Appraisal and Gender*

James N. Conklin[†], N. Edward Coulson[‡], Moussa Diop[§], Ruchi Singh[¶]

May 9, 2026

Abstract

Using a nationwide panel of mortgages for the period 2000 to 2007, we test for gender differences in the real estate appraisal industry. We ask whether female appraisers evaluate different types of properties and whether they value the properties differently compared to their male counterparts, especially with respect to gender, racial, and ethnic differentials. We mostly do not find any statistically or economically significant differences between male and female appraiser practice, nor does gender play a role in appraisal outcomes, though there are some exceptions to this.

*We acknowledge the helpful comments of the journal editor and reviewers, as well as Lauren Lambie-Hanson, Maskai Mori, and seminar participants at Penn State, West Virginia University, University of Alabama and AREUEA meetings in Barcelona and Philadelphia.

[†]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
[¶]Terry College of Business, University of Georgia, Athens, GA

1. Introduction

Appraisal plays a critical role in real estate finance, whether its use is for a home purchase or the refinancing of an existing mortgage. Lenders hire appraisers to obtain unbiased estimates of property value that, in turn, will determine the loan amount and pricing.[1] However, only about 25% of residential appraisers are female, mirroring their relative under-representation in other financial industry occupations. This under-representation raises a number of questions regarding gendered differences in performance outcomes, potential bias against female appraisers and the role of gender in labor supply. In light of the examination of gender differences in other stages of the home acquisition process, including agency and brokerage (Andersen et al., 2021; Seagraves and Gallimore, 2013), and lending (Beck, Behr, and Guettler, 2013), it is of interest to document the extent of such differences in the appraisal stage as well.

To promote fair and unbiased home appraisals, the Appraisal Foundation requires appraisers to follow a systematic process to estimate property values.[2] Notwithstanding this strict guidance, appraisals produce noisy estimates of property values, because appraisers are expected to use their judgment at various stages of the process, including to select comparable property transactions, make necessary adjustments to those transaction prices to account for differences in attributes between the comparables and the subject property, and independently decide how to weight value estimates derived from these comparable transactions in order to provide a final estimate of value for the subject property.

Because appraisals are a necessary part of the lending process, the uniqueness of real estate

[1]For purchase loans, both the appraised value and the purchase price serve as estimates of market value, and loan terms are based on the lower of the two. In contrast, for refinance loans, there is no contemporaneous purchase price, so the appraisal usually serves as the primary estimate of collateral value that impacts loan terms. Accordingly, appraisals tend to be more consequential in refinances.

[2]The Appraisal Foundation was authorized by Congress as the nation's foremost authority on the valuation profession. In addition to promulgating qualifications for real estate appraisers, it sets ethical and performance standards for the profession, i.e., the Uniform Standards of Professional Appraisal Practice (USPAP), to ensure that appraisals are independent, consistent, and objective.

properties necessitates a reliance on an appraiser's skills and personal judgment in performing the steps outlined above. The valuation of properties with similar observable and especially unobservable characteristics can potentially vary in systematic ways because of differences in appraiser skills, methods, and/or bias, conscious or not.

In this paper, we examine gender differences in appraisal outcomes, addressing differences in appraisal market share, fees, time to delivery, and, perhaps most importantly, differences in appraised valuations, using a data set generated from a major subprime lender from the period just before the market crash of 2008.

Recognition of the potential gender differentials in appraisal is of importance, particularly because appraisal has come under increased scrutiny in the past few decades. First, there were questions about the profession's role in the Great Financial Crisis (GFC). In the housing boom that preceded the GFC, appraisers were often thought to be passive participants, conveniently valuing property at the proposed contract price, rather than providing an informed, objective critique of the home's value, one potentially below that price (Calem, Lambie-Hanson, and Nakamura, 2015; Nakamura et al., 2010)[3]. This was perhaps the result of pressure on appraisers to not complicate the completion of potential transactions, with the threat of withholding commissions in the future (Conklin et al., 2020). It is possible in such an environment that female appraisers are more vulnerable to pressure from lenders to produce a favorable appraisal.

More recently, there has been concern over racial disparities in home appraisals (Ambrose et al., 2025; Freddie Mac, 2022; Pinto and Peter, 2021; Williamson and Palim, 2022) wherein refinance appraisals for homes owned by racial minorities are appraised at lower values than comparable homes owned by whites. After news reports of significant undervaluation of minority-owned properties, several studies have confirmed disparities in appraisals across races and examined the potential sources of such disparities (Ambrose et al., 2025; Freddie Mac, 2022; Pinto and Peter,

[3]When appraisals are below the transaction price, the lender uses this lower value to set the terms of the mortgage loan. This will result in a costly renegotiation or a voiding of the transaction.

2021; Williamson and Palim, 2022). Prior research has largely examined only the owner's race, however Ambrose et al. (2025) also incorporated both owner and appraiser race into the analysis. Building on this, we explore the role of appraiser gender in racial bias. We build on this prior research on appraisal bias against racial and ethnic minority homeowners (Ambrose et al., 2025) by examining whether such disparities vary with the gender of the appraiser.

Related to this, of course, is the possibility of bias against female borrowers. This is the focus of Bosshardt, Kedia, and Zhang (2025) who use post-crisis data and find that female homeowners receive appraisals that are 2.5% lower than comparable homes owned by males. There is only a very slight improvement in that differential when the appraiser is female. We extend this analysis by using our subprime database to examine whether male and female appraisers value properties differently depending on the homeowner's gender.

Our contribution is to examine whether appraiser gender affects appraisal outcomes in the pre-crisis mortgage market, a setting in which appraisers operated with substantial discretion and faced stronger potential pressure from loan production than in the post-HVCC environment. This setting provides a useful benchmark because, if gender differences in valuation behavior were likely to emerge through differences in conservatism, responsiveness to pressure, or interaction with borrowers, they should have been especially plausible in this institutional context. Using a large nationwide sample of mortgages from 2000 to 2007, we find that female appraisers are substantially underrepresented and complete fewer appraisals, but average appraisal outcomes differ little by appraiser gender. Importantly, these headline differences are not merely statistically insignificant; they are also economically small and, for the main outcomes, estimated with considerable precision.

Ex-ante, there are several plausible reasons why female appraisers might systematically provide valuation estimates that differ from those of male appraisers. Female appraisers may be inherently less confident, more risk-averse or valuation-conservative, a behavioral tendency well-documented in finance and real estate contexts (Barber and Odean (2001); Croson and Gneezy (2009);Sunden and Surette (1998); Agnew, Balduzzi, and Sunden (2003); Niederle and Vesterlund (2010)). If so, female appraisers may be more likely to provide lower or more cautious valuations. In addition, because women in male-dominated occupations may face greater professional scrutiny or a higher bar for perceived performance, female appraisers may adhere more strictly to appraisal standards in order to mitigate professional risk (Egan, Matvos, and Seru (2019); Huang, Mayer, and Miller (2024)). In a setting where appraisals involve substantial judgment, these forces could generate systematically different valuation outcomes by appraiser gender.

A second possibility is that gender differences operate through borrower interaction or workflow rather than valuation conservatism. If female appraisers gather more detailed soft information from homeowners during the appraisal process, they may arrive at systematically different—and potentially more accurate—valuations. Related evidence from mortgage lending suggests that female loan officers may be better at building trust with borrowers, which can improve loan outcomes even after controlling for selection, screening, workload, and experience (Beck, Behr, and Guettler (2013)). More generally, women may also supply fewer market hours on average than men (Lavergne and Mullainathan (2004)), which in this setting could translate into lower observed appraisal volume, different experience accumulation, or different turnaround-related outcomes. These mechanisms do not yield a clear directional prediction, but they suggest that appraiser gender could matter for both valuation and non-valuation outcomes.

A third possibility is that appraiser gender affects the extent of racial or gender-related bias in valuations. Having documented the existence of bias against minority homeowners (Ambrose et al. (2025)), we ask below whether this bias, as well as gender bias, varies with the appraiser's gender. Prior literature on differences in the level of bias between male and female evaluators, across a variety of contexts, is nuanced. The evidence suggests that males are, if anything, slightly more biased against racial minorities than women. Ekehammar, Akrami, and Araya (2003) note that men exhibit higher levels of explicit (that is, conscious) prejudice against minorities than women, but their experiments also suggested that women display higher levels of implicit bias, which, according to these authors, is more unconscious and reactive. In studies using the well-known Implicit Associations Test (IAT) ((Nosek et al., 2007; Sabin et al., 2009)), it is found that males' responses showed greater levels of implicit bias against Blacks. With respect to gender, Rudman and Goodwin (2004) suggests that women are biased in favor of women more than men are biased in favor of men. On the other hand, Moss-Racusin et al. (2012) suggests that bias against women STEM students is slightly stronger among female faculty evaluators. In all studies of this nature, there is a substantial heterogeneity that depends on context, framing, and other situational characteristics. In the real estate context, observed gender differences in outcomes may also reflect assignment rather than differential treatment: for example, the finding that male agents tend to obtain higher sale prices is often attributed not to better negotiation skills but to differences in property type allocation across the two genders (Andersen et al., 2021; Seagraves and Gallimore, 2013). How these considerations apply to home valuation, and whether racial or gender disparities in appraisal outcomes vary systematically with appraiser gender, therefore remains an open empirical question.

To explore these questions, we use a novel mortgage origination data set from New Century Financial Corporation (NCEN) from 2000 to 2007[4] that includes the names of the appraisers, which we use to infer their gender using the most popular baby names by gender from the Social Security Administration as described in the data section. In addition, the NCEN data records the gender(s) and race of the homeowners. This study examines appraisals conducted across the country by roughly 47,000 male appraisers and 16,000 female appraisers.

