krivo and Kaufman, 2004).

[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.

ing us to use a race classification algorithm similar to 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 dataset 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 or appraiser fixed effects.

Our primary sample consists of appraisals conducted for over 220,000 mortgages that were refinanced between 2000 and 2007 (inclusive) and appraised by over 34,000 individual appraisers. 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.[8] In doing so, we make four key contributions.

First, although we find that appraisals for all borrowers are on average 5% to 8% higher than AVM values, which is consistent with prior studies (Conklin et al., 2020; Kruger and Maturana, 2020; Shi and Zhang, 2015), we find that Black and Hispanic homeowners experienced -0.9% and -0.7% lower appraisals, on average, than comparable white borrowers after conditioning on an extensive set of control variables, as well as location and time fixed effects. For a typical home owned by a white household and appraised at $300,000, the estimated coefficients imply that it would be appraised at $297,600 (or $2,400 less) if owned by a black household. While these differences are not as large as the anecdotal reports in the popular press, they are statistically

[7]Details of the merging process are discussed in Section **??**. We explicitly test the assumption of race blind value estimates from the AVM and find that AVM property value estimates for minorities are actually lower than for similar white owned properties.

[8]Appraiser valuations may target the contract price on purchase transactions, and thus leave less scope for racial bias.

significant and consistent with the perception of differential treatment for minority borrowers.

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 are able to examine racial interactions and provide additional insights to the literature that focuses on ethnic and racial group interactions (Agarwal et al., 2019; Bayer, McMillan, and Rueben, 2004; Bertrand, Luttmer, and Mullainathan, 2000; Li, 2014; Wong, 2013; Zhang and Zheng, 2015). In contrast to the popular press accounts, our analysis points to Black and Hispanic owners receiving lower appraisals than white owners regardless of the race of the appraiser. For example, in contrast to similar properties with white owners, we find that Black owners received values estimates that were -0.8% lower from white appraisers and -0.6% lower from black appraisers.[9] Thus, our results do not point to implicit bias on the part of 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. Interestingly, we also find that white owners receive appraisals that are 1.7% higher from Black appraisers than similar white owners interacting with white appraisers.

Third, since our analysis of appraisal bias rests on the comparison of appraisals to value estimates obtained from an automated-valuation-model (AVM), we investigate whether the AVM exhibits a bias toward minority owners. 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 transaction, where the purchase price is known and which should reflect the property's true value, we find evidence suggestive of the AVM undervaluing properties of Black and Hispanic owners by 1.8% and 0.5%, respectively, compared to white owners. Since the AVM

[9]We see a similar pattern for Hispanic owners of -0.6% and -0.7% valuation differences from white and Hispanic appraisers relative to similar properties with white owners.

appears to be biased against Black and Hispanic owners, this implies that the downward valuations observed for appraisers could actually be larger–perhaps as much as -2.6% for Blacks and -1.1% for Hispanics. However, again, we note that even these estimates are significantly lower than the anecdotal evidence reported in the popular press.

Fourth, we also investigate whether minority and white owners pay a difference in appraisal fees. If the observed differences in appraisals by race were the result of systematic discrimination by white appraisers, then we would also expect to see evidence of discriminatory pricing by white appraisers charging minority owners higher fees. However, our results indicate that Black and Hispanic owners pay a trivial difference in appraisal fees compared to white 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 $-0.21 and $-0.13 less than similar white owners.

Our results suggest that the appraisal stage of the mortgage process also contributes to the 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 (Ambrose, Conklin, and Lopez, 2021; Bartlett et al., 2021; Black, Schweitzer, and Mandell, 1978; Black, Boehm, and DeGennaro, 2003; Munnell et al., 1996).[10] However, our study does not point to systemic bias on the part of white appraisers as driving the observed disparity in valuation estimates as the anecdotal evidence in the popular press might suggest.

Nonetheless, caution is required when interpreting the findings of this study. First, the refinancing data used in our study consists of only funded loans. There is the slight possibility that

[10] Numerous studies document significant disparities in homeownership experiences across racial and income groups (Boehm and Schlottmann, 2004; Bostic and Surette, 2001; Coulson and Dalton, 2010; Dawkins, 2005; Dietz and Haurin, 2003; Flippen, 2001, 2004; Gyourko, Linneman, and Wachter, 1999; Krivo and Kaufman, 2004). These findings are intertwined with evidence of disparate treatment or disparate impact in housing and credit markets (Ambrose, Conklin, and Lopez, 2021; Bayer et al., 2017; Berkovec et al., 1994, 1998; Boehm and Schlottmann, 2007; Courchane, Darolia, and Zorn, 2012; Munnell et al., 1996, ,among others). See Yezer (2006), Ladd (1998), Courchane and Ross (2019) for a review of the literature on discrimination in mortgage markets.

appraisal bias is only observed in unfunded refinance loans as we discuss below. Second, our use of AVMs to anchor the appraisal estimates may induce noise into our measure of bias. We use a sample of purchase loan applications in order to examine both of these issues. Although they introduce a new set of issues, which we discuss below, the purchase applications allow us to observe both funded and unfunded loans, which allows us to use the actual purchase price as the anchor. Our basic findings hold in this alternative data. 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.

Our findings contribute to three strands of the literature. First, 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 (Agarwal, Ambrose, and Yao, 2020; Bogin and Shui, 2020; Conklin et al., 2020; Demiroglu and James, 2018; Diaz-Serrano, 2019; Ding and Nakamura, 2016; Eriksen et al., 2020; Fout, Mota, and Rosenblatt, 2021; Griffin and Maturana, 2016; Kruger and Maturana, 2021; Mayer and Frank, 2021; Piskorski, Seru, and Witkin, 2015). For example, our analysis showing that appraisal bias is unrelated to individual appraiser race expands on the work Tzioumis (2018), who show 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.

Second, 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 (2019) and Eriksen et al. (2019).

Finally, our analysis speaks directly to the current policy debate over the role of individual appraiser race in promulgating the observed differences in homeownership experiences across races (Freddie Mac, 2021; Perry, Rothwell, and Harshbarger, 2018; Pinto and Peter, 2021a,b). Our analysis documenting lower appraisals for minority borrowers is consistent with the findings of Perry, Rothwell, and Harshbarger (2018), who show that homes in predominately minority areas have lower valuations than similar homes in predominately white neighborhoods. However, on average, we do not find evidence suggesting implicit bias on the part of individual white appraisers, which is consistent with the findings in Pinto and Peter (2021b). We caution that our results suggest the need for more research before accepting either the view that a few "bad" appraisers produced the small "average" effect found in our study or the view that the "average" effect is the result of industry wide practices that result in small average effects that we detected.

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.[11] The data include both funded and unfunded mort-

[11]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,

gage applications from 2000–2007. 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 data contain several fields that are central to our analysis. First, it includes the borrower's Home Mortgage Disclosure Act (HMDA) race code.[12] Second, it contains 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).