Our study makes a unique contribution by examining pre-crisis subprime data, establishing an important baseline for evaluating post-2008 regulatory reforms. The Home Valuation Code of Conduct (2009) and Dodd-Frank Act (2010) fundamentally altered the appraisal landscape by introducing third-party Appraisal Management Companies (AMCs) to reduce lender influence over

[4]This period is characterized by a surge in mortgage credit, particularly to minorities, increased competition in lending, and relatively loose lending regulations.

appraisers. By analyzing the pre-reform environment, we can better assess whether these changes effectively reduced biases or introduced new complications.

As explained in the data section, we use various subsets of our database to test for gender gaps in various mortgage appraisal outcomes: appraised value, the likelihood of an appraisal falling below the sales contract price, days to appraisal (the time between NCEN receiving the loan application and appraisal completion), and appraisal fees.

Following Ambrose et al. (2025), we test for gendered differences by comparing refinance loan appraisals to property value estimates from a leading automated valuation model (AVM) company.[5] We test whether the appraiser's gender affects the ratio of appraisal to AVM after including a rich set of control variables including property purpose (primary residence, second home, or investment property), property type (single family residence, multi-unit, condo, planned unit development), location and time fixed effects, and proxies for value relevant factors that are observable by the appraiser, but that may be missed by an AVM, such as property quality and condition. This analysis shows very little difference in valuation between female and male appraisers based on this measure. We also consider the likelihood of an appraisal falling below the sales price for purchase loans and again find no difference between male and female appraisers. This suggests that appraisals by females are no different than those performed by males in terms of appraisers' tendency to value properties at or above sales prices (Calem et al., 2021; Conklin et al., 2020).

An appraisal needs to be completed in a timely manner for the loan to proceed. Using the length of time between NCEN's receiving the application and the appraisal completion date (days to appraisal) as a measure of appraisal turnaround times, we find that this time period is very slightly shorter for female appraisers by 0.17 days. (We discuss the interpretation of this below.) We also find no real gender difference in fees earned by appraisers. Taken together, these results

[5] AVMs are sophisticated statistical models that produce property-level value estimates using property characteristics, local market conditions, and granular location attributes. According to Jensen and Reifler (2010), these models rely on "public record and local market sold, active and off-market price data, including property listing data information, and corresponding property characteristics". These models are proprietary, and their exact specifications are unknown to us.

suggest that there is very little difference in appraisal outcomes across genders except in the volume of appraisals.

Next, we explore whether the gender of the appraiser matters for the measurement of racial and gender bias in home appraisals. These tests are conducted on refinanced loans, where the appraiser is likely to meet with the owner, and so is aware of the owner's race and gender, and where the appraiser is the lender's only objective source of information on the property value.

First, we test whether the racial bias in appraisals observed in Ambrose et al. (2025) varies across appraiser gender. For the most part, we find that it does not, depending on the type of comparison.

Next, following Bosshardt, Kedia, and Zhang (2025), we ask whether there are gendered differences in appraisal outcomes. Male homeowners receive more generous appraisals from female appraisers; compared to appraisals of male-owned homes by male appraisers, the nearly 1 percentage point difference is both statistically and economically significant and robust. At first, female owners appear to receive significantly lower appraisals irrespective of the gender of the appraiser. However, the effect disappears after controlling for owner income, wealth, family status, property age, etc. In contrast, regardless of the appraiser's gender, properties owned by both a male and a female (mixed owner) receive lower appraisals than male owned homes appraised by males. Although some valuation differences across appraiser and owner gender exist, they do not point to homophily in appraisals based on gender.

Access to mortgage financing is key to homeownership and wealth accumulation. As a result of documented racial disparities in appraisals, there have been calls for a more diverse appraisal profession. While only 19 percent of appraisers in our data are female, and those females are called upon much less often, our study suggests that female appraisers perform their tasks in an essentially identical fashion. While our empirical outcomes are almost always of the null variety, the lack of traditional statistical significance does not mean that the results are without interest. To the contrary, the finding that there are only small differences in outcomes, productivity, and earnings stands in stark contrast to much of the literature on gender differences in the workplace (Blau and Kahn (2020), Lundberg and Stearns (2019)).

The historical perspective that our study provides is particularly valuable because appraisal biases from earlier periods continue to impact wealth accumulation through home equity extraction and property value appreciation. Furthermore, the economics of the appraisal industry have changed dramatically, with AMCs now capturing 50-70% of appraisal fees, substantially reducing appraiser compensation despite the workforce remaining largely unchanged. Our analysis thus provides crucial context for interpreting contemporary findings, including those in Bosshardt, Kedia, and Zhang (2025), within a broader historical and institutional framework.

The paper reviews the home appraisal process in Section 2, followed by a description of our data, including the determination of appraiser gender, in Section 3. Section 4 presents summary statistics and a preliminary comparison of male and female appraisers. Section 5 presents the main appraisal outcome results and heterogeneity analyses, Section 6 examines the likelihood of using a female appraiser, Section 7 considers potential misclassification of owner gender, and Section 8 concludes.

2. The Home Appraisal Process

The main purpose of home appraisals is to provide realistic, independent estimates of fair market property values, which represent crucial information for home buyers, owners, and lenders, regardless of the purpose of the financing sought against the property. In most lending situations, appraisals are required by law when real estate is used as collateral for a loan.[6] Separate from

[6]The federal Financial Institutions Reform, Recovery, and Enforcement Act of 1989 (FIRREA) requires federally-regulated financial institutions to obtain appraisals for most real estate-related financial transactions, especially when the real estate is being used as collateral for a loan; state-regulated banks generally are also required to obtain appraisals for real estate-related financial transactions. More importantly, the two government-sponsored enterprises (GSEs), Fannie Mae and Freddie Mac, generally require appraisals for mortgages they purchase, thus setting the standard for the industry. The GSEs may waive the requirement for an in-person appraisal for certain properties underwritten through their automated underwriting systems. Even when an appraisal is not mandated, the lender may still require

lending regulatory requirements, appraisals are indispensable for the underwriting of refinancing mortgages because there is no transaction price that could be used as an alternative estimate of the property value. But even when a transaction price exists, it is common practice for mortgage lenders to validate the transaction price agreed upon between the buyer and the seller by having the property appraised and then using the lower of the appraisal value or the transaction price for the underwriting of the mortgage.[7] Due to the importance of housing finance for homeownership, in addition to requiring appraisals for most real estate financing transactions, the government established the Appraisal Foundation to regulate the appraisal profession and, to ensure unbiased appraisals, set the Uniform Standards of Professional Appraisal Practice (USPAP) that appraisers must systematically follow.[8]

During the period covered in our study, the appraisal process typically followed this approach; we later discuss how post-mortgage crisis changes to the process may affect our findings. After the borrower (the home buyer for a purchase mortgage or the property owner for a refinancing loan) has agreed to the mortgage financing terms and signed the loan application, the lender or the mortgage broker will order an appraisal of the property on behalf of the borrower.[9] The loan originator (the lender for a retail mortgage or the broker for a wholesale mortgage) would choose the appraiser and attach all required information for the appraisal (e.g., the property information, the purpose of the appraisal, the sales contract for purchase appraisals) to the order form. For the sake of convenience and efficiency, rather than expediency, the loan officer would generally choose an appraiser from a list of local appraisers. This choice is often based on the appraiser's

one for caution's sake.

[7]Federally-regulated banks are required to use the lower of the appraisal or transaction price for a purchase mortgage; this is also a condition for loan repurchases by the GSEs (Calem, Lambie-Hanson, and Nakamura, 2015).

[8]The Appraisal Foundation is also responsible for setting professional qualifications for real estate appraisers who have to complete education requirements and must be licensed or certified by their state.

[9]The expansion of the non-conforming mortgage market during that period was facilitated by independent mortgage brokers. This source of mortgage loans is referred to as the wholesale channel, in contrast to the retail origination channel, which consists of loans originated directly by the lenders with no intermediary between the lender and the borrower. Typically, mortgage brokers would gather the required information from the borrower, directly order the appraisal, and, after securing the loan's pre-approval, submit the application package to the lender.

availability, turnaround time, and possibly experience.

After accepting the request, the appraiser will estimate the value of the subject property as per the USPAP guidelines. After completing the appraisal, the appraiser will send the mortgage broker or lender a comprehensive report explaining the appraisal, including the comparables used, price adjustments made, and how the final appraisal value was computed. The appraiser charges a fixed fee for her/his services that is independent of the property value or the outcome of the appraisal but can vary depending on the property characteristics, the property location, and market conditions (Conklin et al., 2020). The mortgage broker or lender may give a copy of the appraisal report to the borrower, who has the right to challenge the appraisal if it is deemed too low relative to the transaction price for a purchase mortgage or the borrower's own (perhaps subjective) estimate of the value of the property for a refinance mortgage.[10]

Normally, the selection of an appraiser should depend on qualifications, local market experience, ability to complete the appraisal within a reasonable time, and possibly an existing relationship with the loan officer. Appraiser gender should not matter directly in this decision, although unobservable factors may still influence assignment in practice. Because male and female appraisers are subject to the same industry qualifications and professional standards, one might not expect large systematic differences in appraisal outcomes on that basis alone. At the same time, racial disparities in appraisals documented by Ambrose et al. (2025) may vary with appraiser gender, and, for somewhat similar reasons, appraisals may also vary with owner gender. In the end, there is no unambiguous prediction about how appraisals by female appraisers should differ from those by male appraisers, and the net effect of these channels is ultimately an empirical question.