Our main analysis focuses on appraisals for refinance (as opposed to purchase) mortgage applications for several reasons. First, appraisers are much more likely to observe the race of the applicant on a refinance since the borrower (the current owner) usually occupies the property and interacts with the appraiser. It is common for the borrower to meet the appraiser face-to-face when the onsite property inspection is conducted. In contrast, to value a property for a purchase transaction, the appraiser generally meets with the current property owner—who is the current seller—-when inspecting the property. Thus, it is unclear whether the appraiser knows the buyer/borrower's race on a purchase transaction. Second, for purchase mortgage applications, lenders generally value the property at the lesser of the purchase price or the appraised value. For refinance mortgage applications, the appraisal is often the only estimate of value because there is no new purchase price, per se. In other words, the appraisal plays an outsized role in the refinancing process of mortgages. Third, and related to the previous point, 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

but because this variable 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.

[12]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.

seller. It is well documented that appraised values are rarely below the contract price. In fact, the appraised value equals the purchase contract price on a large share of appraisals, which is consistent with the concept that appraisers target the contract price in property valuations (Calem et al., 2021; Cho and Megbolugbe, 1996; Conklin et al., 2020; Ding and Nakamura, 2016). Purchase price targeting may leave less room for appraiser racial bias in purchase mortgage applications than refinance mortgage applications. Although our primary analysis focuses on appraisals used in refinancings for these reasons, we also compare appraised values to contract prices on purchase applications as a robustness check.

2.2. Automated Valuation Model (AVM) Value Estimates

To obtain AVM valuations, 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 estimated of value (at the time of origination) of the property serving as collateral for the mortgage. This value estimate comes from a proprietary automated valuation model (AVM) developed by Collateral Analytics, an industry-leading provider of valuation solutions.

We follow the procedure from Kruger and Maturana (2020), which merges the New Century and ABSNet/HomeVal data sets based on: *ZIP Code*, *First Payment Date*, *Interest Rate Type* (fixed or adjustable rate), *Credit Score*, and *Loan Amount*.[13] We keep 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 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

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

125%. Both an appraised value and an AVM valuation must be available for inclusion in our main sample. Following Kruger and Maturana (2020) we exclude observations where the appraisal to AVM ratio is less than 0.3 or greater than 3.

Notice that this merged sample, referred to hereafter as the ABSNet-NCEN merge, only includes applications that resulted in funded mortgages. Thus, we cannot speak directly to valuation differences across borrower and appraiser 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 homeowner and appraiser race. Although the property owner's race is observed in the New Century data, we do not directly observe the race and ethnicity of the appraiser. However, we are able to infer the appraiser's race using a Bayesian Based classifier approach which is similar in spirit to the methodology used by regulators to determine consumer race and ethnicity (Consumer Financial Protection Bureau (2014)). 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)).

We infer the appraiser's race using a Bayesian Improved First Name Surname (BIFS) method. The intuition of the approach is to calculate the probability (Bayesian score) that a person self-identifies with a certain race/ethnicity based on the same person's first name and surname. A Bayesian score for each race is calculated for every appraiser in our sample. We then obtain 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.[14] Although we cannot directly test the accuracy of BIFS within our sample, we can compare the racial distribution of appraisers using our methodology to appraiser demographic 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. The overwhelming majority (91%) of appraisers are identified as white using our race classification methodology, which is similar to the figures reported by the Appraisal Foundation (89%) and the Appraisal Institute (93%). In our sample using MAP BIFS to infer race, 2%, 3%, and 4% of appraisers are classified as Asian, Black, and Hispanic, respectively. These numbers are in-line with the Appraisal Foundation and Appraisal Institute reported shares, and suggest that minorities are underrepresented in the appraisal industry.

2.4. Descriptive Statistics

Descriptive statistics for the NCEN-ABSNet sample are reported in Table 1.[15] The average appraised value is $278,000, which is slightly higher than the average AVM value of $271,000. Notice that maximum appraisal value and AVM value are quite high, but our results remain unchanged when we perform our analysis excluding observations where the appraisal or AVM value are above $1 million. 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) and Kruger and Maturana (2020)). Although the average app-to-

[14] Ambrose, Conklin, and Lopez (2021) use a similar method to examine disparities in mortgage pricing across borrower and broker race.

[15] Appendix Table A.2 provides descriptive statistics for the sample of appraisals associated with purchase mortgage applications, which will be discussed further in a later section of the paper.

AVM value is positive, 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<.8). The appraisal fee charged to the borrower is recorded for approximately 35% of the appraisals in our sample.[16] Appraisal fees range from $75 to $1200 with an average of $345. 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 below.

The majority of property owners in our sample are white (53%). Hispanic and Black owners represent 23% and 20% of our sample, respectively. Asians owners only account for 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)), 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. Most of the appraisals are for owner-occupied single-family residences.

Panel B of Table 1 reports mean values of the variables by owner race. Property values, whether estimated by appraisal or AVM, vary considerably across race categories. Asian-owned properties are significantly higher, on average, than the other three racial groupings. Hispanic- and white-owned properties are similar in value, while Black-owned properties are worth less (unconditionally). For all races, the appraised value tends to be higher than the AVM value estimate. white-owned properties do not have the highest app-to-AVM ratio, which provides some sugges-

[16]The appraisal fee field is missing or zero for many of our observations. 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 $1200.

tive evidence that whites are not getting extremely favorable appraisal valuations. In fact, whites are the most likely to get extremely low valuations (app-to-AVM$<.8$), but the difference with the other race categories is quite small. We also plot the distribution of appraisal to AVM values by owner race in Figure 1. The distributions are not identical; however, no glaring differences emerge. Although there are some unconditional differences across groups in Table 1 and Figure 1, they appear to be quite modest and do not support the hypothesis that white owners receive more favorable valuations.

Asians do pay more for their appraisals, on average, but the other three groups pay similar appraisal fees. There are some differences across race in terms of property type. Appraisals for Asians and Blacks are more likely to be on investment properties, while both Hispanic and Black owners are more likely to have multi-unit properties. Asian owners are also more likely to have condos and properties located in a planned unit development (PUD).

3. Racial Disparities in Appraisals on Refinance Loans

3.1. Appraisals and Owner Race

Columns 1 - 5 of Table 2 present ordinary least squares (OLS) regressions of the app-to-AVM ratio on indicators for the property owner's race. The omitted category in all columns is white owner. Column 1 includes only the race indicators, and thus mirrors the unconditional app-to-AVM differences reported in Table 1.