Following evidence of widespread appraisal inflation—especially among non-conforming loans securitized in the non-agency market (Conklin et al., 2020; Diop, Yavas, and Zhu, 2021; Kruger

[10]Because loan amounts are determined with respect to the lesser of the sale price and appraised value, a below-transaction price appraisal may precipitate deal failure absent a renegotiated purchase price, a larger downpayment, or altered loan terms. LaCour-Little and Green (1998) find that a low appraisal decreases the probability of a completed sales transaction. For a refinance, a low appraisal may reduce the maximum loan amount, limit equity withdrawal, or increase borrowing costs.

and Maturana, 2021)—policymakers moved to curb problematic appraisal practices. In May 2009, under FHFA oversight, Fannie Mae and Freddie Mac adopted the Home Valuation Code of Conduct (HVCC), and the following year the Dodd–Frank Act incorporated HVCC principles into federal statute (Eriksen et al., 2019). These reforms sought to enhance appraiser independence and improve valuation accuracy—for example, by prohibiting lenders and other parties from attempting to influence valuations and by mandating that the appraisal function operate independently of loan production. In parallel, post-crisis reforms introduced standardized reporting and centralized appraisal quality monitoring through the Uniform Mortgage Data Program (UMDP) and the Uniform Appraisal Dataset (UAD), which impose machine-readable standards on appraisal inputs—particularly property condition and quality—thereby constraining appraiser discretion and enabling automated, portfolio-level screening. More recently, the Property Appraisal and Valuation Equity (PAVE) initiative has explicitly focused on identifying and reducing bias in property valuation.

While Dodd–Frank's appraisal-independence framework was designed to curb undue influence, it does not necessarily eliminate all channels of pressure. In practice, creating a firewall between loan production and the appraisal process can redirect incentives from direct loan production–appraiser interactions to intermediated channels (e.g., an internal ordering desk or a third-party coordinator such as an appraisal management company). Consistent with this idea, several studies find that these independence reforms likely did not fully eliminate appraisal inflation (Agarwal, Ambrose, and Yao, 2014; Ding and Nakamura, 2016; Shi and Zhang, 2015). Importantly for our setting, these post-crisis regulatory changes primarily target process independence rather than appraiser attributes. For that reason, our pre-crisis estimates provide a useful benchmark for thinking about gender and appraisal behavior, even though we do not interpret them as establishing that the same patterns must hold in the current appraisal environment.

Although the post-crisis mortgage market differs meaningfully from the 2000–2007 environment we study, these differences do not eliminate the value of the pre-crisis setting for our purposes. Rather, we view this period as a useful benchmark. Before HVCC and related reforms, appraisers operated in an environment with greater discretion and stronger potential exposure to pressure from loan production. If appraiser gender were likely to matter through differences in conservatism, responsiveness to pressure, or interaction with borrowers, such differences should have been especially plausible in this institutional setting. For that reason, the pre-crisis market provides a particularly stringent setting in which to test for gender differences in appraisal outcomes. At the same time, we do not interpret our results as establishing that the same patterns must hold in the post-crisis environment, where appraisal assignment and oversight have changed substantially. Instead, we view our estimates as providing a historically important benchmark against which post-reform evidence can be compared.

During our sample period, the selection of appraisers by loan originators using internal lists may have introduced non-randomness into the appraisal assignment process, since those lists may not have included all qualified appraisers. Appraisal management companies may have access to broader pools of appraisers than lenders, although they too are likely to rely on internal panels shaped by prior experience. In our setting, this concern is mitigated somewhat by the size and geographic footprint of the lender, which worked with thousands of appraisers nationally. Nevertheless, non-random assignment remains a relevant concern, and we examine directly whether appraiser gender appears to have influenced appraisal assignment in our data.

3. Data

3.1. NCEN and ABSNet/HomeVal

Our primary data is obtained from New Century Financial Corporation (NCEN), a prominent player in the subprime mortgage market prior to the global financial crisis. NCEN acquired the majority of its loan applications through independent mortgage brokers who engaged third-party residential real estate appraisers for property valuations. While our dataset is sourced from a single lender, prior studies suggest that New Century's practices were indicative of the broader subprime mortgage market (Ambrose, Conklin, and Yoshida (2016) and Ambrose, Conklin, and Lopez (2021)) [11].

Our dataset comprises mortgage applications facilitated by approximately 45,000 distinct mortgage brokerage firms as well as NCEN's retail operations,[12] involving 63,000 unique residential real estate appraisers.[13] The large number of mortgage brokerage firms and appraisers represented in the data mitigates concerns that our findings may be overly specific to a single lender. The data cover mortgage applications from 2000 to 2007 and encompass both funded mortgages and unfunded applications. Each application file includes information on property purpose and type (e.g., primary residence, investment property, second home, SFR, multi-unit, condo, PUD), and the zip code where the collateral property is located. Detailed borrower characteristics are also included (e.g., applicant gender, applicant income, marital status, and number of dependents), as well as loan purpose (purchase, refinance).

The NCEN data includes several fields that are crucial for our analysis. First, it provides the full name of the appraiser, which we utilize to infer the appraiser's gender. We elaborate on our gender classification algorithm in a subsequent section. Second, we have access to the appraised value for the subject property, which serves as a point of comparison against valuation benchmarks. Third, we observe the number of days from the initial application to NCEN and the date when the appraisal was completed. Finally, for a subset of the applications, we observe the appraisal fees paid by the mortgage applicant. Taken together, these variables allow us to study whether appraisal

[11] NCEN represents approximately 1–2% of annual HMDA-reported mortgage originations during the 2000–2006 period. For comparison, the single largest lender in HMDA never exceeds 7–8% of the national market in these years, reflecting the highly fragmented structure of the pre-crisis mortgage market. Thus, NCEN's market share appears to be broadly in line with what one would expect for a large subprime lender.

[12] Only about 10% of NCEN's business was generated through its own retail operations.

[13] The original dataset includes an appraiser ID field, but it is sparsely populated. We consider each unique appraiser name/property state combination as a unique appraiser, which may slightly overstate or understate the actual count of appraisers in our dataset.

outcomes vary with appraiser gender.

One of our outcomes of interest compares a property's appraised value to a benchmark valuation obtained from an automated valuation model (AVM). NCEN does not include an AVM estimate, so we merge the NCEN data with Lewtan's ABSNet Loan and HomeVal datasets to obtain AVM property value estimates. The ABSNet dataset offers comprehensive loan-level information on mortgages bundled into private-label (non-agency) mortgage securitizations (PLS). ABSNet covers approximately 90% of the PLS market throughout our study period (Kruger and Maturana (2021)). ABSNet is linked to HomeVal data, which provides an estimated property value at the time of origination for each mortgage. Although these AVM estimates were produced retroactively—HomeVal was launched in 2009, after the end of our sample period—they are based exclusively on information available at the loan closing date, providing an objective estimate of the market value at the time of loan origination. The estimates were generated using a proprietary automated valuation model developed by Collateral Analytics, an industry-leading provider of valuation solutions, and were designed to assist investors in assessing the underlying collateral of existing private-label securities.[14] Further details on the AVM are provided in Online Appendix Section A.1. ABSNet includes only originated loans, so the AVM estimates are only available for funded loans in the NCEN data.

We adopt the matching procedure outlined in Kruger and Maturana (2021), hereafter KM, which involves merging originated mortgages in NCEN with funded mortgages that appear in the ABSNet/HomeVal data based on several key variables: zip code, first payment date, interest rate type (fixed or adjustable rate), credit score, and loan amount. We require that the credit score must fall within a 10-point range across the two datasets, while the loan amount must be within $1,000. By retaining only unique matches, we achieve a successful match rate of 40% for funded loans in the New Century data, consistent with the match rate reported by KM (38%) over a slightly

[14] Because HomeVal was introduced after the conclusion of our sample period, appraisers would not have had access to its AVM estimates at the time of valuation.

different sample period.[15]

Our sample includes observations where the loan amount falls between \$30,000 and \$1,000,000, the loan-to-value ratio is less than 103%, and the combined loan-to-value ratio (CLTV) ranges between 25% and 125%. As in KM, we exclude observations where the appraisal to AVM (or app-to-AVM) ratio falls below 0.3 or exceeds 3. For clarity, we refer to this dataset as the ABSNet-NCEN matched sample.

3.2. Identifying Appraiser and Property Owner Gender

We infer the appraiser's gender based on the appraiser's first name recorded in the NCEN data. We start by collecting a list of the top 200 male and female baby names of each decade from 1940-2010 provided by the Social Security Administration (SSA). 463 and 574 names appear in the female and male name lists over this period, respectively. If a name appears only on the male (female) list, we classify that name as male (female). Only 24 names appear in both the top male and female name lists. For names that appear on both lists, we manually classified them as female names if the proportion of females with that first name was significantly larger than the proportion of males with that first name. Similarly, if the proportion of males with that first name is significantly higher than the proportion of females, we classified the name as male.[16] We then merge this list of male and female first names with the appraiser's first names in the NCEN data to classify the appraiser's gender. If the appraiser's name did not match with the SSA name list, we merged it to a list of frequently occurring male and female names from Census 1990 names files to classify appraiser

[15] The app-to-AVM analysis focuses on funded refinance mortgages. Appendix Table A.3 compares the matched and unmatched (with ABSNet) samples of funded refinances. Although many of the mean differences across the matched and unmatched samples are statistically significant, the magnitude of the mean differences is quite small for most of the variables. A notable exception, however, is that the average appraised value is higher in the matched sample than in the unmatched sample (\$260,590 vs. \$240,447).

[16] We manually classified the following names as female: Alexis, Avery, Dana, Jackie, Jaime, Jamie, Kelly, Kim, Leslie, Lynn, Marion, Peyton, Riley, Robin, Shannon, Taylor, and Tracy. We manually classified Angel, Jordan, Terry, and Willie as male. Three names – Casey, Jessie, and Kerry – had similar proportions of males and females with that name. For these three names, we do not assign a gender in the SSA data.

gender.[17,18] Of the observations in NCEN with an appraiser's first name, 75% are classified as male, and 18% are classified as female. We exclude the remaining 7% of observations where we are unable to classify the appraiser's gender.[19]

We cannot directly verify the accuracy of our appraiser gender classifications. However, we can assess the reliability of our inference method using publicly available 2018 voter registration data from Florida, which includes both first names and self-reported gender for approximately 14 million individuals. We apply the same gender classification approach used for appraisers—merging first names with SSA and Census name data—to this voter file and are able to infer gender for 74% of the records. Among these, our inferred gender matches the recorded gender in 99% of cases. This high rate of accuracy in the voter data provides strong evidence that our gender classifications for appraisers in the NCEN data reflect true gender in nearly all cases.

Mortgage applicant gender is recorded in the NCEN data for HMDA reporting purposes. We create three mutually exclusive binary indicator variables to capture the gender of the property owner. If all mortgage applicants are male (female), we classify the property as male (female) owned. The overwhelming majority of male (female) owned properties have only one mortgage applicant. On the other hand, when there are both male and female applicants on the same mortgage application, we refer to this as "Mixed Owners." Mortgage lenders do not necessarily require that all owners are applicants on the mortgage, thus, some mixed owner properties may be incorrectly classified as male or female owned properties. We provide robustness checks in Section 7 to address potential measurement error in owner gender classification.

[17] `https://www.census.gov/topics/population/genealogy/data/1990_census/1990_census_namefiles.html`.

[18] Names that appear on both the male and female frequently used names from the Census are classified as female (male) if a greater share of females (males) have the name than males.

[19] 99.9% of our observations where the appraiser's first name matches both the SSA and Census names list have the same gender classification using either list.

3.3. Appraisal Outcomes Subsamples

For each observed appraisal outcome, we utilize distinct subsets of the NCEN data. We employ originated refinance mortgages that are uniquely matched to the ABSNet data for our analysis of app-to-AVM ratios, referred to as the *Refi-ABS* sample. When investigating the below sales contract price appraisals, we utilize both funded and unfunded purchase mortgage applications, forming the *Purch* sample.[20] For the days-to-appraisal analysis, we use purchase and refinance applications where both the initial NCEN application date and the appraisal date are observed – the *Dates* sample. Lastly, the *Fee* sample comprises the purchase and refinance mortgage applications where an appraisal fee is observed.[21]

4. Descriptive Statistics

Table 1 reports appraiser-level descriptive statistics in our full sample broken out by appraiser gender. Note that we observe appraisals (and appraisers) only for applications that ended up at NCEN. Thus, the figures, such as appraisal volume, will likely not capture the appraiser's total volume of business from 2000-2007, but rather, the number of appraisals that ended up at NCEN.

There are 46,886 male appraisers and 16,189 female appraisers. Male appraisers in our data complete 21 appraisals, on average, with the most prolific appraiser completing over 1,400 appraisals. The average male undertakes appraisals in 12 different zip codes across three counties. Male appraisers receive appraisal orders from 10 different mortgage loan officers (MLOs) on average.[22] We also calculate zip code, county, and MLO concentration ratios (Herfindahl-Hirschman

[20] In some of our regression models we include the gender of the property owner. In the purchase sample, the "owner" will be the individual(s) on the mortgage application who are purchasing the home (not the property seller(s)).

[21] We require that the fee is between \$75 and \$1200. Figures outside of this range are unlikely to represent the true cost of the appraisal.

[22] MLOs in our sample primarily consist of mortgage brokers. We consider each MLO name/brokerage office combination as a unique MLO. MLO information is not available on all applications, which explains the decrease in observations for fields that use MLO.

Indices) to measure how concentrated each appraiser's business is at each of these levels. This variable is greater than zero but less than or equal to one, with higher values indicating greater concentration. A value of 1.00 indicates that all of the appraiser's appraisals that went to NCEN were concentrated in one zip code, county, or with one MLO. The average county concentration ratio is relatively high, suggesting that appraisers tend to focus their business along geographic lines. However, the zip code and MLO concentration ratios are much lower.

Panel B of Table 1 reports the corresponding figures for the 16,189 female appraisers. On average, female appraisers complete fewer appraisals (15) than males (21). They also complete appraisals across fewer zip codes and with fewer MLOs. The concentration ratios for female appraisers in Panel B are quite similar to those in Panel A. Taken together, there are some slight differences in appraiser-level statistics in Panels A and B, but most of them are likely due to the lower appraisal volume, on average, for female appraisers.

Figure 1 illustrates the share of appraisals completed by female appraisers in the NCEN data. Female appraisers accounted for 16% of all appraisals in 2000. This share steadily increased over the following years, reaching 21% by 2007. The female share in the latter years of the NCEN data is consistent with a 2019 report by the Appraisal Institute–a professional association of real estate appraisers–which indicated that 21.3% of appraisers were female.[23] However, both the female appraiser share reported by the Appraisal Institute and the NCEN female share fall below the 32% reported in a recent survey by The Appraisal Foundation.[24]

Next, we look at whether there are any geographic patterns in appraiser gender. We calculate the county-level female appraiser share as the number of appraisals completed by females in a county divided by the total number of appraisals in that county over our sample period. Here we only include counties with at least 30 appraisals. Figure 2 plots density estimates based on an Epanechnikov kernel with bandwidth 0.0208 for the 1,596 counties with at least 30 appraisals.

[23] Available at https://careersbuildingcommunities.org/wp-content/uploads/2019/04/2019_fact_sheet1.pdf.

[24] Available at https://mn.gov/commerce-stat/pdfs/appraisal-foundation-results.pdf.

Female market share ranges from 0% to 89%, with a mean (median) of 23% (21%). The bottom and top 15 counties in terms of female market share are reported in Table 2. Fourteen counties have no appraisals completed by females, while Warren County, Pennsylvania, has the largest female appraiser market share (89%). Figure 3 maps the county-level female market share. While substantial variation exists in the female market share across counties, evidenced by a standard deviation of 12% – representing over half of the mean – no discernible geographical patterns emerge.

Table 3 reports mean values of mortgage application-level variables by appraiser gender for our full sample. Variable names and descriptions are provided in Appendix Table A.1[25] Although the average appraised value is slightly higher for male-appraised properties, the other appraisal outcomes are similar across the two columns. Appraised values are 8-9% higher than AVM estimates on average, consistent with previous studies (Agarwal, Song, and Yao, 2020; Ambrose et al., 2025; Griffin and Maturana, 2016). As has been widely documented, the appraised value rarely comes in below the sales contract price on purchase mortgage applications (Agarwal, Song, and Yao, 2020; Calem et al., 2021; Cho and Megbolugbe, 1996; Conklin et al., 2020; Ding and Nakamura, 2016), but this empirical regularity does not vary with the appraiser's gender.

Ideally, for appraiser efficiency, we would measure the number of days between the date when appraisal i was completed (C_{it}) and the date when it was initially ordered or requested (R_{it}) by the mortgage loan officer (typically an independent mortgage broker):

$$\text{Turnaround time} = C_{it} - R_{it}. \tag{1}$$

Although we observe C_{it} in the data, we are unable to observe the date that the appraisal was ordered. We do, however, observe the date that New Century received a formal loan application, NC_{it}, which can occur before or after the appraisal is completed. We define days to appraisal as

[25] Appendix Table A.2 reports the number of observations with non-missing values for each of these variables.

the number of days between when the appraisal is completed and when New Century received the loan application:

$$\text{Days to appraisal} = C_{it} - NC_{it}, \tag{2}$$

with a negative (positive) value indicating the appraisal was completed before (after) New Century received the loan application. This can be rewritten as:

$$\text{Days to appraisal} = \underbrace{(C_{it} - R_{it})}_{\text{Turnaround time}} - \underbrace{(NC_{it} - R_{it})}_{\text{Request to submission}} \tag{3}$$

Thus, our dependent variable in this case is the convolution of two distinct actions, both of which may be correlated with gender. If female appraisers are less efficient than males, we would expect the first term to be higher for female appraisers. If the loan officer only uses females as (say) a backup choice, the second term will be higher for females. While we will model this variable in a regression context shortly, it is worth noting here that the average number of days to appraisal for both male and female appraisers is -11.4 (on average appraisals are completed before NCEN receives an application), indicating that neither component is correlated with gender[26]. Because Days to Appraisal is virtually identical across male and female appraisers—and because this measure is a proxy for turnaround time (efficiency) rather than turnaround time itself—we do not focus on Days to Appraisal as a primary appraisal outcome in the regressions below.[27]

Turning to our final appraisal outcome in Table 3, we see that both male and female appraisers charge $350, on average, for an appraisal. Male and female appraisers also tend to appraise properties used for similar purposes, and similar property types. No other large disparities are apparent in the other application level characteristics across gender. Overall, Table 3 provides no evidence

[26]It is possible that an appraisal assignment comes with a deadline from the lender, and delays in the assignment (the second term in equation (3)) would need to be met with an equivalent reduction in turnaround time (the first term). In such a scenario, the use of female appraisers as backups would not be observable in this data, but indeed would be congruent both with lender discrimination and quicker productivity by females.

[27]Appendix Section A.2 provides a more detailed analysis of Days to Appraisal.

of systematic selection into appraiser gender based on property or applicant-level observables.

5. Results

5.1. Appraisal Outcomes by Appraiser Gender

In this section we examine whether appraisal outcomes vary with appraiser gender. We estimate regressions of the following form:

$$Y_{it} = \alpha \text{Female Appraiser}_i + \delta_z + \gamma_t + e_{it}, \tag{4}$$

where Y_{it} is the appraisal outcome of interest on mortgage application i at time t. Female Appraiser is an indicator variable that takes a value of one if the appraiser for the property associated with application i is female and zero otherwise. δ_z represents location (zip code) fixed effects to account for time invariant spatial factors that impact appraisals (e.g., differences in appraisal completion times in rural versus urban areas). γ_t are appraisal year fixed effects to account for temporal changes in appraisal outcomes at the national level (e.g., appraisal fee increases over time), while e is the error term. Our primary coefficient of interest, α, represents the average difference in appraisal outcome for female appraisers relative to male appraisers.