Adding ZIP code fixed effects in column 2 results in a large jump in the adjusted R-squared, indicating considerable variation in app-to-AVM across locations. More importantly, the race coefficients change dramatically relative to column 1. All of the coefficients are now negative, but the magnitudes of the coefficients are small, ranging from -0.4% to -0.8%. To put these numbers in perspective, a property that is owned by a white household and appraised at $300,000 would, if owned by a Black household, be appraised at $297,600. The resulting capacity for a cash out refinance would be reduced (assuming loan to value ratio of 78%) by only $1,872.[17] This suggests that during our sample period racial valuation disparities were much smaller than the figures ($\approx$ 25% discount for Black owners) reported in recent anecdotal reports in the popular press (Kamin (2020), Malagón (2020), and Haythorn (2020)). Our results are more in line with the findings of Pinto and Peter (2021a) based on a sample of more recently originated (2018-2019) agency-backed (GSE) mortgage loans.

Column 3 includes appraisal year fixed effects and the results are nearly identical to column 2. In column 4, we add property type controls, including indicator variables for second homes, investment properties, multi-unit properties, condominiums, and PUDs. The Hispanic discount increases slightly, however, the results are largely unchanged – disparities remain small. We plot the coefficients from column 4, our preferred specification, with the corresponding 95% confidence intervals in Figure 2. As already described, all of the coefficients are negative, but they are small in magnitude, and not statistically different from one another. Overall, Figure 2 does not support the existence of large valuation differences across owner race.

Returning to Table 2, column 5 adds appraiser fixed effects. This approach controls for appraiser heterogeneity and approximates the identification strategy in experimental paired-audit studies (e.g., Ayers and Siegelman (1995)), Intuitively, does the same appraiser treat whites and minorities differently? Exploiting within-appraiser variation comes at a cost, though, because many individual appraisers complete only a few appraisals. For example, 33% of the appraisers in our sample complete only one appraisal. Obviously, there is no within-appraiser variation in borrower race for these appraisers. Fortunately, most (85%) appraisals 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 the appraiser fixed effects analysis in column 5 rely on valuation and race vari-

[17]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%.

ation within this set of appraisers. The small racial disparities are nearly identical after including appraiser fixed effects.

Finally, we examine whether owner race is conditionally related to extremely low valuations. Although we find no evidence of a large average effect of race on app-to-AVM, the possibility remains that certain groups may be more likely to get extremely low valuations, which would be consistent with some of the anecdotal evidence in the popular press. We create an indicator variable 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.[18] Column 6 of Table 2 reports results of a linear probability model (OLS) using this indicator as the dependent variable. We find no evidence that Asian or Black owners are more likely to get extremely low valuations; however, properties owned by Hispanics are slightly more likely (0.8%) than white-owned properties to be appraised one or more standard deviations below the average app-to-AVM value.

3.2. Do the App-to-AVM Results Vary with Zip Demographics, House Price Levels, or Appraisal Year?

Next, we examine whether the impacts of owner race on valuation vary with ZIP code racial composition. 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 supplement our data with population racial distribution information at the ZIP code level from the 2011 American Community Survey 5-year estimates. We then estimate our models separately for ZIP codes with a high white population share ($\geq$80%), those with a high minority population share ($\geq$80%), and "mixed race zips" (<80% white and <80% Minor-

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

ity share).[19] Figure 3 plots coefficient estimates from the app-to-AVM regressions.[20] In the top left panel (mixed race zips), all of the coefficient estimates are negative, but the absolute magnitudes are small (<1%). In primarily white zips (top right panel), the magnitude of the discounts increase, consistent with the hypothesis that minorities face larger racial valuation bias in white neighborhoods. Note, though, that the confidence intervals are relatively wide in this sample, and the differences remain fairly modest. For example, valuations on Black owned properties are 1.6% 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, however, 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.[21]

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.[22] We then run our regressions separately for the three different house price level categories and plot the coefficients in Figure 4.[23] The only minority coefficient that is positive is the Asian owner coefficient 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,

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

[20]The estimates are also reported in Appendix Table A.3.

[21]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.

[22]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.

[23]The underlying results for this figure are reported in Appendix Table A.4.

the results are quite similar across ZIP code house price levels. Minority owners generally receive lower appraisal values relative to AVM values, but the magnitudes are small.

Next, we examine whether the appraisal racial disparities vary over time. We first estimate the app-to-AVM regressions separately for each application year.[24] Figure 5 shows the coefficient estimates across years. 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 the 2006 Black owner coefficient in 2006 is not statistically different from the Black owner coefficient in the other three years. Whereas 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 small.

3.3. Individual appraiser analysis

Using app-to-AVM as our valuation metric, we now examine the appraiser-level incidence of valuation differences across owner race. Because we can identify individual appraisers in our data, we first define a measure of individual appraiser racial bias for appraiser j as follows:

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

where n_w and n_m are the number of appraisals for white and minority owners, respectively, completed by appraiser j. $\frac{Appraisal_i}{AVM_i}$ is the app-to-avm value on appraisal i performed by appraiser j, with the w and m subscripts indicating borrower race. Thus, Φ_j is the mean difference in app-to-AVM across race for the individual appraiser. Notice that a positive value for Φ suggests that the individual appraiser gives higher valuation estimates for whites, on average.

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

To provide meaningful inference, we require that an appraiser completes a minimum of two appraisals for white owners and two appraisals for minority owners to be included in this analysis. There are 7,922 appraisers that meet this criteria, and these appraisers account for approximately 142,000 of the appraisals in our data

We plot the distribution of Φs in Figure 6. The distribution is centered around -0.01, and appears fairly symmetric, which suggests 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 individual appraiser. Under the null hypothesis of no mean difference, the tests statistic is

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

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

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

For each appraiser we perform a one-sided t-test where we reject the null hypothesis if $T > t_{1-\alpha,v}$, where we use $\alpha = 0.025$. A rejection implies that the appraiser may be biased against Black 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 $T < t_{0.025,v}$, 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.

3.4. Appraiser Race

In this section we test whether appraiser race and its interaction with owner race is related to the app-to-AVM ratio. We infer appraiser race using the MAP BIFS approach described above and discussed in detail in the appendix. Appraisal counts by appraiser and owner race are presented in Table 3.[25] To ease interpretation of our regression results below, we exclude a small share of observations (4%) where both the appraiser and the owner are minorities, but not of the same race.

Most (90%) of the 197,987 appraisals are completed by white appraisers. Hispanic appraisers account for 7% of the appraisals, whereas Black and Asian appraisers each have about a 2% share. Notice that the share of owners in each minority race is higher than the share of appraisals performed by the same minority race. For example, Black owners represent 19% of the sample, but Black appraisers only account for 2% of the appraisals. Interestingly, minority owners tend to work with appraisers of the same race. To see this, note that Hispanic appraisers account for only 7% of the appraisal overalls, but conditional on the owner being Hispanic, they complete 18% (8,015/43,780). The same pattern holds for Black and Asian appraisers.

Columns 1-3 in Table 4 present 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 4 of Table 2 (the sample is slightly different). 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%).