Table 4 reports OLS estimates based on equation 4 for our three primary appraisal outcome measures. The dependent variable in column 1 is the App-to-AVM ratio, which has a mean value of 1.09, as reported at the bottom of the table. The female appraiser coefficient is positive but indistinguishable from zero. The economic magnitude is negligible as well. Appraisals completed by female appraisers have app-to-AVM ratio which is 0.2 percentage points higher, on average, than those completed by males.[28] Given that appraisals are more consequential for financing at

[28]The coefficients can roughly be interpreted as percentage point changes. For example, suppose the app-to-AVM ratio on a home appraised by a male is $\frac{\$100}{\$100} = 1$. If the appraiser is female, the app-to-avm ratio increases to $\frac{\$100.2}{\$100} = 1.002$, approximately a 0.2 percentage point change in value.

key CLTV notches (Calem, Lambie-Hanson, and Nakamura, 2016; Fout, Mota, and Rosenblatt, 2022), we also examine whether appraisal values at those notches differ by appraisal gender. We run an App-to-AVM regression interacting CLTV threshold dummies (e.g., 69-70%, 74-75%, 79-80%, 84-85%, 89-90%, 94-95%, 99-100%) with appraiser gender. Although female appraisers appear to be slightly more conservative at high CLTVs, our gender-CLTV interaction terms are generally not significant.[29]

In column 2, the dependent variable indicates whether the appraised value comes in below the sales contract price on a purchase mortgage application. As mentioned above, below contract appraisals are rare. Only 2% of the appraisals associated with home purchases had an appraised value lower than the contract sales price. The coefficient in column 2 shows no meaningful differences in the likelihood of a below contract appraisal based on the appraiser's gender.

Finally, in column 3, we look at differences in appraisal fees between male and female appraisers. Female appraisers charge \$0.90 less than their male counterparts, on average. Although statistically distinguishable from zero, this difference is trivial relative to the average appraisal fee of \$349.

Collectively, the results presented in Table 4 do not indicate significant differences in appraisal outcomes based on appraiser gender.[30]

Because several of our headline estimates are small or statistically insignificant, it is important to distinguish between imprecision and tightly estimated near-zero effects. In our baseline specifications, the female-appraiser coefficient in the appraisal-to-AVM regression is 0.002 with a

[29]For the sake of space, this regression is not included in the paper. However, it is available upon request. We thank an anonymous referee for this suggestion.

[30]Property sales transaction prices are not publicly available in some states, which may affect the valuation process (Garate, Hilterbrand, and Pennington-Cross, 2023). Appendix Table A.5 replicates the regressions from Table 4, presented separately by whether transaction prices are publicly disclosed. The classification of disclosure and non-disclosure states follows Garate, Hilterbrand, and Pennington-Cross (2023). Panel A includes observations from states where sales transaction prices are fully disclosed, while Panel B includes observations from states where prices are not fully disclosed (AK, ID, KS, MT, MS, NM, WY, TX, and UT). The majority (70%) of observations from non-disclosure states in our sample come from Texas. Missouri is excluded from both panels due to variation in disclosure status across counties. Consistent with the results in Table 4, a few coefficients are statistically distinguishable from zero, but the economic magnitudes are small in both disclosure and non-disclosure states.

standard error of 0.002, implying an approximate 95% confidence interval of [-0.002, 0.006]. Thus, the data rule out anything other than very small average valuation differences. For below-contract appraisals, the estimated coefficient is essentially zero with a similarly tight interval around zero. For appraisal fees, the estimate is statistically distinguishable from zero, but less than one dollar in magnitude relative to an average fee of roughly $349. Taken together, these results suggest that the headline average effects are best interpreted as economically small and, for the primary outcomes, precisely estimated rather than merely underpowered non-results.[31]

At the same time, these results should be interpreted as differences in observed appraisal outcomes conditional on the assignment process captured by our controls and fixed effects, rather than as definitive evidence of equal performance in a structural sense. If male and female appraisers are assigned systematically different properties, borrowers, or loan situations along dimensions not fully observed in the data, then small average differences in outcomes may reflect a combination of assignment and behavior rather than identical appraisal practices. We return to this issue below by examining the role of appraiser assignment more directly and by considering specifications that absorb originator-level assignment patterns.

5.2. Appraiser Gender and Owner Race

We now examine the interaction of appraiser gender and owner race. This follows the analysis of Ambrose et al. (2025), among others, who examine the extent of racial and ethnic bias in property appraisals. These authors found that properties owned by ethnic minorities were appraised at values 1-4% less than comparable white-owned properties. We now examine whether this differential obtains equally for male and female appraisers.

Table 5 displays the cross-tabulation of owner race and appraiser gender. It can be seen in this table that there is almost no variation in the proportion of appraisals performed by females across

[31] As suggested by one of the referees, we also run quantile regressions for App-to-AVM and Fee, but find no gender difference in these distribution regressions either. These results are not included in the paper but are available upon request.

racial categories. In each column, there are about four times as many male appraisers as females, congruent with the overall proportion previously observed. Thus there does not appear to be any sorting of appraisers by gender across races.

In order to test whether the racial bias observed in Ambrose et al. (2025) varies by appraiser gender, we employ the following regression:

$$
\begin{aligned}
Y_{it} = & \alpha_{fw}\mathrm{A}^f\mathrm{O}^w + \alpha_{ma}\mathrm{A}^m\mathrm{O}^a + \alpha_{fa}\mathrm{A}^f\mathrm{O}^a + \alpha_{mb}\mathrm{A}^m\mathrm{O}^b + \alpha_{fb}\mathrm{A}^f\mathrm{O}^b + \alpha_{mh}\mathrm{A}^m\mathrm{O}^h + \alpha_{fh}\mathrm{A}^f\mathrm{O}^h \\
& + X_i\beta + \delta_z + \gamma_t + e_{it}. \qquad (5)
\end{aligned}
$$

In the above equation, A^j indicates the gender of the appraiser with j $\in \{f, m\}$ (female or male). O^k indicates owner race with k $\in \{w, a, b, h\}$ (white, asian, black, hispanic) . For example, $\mathrm{A}^f\mathrm{O}^b$ indicates that the appraiser is female and the owner is black. The omitted category in equation 5 is white-owned properties appraised by a male appraiser ($\mathrm{A}^m\mathrm{O}^w$). X_i includes application-level control variables, discussed momentarily. As in equation 4, δ_z and γ_t are zip code and appraisal year fixed effects, respectively. Each α_{jk} can be interpreted as the average marginal difference in appraisal outcome for appraiser gender j and ownership type k, relative to white-owned properties appraised by male appraisers.

Table 6 presents the results from estimating the above equation. In line 1 of the table, we present the coefficients of the interaction term of the female appraiser and the white owner. This coefficient is effectively zero across the various specifications in columns 2 through 7 (which are discussed shortly). Thus there is no difference in appraisal outcomes for white borrowers when the appraiser is female.

In the next several lines we display the coefficients for the key interaction terms described above: appraiser gender interacted with owner (minority) ethnicity. For these coefficients, the differential outcomes for male and female appraisers do depend on the specification, and so we proceed to describe those specifications here.

In column 1, the specification is limited to zip code and year fixed effects. It can be seen that for Hispanic and Asian households, the App to AVM ratio is lower for both male and female appraisers, but the difference across genders in each of these two cases is small. However, for Black households, the bias is rather greater for male appraisers than for female appraisers.

In Column 2, we add property characteristics (second home, investment property, multi-unit property, condo, and location in a PUD). We note here that the inclusion of these controls, while presumably important for valuation purposes, have little effect on any of the coefficients of interest.

In Column 3, we add variables that are plausibly related to the condition and quality of the property. One of the important differences between an appraiser's valuation and that of an AVM is that the appraiser conducts an in-person examination of the home and so can observe first-hand its condition. The AVM might not have adequate information on these characteristics, and so the App-to-AVM ratio will vary according to these unobservables. Therefore, if condition and quality vary systematically with ethnic group, our key coefficient estimates will be biased. Our New Century database does not have any information on the physical characteristics or condition of the unit; however, it does contain several borrower characteristics that are likely correlated with condition. These include marital status, income, assets, number of dependents, property age, and years living at residence all of which can, in various ways, be related to condition[32].

Including these variables changes the value of the coefficients substantially. In the case of Black and Hispanic households, there is a marked reduction in the absolute value of the estimated bias of both male and female appraisers. This would seem to be due to the correlation of our condition proxies with the borrower's race. In particular, Black and Hispanic households on average have lower income and wealth, which affords them fewer resources to maintain and improve the property. Thus the large negative coefficients observed in column 2 were in part a reflection of the

[32] As Appendix Table A.2 shows, these application level characteristics are not available for all observations. Following Ambrose et al. (2025), we create a "missing characteristic" dummy variable for each of these characteristics. If the information is missing on the loan application, the missing characteristic dummy is set to one, and the characteristic itself is set to zero. For example, if the number of dependents is missing on the loan application, we set the number of dependents to zero and the "Missing Dependents" dummy to one.

lower quality observed by appraisers but not accounted for in the AVM. For Asian household the opposite occurs. The absolute value of the key coefficients rise. The greater resources afforded to this group raise the unobserved quality of their property and bias the coefficients in column 2 downward in absolute value. It should be noted that none of these changes the *relative* bias exhibited by male and female appraisers. For Hispanic and Asian households the male and female coefficients remain relatively close, though the gap for Hispanic households widens a little bit, while for Blacks the female bias effectively disappears while the male measure remains significantly negative.

In column 4, we incorporate a variable that captures the precision of the AVM estimates into our model. In some cases, HomeVal assigns a confidence score to the AVM value estimate, ranging from 50 to 99, where higher scores denote greater confidence in the AVM value estimate.[33] Given that AVM errors can be substantial for certain properties (Jiang and Zhang, 2022; Molloy and Nielsen, 2018), these confidence scores enable our model to account for valuation uncertainty in the point estimates. Nevertheless, the gender coefficients in column 4 are nearly identical to those in column 3.

Research suggests appraisal inflation may be heightened for highly leveraged borrowers (Eriksen, Kuang, and Zhu (2024),Piskorski, Seru, and Witkin (2015), and Agarwal, Ben-David, and Yao (2015)). If leverage is also correlated with appraiser gender or owner race, then our estimates in column 4 may be biased. We include combined loan to value ratio (CLTV) from the loan application as a control in column 5 and find that this entails only minor changes in the key coefficients in column 5. However, the negative coefficient on CLTV suggests that higher leverage is associ-

[33]Panel A of Figure A.1 shows the distribution of AVM confidence scores. Most observations with an AVM value do not have a corresponding confidence score, as indicated by the large mass to the left of 50 in Panel A. The share of AVM values accompanied by a confidence score increases over time: in 2000, only 8% of (retroactive) AVM observations included a confidence score, but by 2007, that share had risen to 65%. Table A.4 compares descriptive statistics between observations with an AVM value but no confidence score and those with a confidence score. The differences in means across these two subsamples are relatively small. Figure A.1 , Panel B displays the distribution of confidence scores for the subset of observations with non-missing values, revealing noticeable bunching at scores of 50 and 90. While higher scores indicate greater confidence in the AVM estimate, the exact interpretation of the score is not provided with the HomeVal data. Appendix Figure A.2 plots the distributions for states where transaction prices are not fully disclosed. Interestingly, in these states, a larger share of the observations have a confidence score, and bunching occurs not only at 50 and 90, but other numbers as well.

ated with lower valuations (relative to the AVM), which is somewhat in contrast to the findings of Eriksen, Kuang, and Zhu (2024),Piskorski, Seru, and Witkin (2015), and Agarwal, Ben-David, and Yao (2015). Note, though, that reverse causality (inflated appraisals reduce CLTV) may be an issue when controlling for CLTV; thus, we are careful not to overinterpret this coefficient.

To address potential selection bias arising from the fact that mortgage brokers were able to choose which appraiser to assign to a given property during our sample period, we next include mortgage broker fixed effects in our regression models. This approach allows us to compare outcomes within brokers, thereby controlling for any time-invariant broker-level preferences or strategies related to appraiser selection. In effect, we are identifying the impact of appraiser gender based on variation in appraiser assignment across otherwise similar applications handled by the same broker.

However, this strategy does not fully eliminate concerns about endogeneity. If brokers systematically assign female appraisers to particular types of loans, properties, or borrowers, and if those assignment patterns are correlated with unobserved determinants of appraisal outcomes, our estimates may still be biased. We interpret the results with this caveat in mind, but we will return to the idea of appraiser selection in Section 6.

We create originator (broker or loan officer) fixed effects as follows. For brokered loans, we treat each individual broker name-brokerage company combination as a unique mortgage broker. Since the individual broker name field was sparsely populated before 2003, any analysis including originator FE covers the 2003-2007 period. Individual NCEN loan officers are not observable in the data, so we treat all retail loans as one originator.

Originator fixed effects are useful because they absorb stable originator-level assignment patterns that could otherwise confound comparisons across appraiser gender. However, they are also a demanding specification: if appraiser-originator relationships are persistent, these fixed effects may absorb much of the variation through which appraiser gender could matter. We therefore view them as a stress test of the baseline results rather than as the only specification that matters.

Column 6 of Table 6 includes these originator fixed effects. The sample size is drastically reduced for two reasons. First, our sample in this column covers a shorter time period (2003-2007). Second, and more importantly, a large number of singleton observations are dropped because many mortgage brokers are associated with only a small number of mortgage applications. The coefficients on the appraiser gender/owner race variables are now all insignificant, and most of the coefficient values exhibit little or no change. This loss of sample size and identifying variation should be kept in mind when interpreting the attenuation of coefficients in the most saturated models.

In Column 7 we deal with the fact that the AVM is not the same thing as transaction price. Ideally, we would compare the appraised value to the market value of the property (e.g., appraisal to market value ratio). However, transaction prices are not available for refinance loans, thus we have relied on AVM estimates for valuation benchmarks in columns 1 through 6 of Table 9. We now turn to an alternative valuation benchmark that perhaps better captures the actual market value of the refinance properties. We follow the methodology outlined in Ambrose et al. (2025) and use data from purchase mortgage applications—where both a sale price and an automated valuation model (AVM) estimate are available—to estimate a predictive model of transaction prices. Specifically, we regress log sales prices on log AVM estimates and largely the same controls included in column 6 (see below). We then use the coefficients from this model to predict market values (expected sales price) of properties in the refinance sample. We then benchmark the appraisal to this alternative valuation estimate, which we refer to as the app-to-$\hat{V}$ ratio. This predictive model for $\hat{V}$ does not include originator fixed effects, as the originators in the purchase sample are not necessarily the same as in the refinance sample. Also, we include the borrower's gender in the prediction model, but not the appraiser's. The borrower's (buyer's) gender is meant to capture unobservable differences in properties across gender. Column 7 reports coefficient estimates using app-to-$\hat{V}$ as the dependent variable.

Consistent with the results in Ambrose et al. (2025) this adjustment has a profound effect on the coefficients of interest, all of which increase in absolute value, indicative of undervaluation of minority-owned property by AVMs. The coefficients now indicate undervaluations by both male and female appraisers by 1 to 4%. Figure 4 presents these results visually. (Again, these are very much in line with results from Ambrose et al. (2025)). Of most interest here, though, are the differences in these undervaluations across genders. We note that there is no difference in the male and female appraisals of Hispanic-owned property (at -2.6%), while the underappraisal of Black-owned houses is less when the appraiser is female (-3.3%) than male (3.8%). However, a Wald test indicates that this difference is not statistically significant. Interestingly, the direction of the differential is reversed for Asian households, where the undervaluation by female appraisers (-2.7%) is substantially greater than when the appraiser is male (-1.2%). The Wald test in this case has a prob-value of .059, so there is some precision to this difference.

With this one exception, our summary judgment is that there is almost no systematic difference in the racial bias in appraisals across genders, and that both genders exhibit this bias to a substantial degree. Where such differences exist, they are less important than the fact that biases exist when either gender performs the appraisal.

In Table 7, we examine differentials for other appraisal outcomes across owner race and appraiser gender, using the saturated model of the final columns in Table 6. In column 1, we find that the probability that an appraisal for a purchase mortgage is below the contract price is minuscule overall, and there are no economic or statistically significant differences across categories for any of the groups.

In column 2 of Table 7, we examine appraisal fee differentials. Again, Table 4 indicates a statistically significant, but economically tiny difference of 90 cents higher fees for male appraisers, and this is echoed in the table. For each group, the male coefficient is higher than the female coefficient. While these differences are minor for most groups, for Asian households the difference is quite large. Compared to the white owner/male appraiser baseline, a male appraiser receives \$3.04 more for an Asian household, while a female appraiser receives \$2.50 less, for an economically significant \$5.54 difference.

5.3. Appraiser and Owner Gender

Next, we examine whether the property owner's gender interacts with the appraiser's gender to affect appraisal outcomes. For example, do female owners receive more favorable outcomes when working with female appraisers? To classify the owner's gender, we rely on the applicant(s) gender reported on the mortgage application. If all mortgage applicants are male, we classify the property as "Male Owner." Similarly, if all mortgage applicants are female, we classify the observation as "Female Owner." When both male and female applicants appear on the application, we categorize ownership as "Mixed Owners." Table 8 reports the share of applications that fall into each appraiser-owner gender combination. 37%, 33%, and 30% of properties are categorized as male, mixed, and female-owned, respectively.[34] Overall, 19% of the appraisals are completed by female appraisers, and this varies little with ownership gender. Female appraisers account for 19-20% of the appraisals within each column of Table 8, suggesting that female owners do not tend to disproportionately match with appraisers that share the same gender. This stands in contrast to the propensity of mortgage loan officers to match with borrowers that share the same race as documented in Ambrose, Conklin, and Lopez (2021) and Frame et al. (2021).

To test whether appraisal outcomes vary by appraiser-owner gender interactions, we estimate appraisal outcome models similar to those of the previous section, of the following form:

$$Y_{it} = \alpha_{fm}\mathrm{A}^f\mathrm{O}^m + \alpha_{mb}\mathrm{A}^m\mathrm{O}^b + \alpha_{fb}\mathrm{A}^f\mathrm{O}^b + \alpha_{mf}\mathrm{A}^m\mathrm{O}^f + \alpha_{ff}\mathrm{A}^f\mathrm{O}^f + X_i\beta + \delta_z + \gamma_t + e_{it}. \quad (6)$$

A^j indicates the gender of the appraiser with j $\in$ $\{f, m\}$ (female or male). O^k indicates owner gender with k $\in$ $\{f, m, b\}$ (female, male, or mixed (b)). For example, $\mathrm{A}^f\mathrm{O}^m$ indicates that the appraiser is female and the owner is male. The omitted category in equation 6 is male-owned

[34]The overwhelming majority of "Male Owner" and "Female Owner" properties only have one mortgage applicant. Note that it is possible for a property to have multiple owners, even though only a subset of them appear on the mortgage application. This may lead to some "Mixed Owner" properties being misclassified as male or female owned. We provide additional tests in Section 7 that deal with potential misclassifications of owner gender.

properties appraised by a male appraiser (A^{m}O^m). X_i includes application-level control variables, discussed momentarily. As in equation 6, δ_z and γ_t are zip code and appraisal year fixed effects, respectively. Each α_{jk} can be interpreted as the average marginal difference in appraisal outcome for appraiser gender j and ownership type k, relative to male-owned properties appraised by male appraisers.