Next we create indicators for each of the owner-appraiser race cells in Table 3. The omitted category in the regression is a white owner matched to a white appraiser. Thus, all regression

[25] The racial distribution of the individual appraisers is reported in Appendix Table A.1.

coefficients in column 3 should be interpreted as the marginal difference in app-to-AVM relative to white owners using white appraisers. To ease interpretation, we plot the coefficients from column 3 in Figure 7. White owners matched with Asian or Hispanic appraisers receive app-to-AVMs that are no different from white owners using white appraisers. Somewhat surprisingly, white owners actually receive higher app-to-AVMs (1.7%) with Black appraisers. Thus, there is no evidence that white owners receive more favorable treatment with white appraisers.

All of the minority owner coefficients, regardless of appraiser race, are negative, albeit small in magnitude, 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 Wald test for equality of the Asian Owner/White Appraiser (A/W) coefficient (-0.4%) and the Asian Owner/Asian Appraiser (A/A) coefficient has a p-value of 0.36. Similarly, B/W is not significantly different from B/B, nor is H/W different from H/H.

To summarize, minority owners do receive slightly lower app-to-AVMs, on average. However, any valuation disparities minority owners face are not reduced by working with an appraiser of the same race.

3.5. Appraisal Fees

To this point, we have examined differences in valuation across race. However, differential treatment may occur along other margins in the appraisal process. For example, minority owners may receive inferior service (e.g., longer appraisal completion times) or be charged a higher appraisal fees than white owners.[26] Although quality of service is not observable in our data, the appraisal fee is recorded for a subset. Thus, we examine whether racial disparities exist in appraisal fees.

Columns 1-5 of Table 5 present OLS regressions of the dollar amount of the appraisal fee on indicators for property owner race. Column 1 includes only race indicators, and thus mirror

[26] Along these lines, Hanson et al. (2016) provide evidence that mortgage loan originators are less responsive to minority applicants,

the unconditional differences reported in Table 1. Asians pay $49 more than a white owner, on average, for an appraisal. The differences are much smaller for Black ($2) and Hispanic ($13) owners. After adding controls in columns 2-5, racial disparities in appraisal fees are tiny (<$5).

In recent press accounts of racial valuation bias, a minority borrower 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. Note that in these accounts, a minority borrower is required to get multiple appraisals on the property to get a fair value. 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 (e.g., multi-unit rental 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. We create an indicator variable that takes a value of one if the appraisal fee is greater than or equal to $600. Column 6 of Table 5 reports estimates from a linear probability model (OLS) with this high appraisal fee indicator as the dependent variable. None of the minority coefficients is positively related to this indicator. In fact, Black owners are slightly less likely (-0.4%) to pay more than $600 in appraisal fees.

In sum, we find no evidence of large, systematic racial disparities in appraisal fees. Our results also do not suggest that minorities are more likely to require multiple appraisals (proxied by high appraisal fees) in the loan application process,

4. Racial Differences in Valuation 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 it seems highly unlikely that any valuation differences across race only occur in unfunded applications. In refinance loans, a low appraisal seems unlikely to materially affect either the lender's decision to approve the loan, nor 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 compare it to the sales contract price, which is another estimate of property value. 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 of 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's relatively little variation in our dependent variable of interest.[27] 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

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

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.

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. 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. The purchase price divided by the AVM value (Price to AVM) is considerably higher for Black Buyers. We will return to this point momentarily.

Columns 1 and 2 in Table 6 present linear probability models (OLS) where the dependent variable indicates whether the appraised value is below the contract purchase price. The omitted racial category in all columns is white buyer. In unfunded applications (column 1), appraisal values for Asian buyers are slightly more likely (0.3%) to come in below the contract price. However, both the Black and Hispanic buyer coefficients are essentially zero, which does not support the hypothesis that large racial valuation bias exists on unfunded loan applications. Column 2 includes only 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's 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 period, and find large racial disparities.

Column 3 in Table 6 presents linear probability model (OLS) where the dependent variable indicates whether the application results in an originated loan. All minority groups are less likely to have an application result in a funded loan, with estimates ranging from -1.1% for Hispanics to -5.3% for Black applicants. A below contract appraisal is associated with a 4.8% decrease in the likelihood of a funded loan, consistent with the findings of Fout, Mota, and Rosenblatt (2021). Interestingly, 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 4.8%. The corresponding figures for Blacks and Hispanics are -12.9% and -7.2%, respectively. In contrast, a below contract appraisal has little impact (0.4%) on the likelihood of origination for Asian buyers.

Taken together, the results in columns 1-3 of Table 6 do not show large, systematic racial bias against minorities in appraisals on purchase mortgage applications on unfunded applications or originated loans. However, the relationship between a below-contract appraisal and the likelihood of loan funding does vary significantly by buyer race.

In our main analysis using the NCEN-ABSNet merge, we compare the appraised value to a "race-blind" benchmark, the AVM estimate, and show that differences in app-to-AVM are small across races. But, if AVM values are racially biased, then differences in valuation across races could be masked by the fact that both the numerator and denominator are biased against minorities. To examine this issue, we use the purchase price divided by the AVM value as our valuation metric.[28]

Column 4 in Table 6 presents an ordinary least squares (OLS) regression of the purchase price-to-AVM ratio on indicators for the property owner's race, as well as location, year, and property controls. For Black and Hispanic buyers the purchase price is 1.8% and 0.5% higher relative to the AVM than for white buyers, respectively. If we view the purchase price as an unbiased estimate of value that does not depend on race, then this would suggest that AVM values are not race-blind – they are biased against Blacks and Hispanics. However, the positive Black and His-

[28] As with our main refinance sample, we need to merge the NCEN data with the ABSNet/HomeVal datasets to get the AVM value.

panic coefficients would also be consistent with minorities paying a price premium for housing.[29] For example, Bayer et al. (2017) provide evidence that Blacks and Hispanics pay approximately 2% more than whites for similar housing. Minority purchase price premiums of this magnitude, combined with race-blind AVMs, would be consistent with the coefficient estimates in our price-to-AVM regressions in column 4 of Table 6.

Ultimately, we cannot determine whether the coefficient estimates in our purchase price to AVM regressions are driven by by minority purchase price premiums (the numerator), racially biased AVM estimates (the denominator), or both.[30] Regardless, the purchase price-to-AVM estimates can help us bound racial disparities in valuation in our earlier using the refinance sample. Let's assume that no purchase price differentials exist across race. Then, based on our results in column 4 in Table 6, Blacks face an AVM discount of 1.7%. We can then add this to the Black app-to-AVM discount of 0.9% in column 5 of Table 2, to get a bound on the valuation differential faced by Blacks of -2.6%. For Hispanics, the corresponding number is -1.2% (-.5%+-.7%). On the other hand, if AVM estimates are race-blind, then the implied discount for Blacks and Hispanics is -0.9% and -0.7% (the coefficient estimates in column 5 of Table 6).

5. Conclusion

The disparate treatment of racial minorities in housing markets has resulted in large gaps in home ownership. Previous research has documented discriminatory behavior at several stages of the home buying process, which in turn results in lower home ownership rates for minority households, even conditioning on other household characteristics. Attention has recently centered on disparate treatment in home appraisals, in both the popular press and academic research settings.