Table 9 reports OLS estimates based on equation 6 with app-to-AVM as the dependent variable in the Refi-ABS sample in parallel with this previous analysis on owner race. All columns include zip code and appraisal year fixed effects. All of the coefficient estimates in column 1 are statistically distinguishable from zero. The Female Appraiser / Male Owner coefficient indicates that male-owned properties are appraised approximately 1 percentage point higher when the appraiser is female. In other words, male owners receive more favorable valuations when the appraiser is female. Next, we see that relative to male owned properties appraised by males, app-to-AVM ratios are higher on mixed-ownership properties (0.006). This difference does not vary with appraiser gender, though; a Wald test fails to reject the null hypothesis that the Male Appraiser/Mixed Owners coefficient equals the Female Appraiser/Mixed Owners coefficient ($\alpha_{mb} = \alpha_{fb}$). Female-owned properties have lower app-to-AVM ratios, but this also does not depend on the gender of the appraiser. The Male Appraiser/Female Owner coefficient is not statistically different from the Female Appraiser/Female Owner coefficient ($\alpha_{mf} = \alpha_{ff}$).

Next, we introduce property purpose and property type controls in column 2 of Table 9. After controlling for property and structure type, the appraiser-owner gender coefficients in column 2 are nearly identical to those reported in column 1.

In column 3, we add borrower characteristics as before. The Female Appraiser / Male Owner coefficient remains unchanged at 0.008 after we introduce these additional controls. However, the mixed owner coefficients sign flips, both for female and male appraisers, but as in columns 1 and 2, mixed ownership valuations do not vary significantly with the appraiser's gender (-.005 for male appraisers versus -.006 for female appraisers). Another important change in column 3 is that Male Appraiser / Female Owner and Female Appraiser / Female Owner coefficients are no longer distinguishable from zero after we incorporate the application level proxies for property characteristics.[35]

In column 4, we incorporate a variable that captures the precision of the AVM estimates into our model. The gender coefficients in column 4 are nearly identical to those in column 3. In column 5 we add the AVM quality control and as before, there is no change in the key coefficients.

Column 6 of Table 9 includes originator fixed effects. And as we discussed earlier, the sample size is drastically reduced. None of the coefficients is statistically distinguishable from zero, and they are not significantly different from one another.[36] Note, though, that this could be due in part to the smaller sample size and large number of originator fixed effects. The magnitudes of the coefficients are relatively small as well. Taken together, the results in Figure 5 (based on column 6 of Table 9) suggest that the gender of the owner and appraiser has a limited impact on valuation.

Column 7 reports coefficient estimates using app-to-$\hat{V}$ as the dependent variable. We also plot these coefficients and their 95% confidence intervals in Figure 5. Consistent with the results in Column 6, the estimated gender coefficients are modest, and none are statistically distinguishable from zero.

Next, we estimate the fully saturated model for each of the other appraisal outcomes and report the results in Table 10. In column 1, modeling the probability of below-contract appraisals, none of the appraiser-owner coefficients are significantly different from zero, and economic magnitudes are small. Importantly, within any given ownership type (e.g., mixed), the likelihood of a below contract appraisal does not vary with the appraiser's gender.[37] Column 2 shows that appraisal fees

[35] These results also indicate that unobserved property characteristics are correlated with applicant gender, such that their inclusion lowers the app-to-AVM ratio for Mixed applicants and raises it for Females. For example, if Mixed applicants (controlling for marital status) have higher incomes, this will presumably raise unobserved quality. The positive coefficient for Mixed applicants in column 1 is actually due to their higher income, and once income is controlled for, the positive coefficient disappears in column 3.

[36] A joint test of the equality of the coefficients yields an F-statistic of 1.76 and a p-value of 0.134; thus, we fail to reject the null hypothesis of equal coefficients at conventional significance levels.

[37] As noted above, "owner" gender refers to the individual(s) purchasing the property (i.e., the mortgage applicant(s)). Although the seller is more likely than the buyer to interact with the appraiser during the site visit, appraisers

vary little with the owner's or appraiser's gender. Mixed owners pay slightly lower fees ($2), but this is trivial relative to the average appraisal fee of $349 and does not vary with the gender of the appraiser.

Taken together, the results in Tables 9 and 10 suggest that appraiser gender does not play a large role in appraisal outcomes.

6. Likelihood of Using a Female Appraiser

This section helps interpret the main results by assessing whether the limited average differences documented above could mask systematic non-random assignment by appraiser gender. In the previous section, we showed that appraisal outcomes differ little by appraiser gender. We also presented two patterns that suggest assignment of female appraisers does not appear to be a major source of concern for our empirical analysis: (i) descriptive statistics are similar for properties appraised by male and female appraisers (Table 3), and (ii) the share of female appraisers is relatively constant across owner gender categories (Table 8). We now examine potential selection concerns by estimating linear probability models in which the dependent variable is an indicator for whether the appraiser is female.

Table 11 reports the results. In column 1, we include appraisal year indicators (with 2000 as the omitted category) as well as zip code-level demographic information (where the appraised property is located) from the 2011 American Community Survey 5-year estimates. The zip code controls include: the share of the population that is White; the share of the adult population with at least a high school education; the share of the population that is foreign born; the employment rate; the natural logarithm of the median household income and its square; and the natural logarithm of the median owner occupied property value. Descriptive statistics for these zip code level variables are

almost always receive a copy of the sales contract, which includes the buyer's name(s). As a result, the appraiser can often infer buyer gender. Whether this information influences the appraisal, either consciously or subconsciously, is an empirical question that we attempt to answer.

provided in Appendix Table A.6.

Column 1 of Table 11 shows that female appraisers are more likely to be used in later years of the sample, consistent with our earlier discussion of Figure 1. Turning to the zip code–level controls, we find that the White population share is positively associated with the likelihood of a female appraiser, though the economic magnitude of this relationship is negligible. In contrast, a one standard deviation increase in the foreign-born population share is associated with a 2 percentage-point decrease in the probability that the appraiser is female ($8.33 \times -0.002 = -0.017$).

The coefficients on log median household income and its square are 0.237 and –0.012, respectively, implying that the likelihood of a female appraiser declines with zip income levels above approximately $19,368.[38] Notably, 99.3% of the sample resides in zip codes with median incomes above this threshold, indicating that the relationship between area income level and the likelihood of using a female appraiser is effectively negative across nearly the entire sample.

The low adjusted R-squared (0.004) in column 1 implies that observable ZIP code characteristics and appraisal year account for only a negligible share of the variation in appraiser gender. While this does not rule out selection on unobservables, it suggests that selection on observables is limited, providing some reassurance regarding potential endogeneity concerns.

Column 2 includes zip code fixed effects, rendering the time-invariant ZIP code controls from column 1 collinear and thus omitted. The inclusion of these locational fixed effects does little to improve the explanatory power of the model. Properties owned by mixed-gender or female-only households are 0.3 and 0.2 percentage points more likely, respectively, to be appraised by a female appraiser than those owned by male-only households. Although both coefficients are statistically significant, the magnitudes are modest relative to the overall female appraiser share in the sample (20%).

The adjusted R-squared of the saturated model in column 3, which includes originator fixed ef-

[38] $\frac{\partial A^f}{\partial \ln(\text{Median HH Income})} = 0.237 - 2 \times 0.012 \times \ln(\text{Median HH Income})$. Setting this equal to zero and solving for $\ln(\text{Median HH Income})$ yields 9.875, or in dollar terms $e^{9.875} \approx \$19,368$.

fects, is substantially higher than in column 2 (0.255 versus 0.035). However, even after accounting for individual originators—who likely played a role in selecting appraisers—a large share of the variation in appraiser gender remains unexplained. It is also notable that, aside from the appraisal year indicators and owner gender variables, most control variables are neither economically nor statistically significantly associated with appraiser gender in column 3. Taken together, these findings suggest that treating appraiser gender as exogenous may be a reasonable assumption in our empirical framework.

7. Potential Misclassification of Owner Gender

As discussed in Section 3.2, our name-based algorithm for classifying appraiser gender is likely highly accurate, as evidenced by testing on Florida voter registration data. However, misclassification of property owner gender may occur because mortgage lenders do not necessarily require all owners to be borrowers on the mortgage application. For example, if a property is truly jointly owned (e.g., by a husband and wife) but only the wife is a borrower, we would incorrectly classify this as a female-owned property. Although the severity of this classification problem is difficult to determine, we provide a robustness check using a sample where misclassification is likely less severe. Specifically, we focus on appraisals for mortgage applications with no co-borrower where the applicant indicated they were unmarried or separated. These applicants have a relatively high likelihood of being the sole owner. We acknowledge this does not entirely eliminate owner gender classification error, as an unmarried or separated mortgage applicant could still co-own the property with someone of the opposite gender (a partner, family member, or co-investor). However, it is likely that the owner's gender measurement error is reduced for unmarried or separated applicants with no co-borrower on the mortgage application.

Column 1 of Table 12 reports results from our saturated regression model with App-to-AVM as the dependent variable, using the subsample of mortgages with no co-borrower and where the applicant indicated they were unmarried or separated. While the Female Appraiser / Male Owner coefficient was positive (0.007) in Column 6 of Table 9, it is now larger in magnitude (0.021) and statistically significant in Table 12, which may reflect attenuation bias in the broader sample due to owner gender misclassification. None of the other gender coefficients in Table 12 is statistically different from zero, consistent with our earlier findings.

Columns 2 and 3 of Table 12 report results for the other outcomes of interest. Most appraiser/owner gender coefficients are either economically small, statistically insignificant, or both. One exception is the Female Appraiser / Female Owner coefficient of 0.005 in the below-contract regression in Column 2, which is sizable relative to the mean of below contract (0.02). This may again suggest attenuation bias in our earlier results; however, the coefficient is only marginally significant at the 10% level.

Taken together, the results in Table 12 provide some evidence that measurement error may bias certain estimates in the full sample. However, the key takeaway from Table 12—that appraiser and owner gender are not strongly related to most appraisal outcomes—is consistent with our findings in Section 5.3.