We provide new insights into the differential appraisal values received by minority homeowners

[29]Evidence is mixed on the size and extent of racial price differentials in housing (Bayer et al., 2017; Chambers, 1992; Kiel and Zabel, 1996; King and Mieszkowski, 1973; Nowak and Smith, 2017; Yinger, 1978).

[30]Of course, other explanations for differences could exist as well.

seeking refinance loans during the housing boom of the early 2000s. We do not find evidence that minority or white appraisers systematically valued minority owned homes differently. This result is consistent across several different stratification of the data, including home value, neighborhood composition and year of origination. However, we do find evidence that minority homeowners do received lower valuations, on average, regardless of the race of the appraiser.

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Table 1. 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			
Appraisal Fee	78,065	$345	$94	$75	$1,200
Appraisal Fee $\geq$ $600	78,065	0.02			
Asian Owner	222,269	0.04			
Black Owner	222,269	0.20			
Hispanic Owner	222,269	0.23			
White Owner	222,269	0.53			
Second Home	222,269	0.01			
Investment Property	222,269	0.06			
Multi-unit	222,120	0.06			
Condo	222,120	0.05			
PUD	222,120	0.11			

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. Variables with missing standard deviation, minimum, and maximum in Panel A are binary.

Table 2. Appraised Value, AVM Estimates, and Owner Race

VARIABLES	(1) App to AVM	(2) App to AVM	(3) App to AVM	(4) App to AVM	(5) App to AVM	(6) App to AVM $< .8$
Asian Owner	-0.044***	-0.004	-0.004	-0.005	-0.003	0.003
	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.003)
Black Owner	0.033***	-0.008***	-0.008***	-0.008***	-0.009***	0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Hispanic Owner	-0.021***	-0.005***	-0.005***	-0.007***	-0.007***	0.008***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Observations	222,269	220,451	220,451	220,306	195,158	220,306
Adj. R-squared	0.004	0.152	0.157	0.158	0.184	0.050
Zip FE	N	Y	Y	Y	Y	Y
Year FE	N	N	Y	Y	Y	Y
Property Type Controls	N	N	N	Y	Y	Y
Appraiser FE	N	N	N	N	Y	N

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. In column 6 the dependent variable is a binary variable that takes a value of one if the appraised value divided by the AVM value is less than 0.80, and zero otherwise. The sample includes refinance applications that resulted in originated loans. *** $p<0.01$, ** $p<0.05$, * $p<0.10$

Table 3. Appraisal Counts by Appraiser and Owner Race

Appraiser Race	Owner Race: Asian	Black	Hispanic	White	Total
Asian	1,515			2,176	3,691
Black		2,032		2,038	4,070
Hispanic			8,015	4,743	12,758
White	6,285	36,462	35,765	98,956	177,468
Total	7,800	38,494	43,780	107,913	197,987

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

VARIABLES	(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)	
White Owner/Asian Appraiser			0.000
			(0.006)
White Owner/Black Appraiser			0.017***
			(0.006)
White Owner/Hispanic Appraiser			-0.001
			(0.004)
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)
Observations	196,002	196,002	196,002
R-squared	0.198	0.198	0.198
Zip FE	Y	Y	Y
Year FE	Y	Y	Y
Property Type Controls	Y	Y	Y

Note: This table presents estimates from regression models where the dependent variable is the appraised value divided by the AVM value. White Borrower/White Appraiser is the omitted category in column 3. *** p<0.01, ** p<0.05, * p<0.10

Table 5. Appraisal Fee and Owner Race

	(1) Appraisal Fee	(2) Appraisal Fee	(3) Appraisal Fee	(4) Appraisal Fee	(5) Appraisal Fee	(6) Appraisal Fee $\geq$ \$600
Asian Owner	49.126***	1.055	0.643	-0.389	3.594*	-0.001
	(1.646)	(1.805)	(1.801)	(1.694)	(2.051)	(0.003)
Black Owner	1.965**	0.738	0.298	-0.216	-1.907	-0.004**
	(0.866)	(1.083)	(1.081)	(1.017)	(1.216)	(0.002)
Hispanic Owner	13.875***	4.102***	3.809***	-0.131	0.937	-0.000
	(0.831)	(0.983)	(0.981)	(0.924)	(1.087)	(0.002)
Observations	78,065	75,907	75,907	75,874	63,662	75,874
R-squared	0.014	0.250	0.254	0.340	0.531	0.196
Zip FE	N	Y	Y	Y	Y	Y
Year FE	N	N	Y	Y	Y	Y
Property Type Controls	N	N	N	Y	Y	Y
Appraiser FE	N	N	N	N	Y	N

Note: This table presents estimates from regression models where the dependent variable is appraisal fee in columns 1 - 5. In column 6 the dependent variable is a binary variable that takes a value of one if the appraised fee is greater than or equal to \$600, and zero otherwise. The sample includes refinance applications where the appraisal fee is available. *** $p<0.01$, ** $p<0.05$, * $p<0.10$

Table 6. Appraisals and Borrower Race on Purchase Applications

	(1) Unfunded Applications Below Contract	(2) Originated Loans Below Contract	(3) Pr(Originated)	(4) Price to AVM
Asian Buyer	0.003**	0.002	-0.022***	0.001
	(0.001)	(0.001)	(0.003)	(0.003)
Black Buyer	0.001	-0.003***	-0.053***	0.018***
	(0.001)	(0.001)	(0.002)	(0.002)
Hispanic Buyer	0.001	-0.003***	-0.011***	0.005***
	(0.001)	(0.001)	(0.002)	(0.002)
Below Contract			-0.048***	
			(0.007)	
Asian Buyer × Below Contract			0.052***	
			(0.017)	
Black Buyer × Below Contract			-0.081***	
			(0.012)	
Hispanic Buyer × Below Contract			-0.024**	
			(0.011)	
Observations	253,041	311,197	568,566	132,508
Adj. R-squared	-0.003	0.004	0.079	0.139
Zip FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Property Type Controls	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 purchase price divided by the AVM value. The samples in column 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

6. Figures

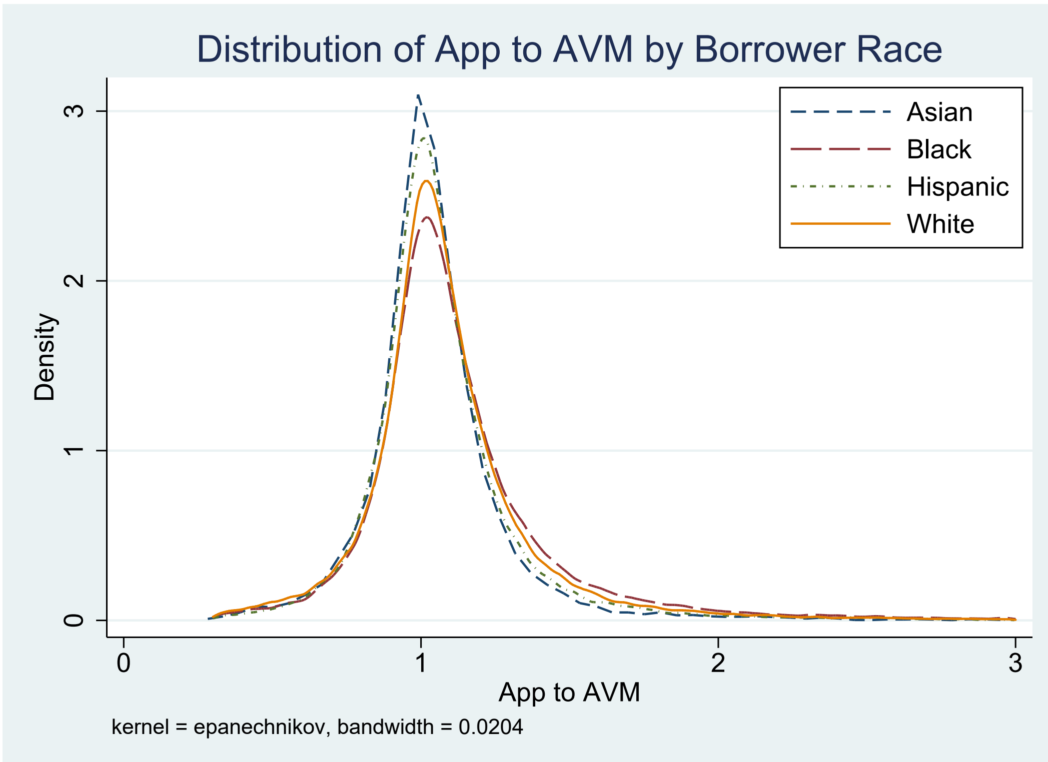

Figure 1. Distribution of App to AVM by Owner Race

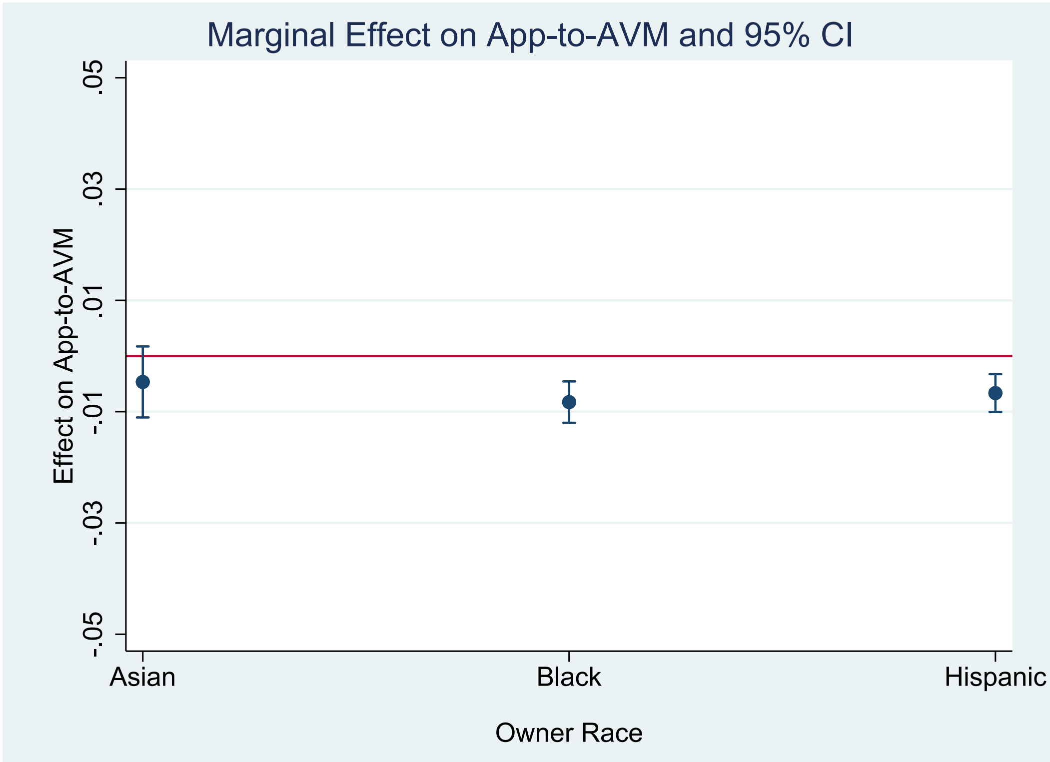

Figure 2. Marginal Effect of Owner Race on Appraisal to AVM

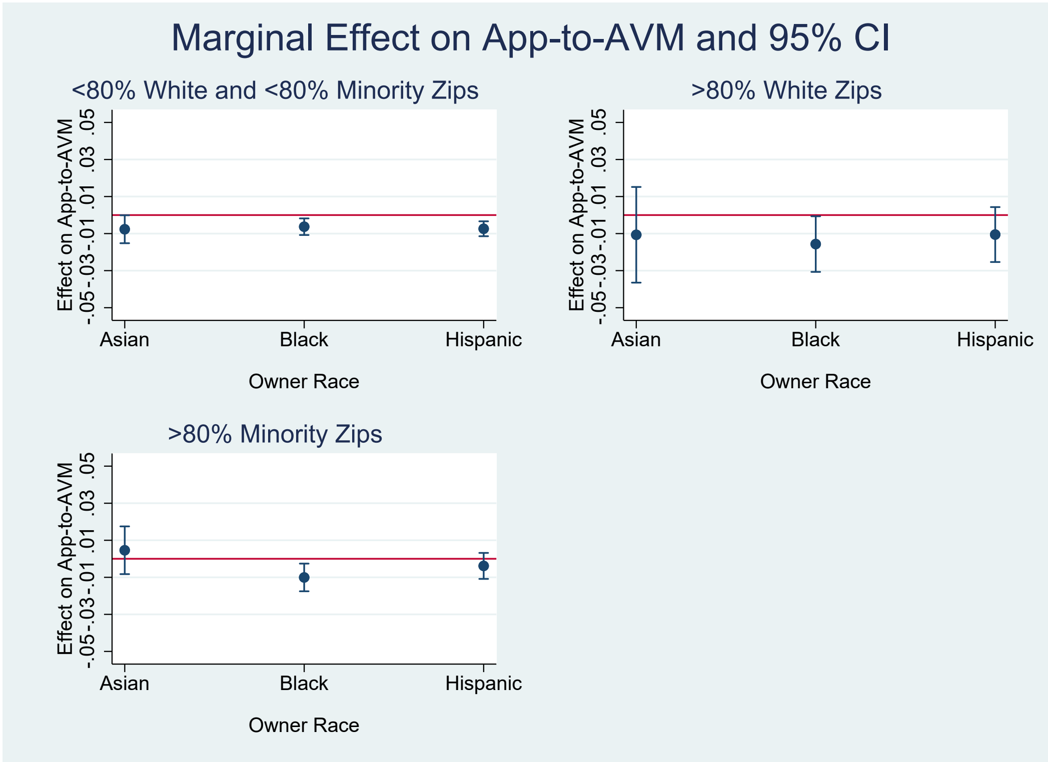

Figure 3. Marginal Effect of Owner Race on Appraisal to AVM by Zip Racial Composition

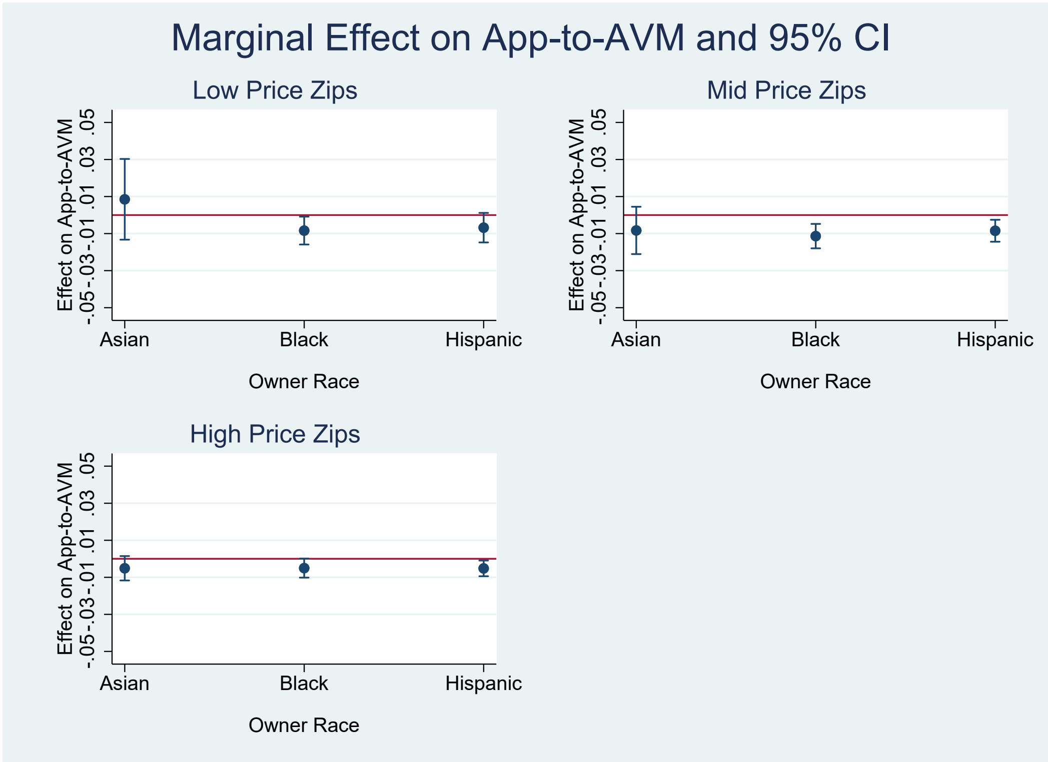

Figure 4. Marginal Effect of Owner Race on Appraisal to AVM by Zip House Price Level

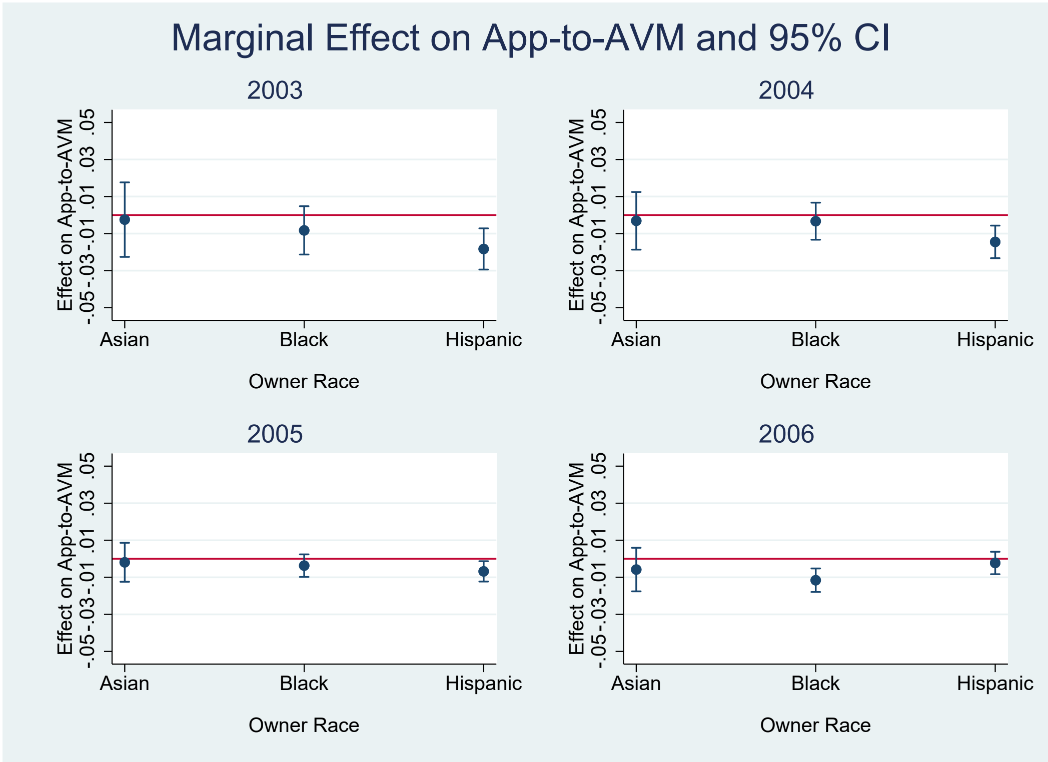

Figure 5. Marginal Effect of Owner Race on Appraisal to AVM by Year

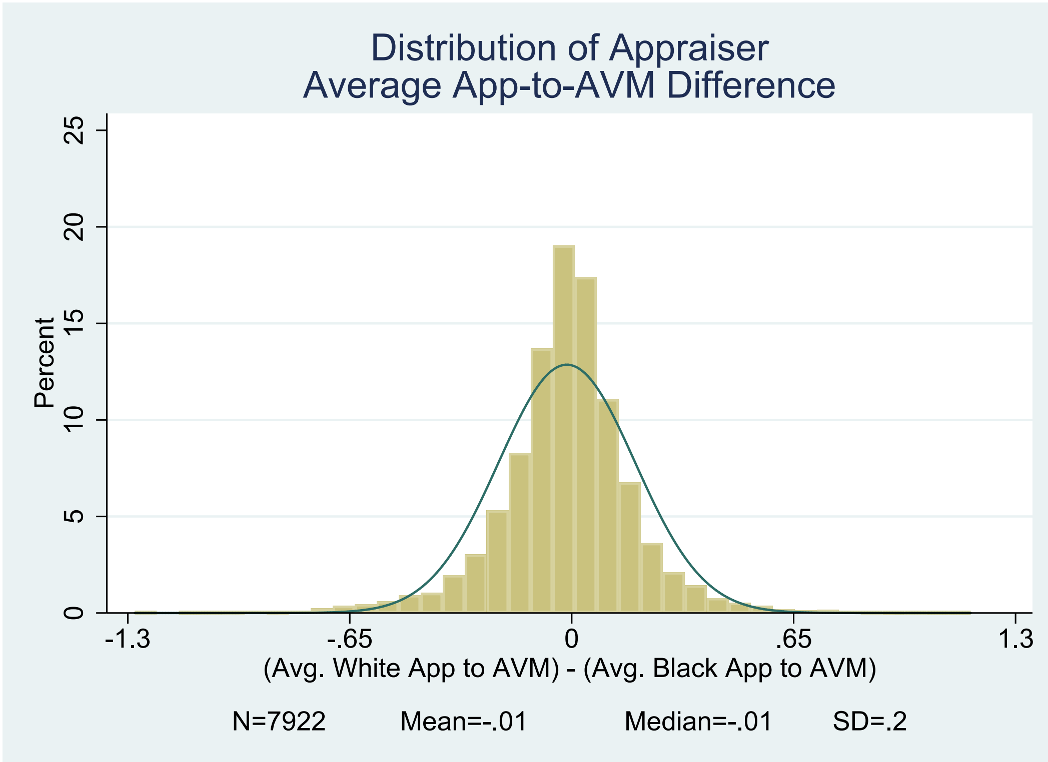

Figure 6. Distribution of Appraiser Level Mean Difference between white App-to-AVMs and Minority App-to-AVMs. Sample includes appraisers that had at least two appraisals for white owners and two appraisals for minority owners.

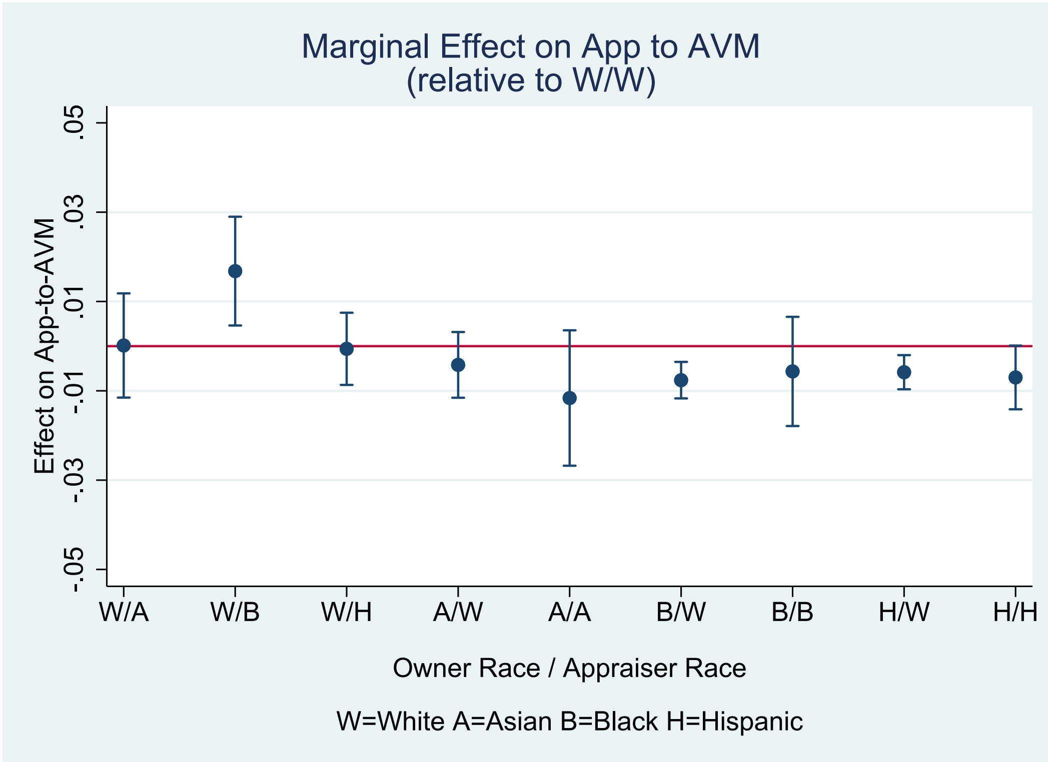

Figure 7. Marginal Effect of Owner and Appraiser Race on Appraisal to AVM

Appendix

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			
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			
Price to AVM	135,152	1.05	0.23	0.30	3
Asian Owner	576,416	0.06			
Black Owner	576,416	0.20			
Hispanic Owner	576,416	0.25			
White Owner	576,416	0.49			
Second Home	576,416	0.03			
Investment Property	576,416	0.13			
Multi-unit	576,416	0.07			
Condo	576,416	0.09			
PUD	576,416	0.12			

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
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 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-squared	0.138	0.110	0.227
Zip FE	Y	Y	Y
Year FE	Y	Y	Y
Property Type Controls	Y	Y	Y

Note: This table presents estimates from regression models where the dependent variable is the appraised value divided by the AVM value. The sample in column 1 includes refinance applications that resulted in originated loans in ZIP codes 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.4. 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-squared	0.160	0.076	0.069
Zip FE	Y	Y	Y
Year FE	Y	Y	Y
Property Type Controls	Y	Y	Y

Note: This table presents estimates from regression models where the dependent variable is the appraised value divided by the AVM value. The sample in column 1 includes refinance applications that resulted in originated loans in ZIP codes in quintiles 1-3 of 2005 zip house price levels. Columns 2 and 3 include refinance applications that resulted in originated loans in ZIP codes in quintiles 4 and 5, respectively, of 2005 zip house price levels *** $p<0.01$, ** $p<0.05$, * $p<0.10$

Table A.5. Appraised Value, AVM Estimates, and Borrower Race Year

	(1) 2003	(2) 2004	(3) 2005	(4) 2006
	App to AVM	App to AVM	App to AVM	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-squared	0.305	0.300	0.174	0.157
Zip FE	Y	Y	Y	Y
Year FE	N	N	N	N
Property Type Controls	Y	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 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

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.[31] 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 (2018a).[32]

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.[33] 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.[34] For each appraiser, we now have the likelihood (BIFS score) that the appraiser falls into each race category, conditional on last name and first name. In other words, each appraiser has six BIFS scores – one for each of the six race categories. Finally, we use the maximum a posteriori (MAP) classification scheme, which assigns the appraiser to the race for which he has the highest

[31] 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.

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

[33] 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,

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

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.