8. Conclusion

This study examines gender differences in the real estate appraisal industry using a comprehensive dataset of subprime mortgages originated by New Century Financial Corporation from 2000 to 2007. Across a wide range of outcomes — including appraisal values relative to automated valuation models, the likelihood of appraisals falling below contract prices, and fees — we find little evidence of economically meaningful average differences between male and female appraisers. Female appraisers are substantially underrepresented in the industry and complete fewer appraisals on average, but the headline appraisal outcomes themselves differ little by appraiser gender. For the primary outcomes, these average effects are also precisely estimated, allowing us to distinguish tightly estimated near-zero effects from merely underpowered non-results.

Although our dataset is limited to the pre-crisis mortgage market, that setting is valuable for our purposes because it predates HVCC and related reforms that altered appraisal assignment and oversight. As a result, our estimates provide a useful historical benchmark for evaluating whether gender differences in appraisal behavior were present in an environment where discretion and potential pressure from loan production were likely to be greater than they are today. We do not interpret these findings as implying that the same patterns must necessarily hold in the post-2008 appraisal market. Rather, the paper's contribution is to show that, in this earlier institutional setting, female appraisers were underrepresented and completed fewer appraisals, but average observed appraisal outcomes differed little by appraiser gender.

We also examine whether appraiser gender affects racial and gender-related disparities in the appraisal process. Consistent with prior research, we find systematic underappraisal of minority-owned properties by 1–4 percent relative to comparable White-owned homes, but this racial bias is pervasive across both male and female appraisers, with minimal differences between them. Regarding owner gender, male homeowners receive slightly higher appraisals from female appraisers (by nearly 1 percentage point) compared to male appraisers, while mixed-gender ownership pairs receive lower valuations regardless of appraiser gender. However, initial indications of lower appraisals for female-owned properties attenuate after controlling for socioeconomic factors such as income and family status. These patterns do not suggest strong gender homophily in appraisals.

Our findings contribute to the broader literature on gender dynamics in finance and real estate by demonstrating that, despite female appraisers' underrepresentation and lower appraisal volume, they perform their roles in a manner essentially identical to males. This paper has shown that, to a very large degree, there are no substantive differences across genders in appraisal outcomes, productivity, and compensation. This degree of gender neutrality is somewhat rare in such studies, and suggests a way forward for gender equality in the workplace generally. In particular, Goldin (2014) suggests that while much progress has been made with respect to gender equality in the workplace, further progress will depend on how flexible work situations can be. The appraisal industry is a canonical example of a profession with such flexibility (FannieMae, 2018), thus providing support for Goldin (2014)'s thesis.

There are two remaining sticking points. First, there is the difficulty in obtaining licensure. In addition to substantial education requirements, states generally mandate that potential licensees be supervised by a licensed appraiser for up to 1000 hours or more. The difficulty in obtaining such a supervisor is well-documented and such supervision is often not available for those with reduced networking potential [39]. This is likely to be more burdensome for women and minorities aspiring to be appraisers.

The second sticking point is the difference in appraisal volume across males and females appraisers. We do not have data on the offer of appraisal assignments, so we do not know the extent to which the large difference in observed appraisals across genders is due to lender discrimination or female appraisers taking advantage of the profession's flexible structure to take on fewer jobs. To the extent that it is the former, the results of this paper should be a signal to lenders to access the skills of female appraisers more than they otherwise do.

[39] See Yap et al (2022). Also note efforts underway to alleviate this burden (www.appraisalinstitute.org/the-appraisal-profession/parea).

References

Agarwal, S., B. W. Ambrose, and V. Yao. 2014. The Limits of Regulation: Appraisal Bias in the Mortgage Market. *Available at SSRN 2487393* .

Agarwal, S., I. Ben-David, and V. Yao. 2015. Collateral Valuation and Borrower Financial Constraints: Evidence from the Residential Real Estate Market. *Management Science* 61:2220–2240. ISSN 0025-1909. doi:{10.1287/mnsc.2014.2002}.

Agarwal, S., C. Song, and V. Yao. 2020. Relational contracts in the housing market. *Georgetown McDonough School of Business Research Paper No. 3076944* .

Agnew, J., P. Balduzzi, and A. Sunden. 2003. Portfolio choice and trading in a large 401 (k) plan. *American Economic Review* 93:193–215.

Ambrose, B. W., J. Conklin, and J. Yoshida. 2016. Credit rationing, income exaggeration, and adverse selection in the mortgage market. *The Journal of Finance* 71:2637–86.

Ambrose, B. W., J. N. Conklin, N. E. Coulson, M. Diop, and L. A. Lopez. 2025. Do appraiser and borrower race affect mortgage collateral valuation? *Review of Finance* (forthcoming).

Ambrose, B. W., J. N. Conklin, and L. A. Lopez. 2021. Does borrower and broker race affect the cost of mortgage credit? *The Review of Financial Studies* 34:790–826.

Andersen, S., J. Marx, K. M. Nielsen, and L. Vesterlund. 2021. Gender differences in negotiation: Evidence from real estate transactions. *The Economic Journal* 131:2304–32.

Barber, B. M., and T. Odean. 2001. The internet and the investor. *Journal of Economic Perspectives* 15:41–54.

Beck, T., P. Behr, and A. Guettler. 2013. Gender and banking: are women better loan officers? *Review of Finance* 17:1279–321.

Blau, F. D., and L. M. Kahn. 2020. The gender pay gap: Have women gone as far as they can? In *Inequality in the United States*, 345–62. Routledge.

Bosshardt, J., S. Kedia, and T. Zhang. 2025. Gender disparities in home appraisals. *Available at SSRN 5110361* .

Calem, P., J. Kenney, L. Lambie-Hanson, and L. Nakamura. 2021. Appraising home purchase appraisals. *Real Estate Economics* 49:134–68.

Calem, P. S., L. Lambie-Hanson, and L. I. Nakamura. 2015. Information Losses in Home Purchase Appraisals. *Federal Reserve Bank of Philadelphia Working Paper No. 15-11* .

———. 2016. Appraising home purchase appraisals. *Working Paper* .

Cho, M., and I. F. Megbolugbe. 1996. An empirical analysis of property appraisal and mortgage redlining. *The Journal of Real Estate Finance and Economics* 13:45–55.

Conklin, J., N. E. Coulson, M. Diop, and T. Le. 2020. Competition and appraisal inflation. *The Journal of Real Estate Finance and Economics* 61:1–38.

———. 2020. Competition and appraisal inflation. *The Journal of Real Estate Finance and Economics* 61:1–38.

Croson, R., and U. Gneezy. 2009. Gender differences in preferences. *Journal of Economic literature* 47:448–74.

Ding, L., and L. Nakamura. 2016. The impact of the home valuation code of conduct on appraisal and mortgage outcomes. *Real Estate Economics* 44:658–690.

Ding, L., and L. I. Nakamura. 2016. The impact of the home valuation code of conduct on appraisal and mortgage outcomes. *Real Estate Economics* 44:658–90.

Diop, M., A. Yavas, and S. Zhu. 2021. Appraisal inflation and private mortgage securitization .

Egan, M., G. Matvos, and A. Seru. 2019. The market for financial adviser misconduct. *Journal of Political Economy* 127:233–95.

Ekehammar, B., N. Akrami, and T. Araya. 2003. Gender differences in implicit prejudice. *Personality and Individual differences* 34:1509–23.

Eriksen, M. D., H. B. Fout, M. Palim, and E. Rosenblatt. 2019. The influence of contract prices and relationships on appraisal bias. *Journal of Urban Economics* 111:132–43.

Eriksen, M. D., C. Kuang, and W. Zhu. 2024. Attribute misreporting and appraisal bias. *Review of Finance* 28:1663–86. ISSN 1572-3097. doi:10.1093/rof/rfad041.

FannieMae. 2018. Appraiser diversity initiative. Accessed: 2025-01-26.

FHFA v. UBS Ams., Inc. 2012. *858 F. Supp. 2d 306 (S.D.N.Y. 2012), Court Opinion* .

Fout, H., N. Mota, and E. Rosenblatt. 2022. When appraisers go low, contracts go lower: The impact of expert opinions on transaction prices: When appraisers go low contracts go lower: The impact of expert opinions on transaction prices. *The Journal of Real Estate Finance and Economics* 65:451–91.

Frame, W. S., R. Huang, E. J. Mayer, and A. Sunderam. 2021. Minority loan officers and minorities' access to mortgage credit. *SMU Cox School of Business Research Paper Forthcoming* .

Freddie Mac. 2022. Racial & ethnic valuation gaps in home purchase appraisals - A modeling approach. *Freddie Mac Economic & Housing Research Note* .

Garate, S., C. Hilterbrand, and A. Pennington-Cross. 2023. The impact of non-disclosure laws on the single-family housing market: Appraisal bias and mortgage default. *Working paper* .

Goldin, C. 2014. A grand gender convergence: Its last chapter. *American economic review* 104:1091–119.

Griffin, J. M., and G. Maturana. 2016. Who facilitated misreporting in securitized loans? *The Review of Financial Studies* 29:384–419.

Huang, R., E. J. Mayer, and D. P. Miller. 2024. Gender bias in promotions: Evidence from financial institutions. *The Review of Financial Studies* 37:1685–728.

Jensen, R. E., and J. Reifler. 2010. Automated valuation models and non-agency RMBS property evaluation and analysis. *The Journal of Structured Finance* 15:43–57.

Jiang, E. X., and A. L. Zhang. 2022. Collateral value uncertainty and mortgage credit provision. *Available at SSRN* .

Kruger, S., and G. Maturana. 2021. Collateral misreporting in the residential mortgage-backed security market. *Management Science* 67:2729–2750.

LaCour-Little, M., and R. K. Green. 1998. Are minorities or minority neighborhoods more likely to get low appraisals? *The Journal of Real Estate Finance and Economics* 16:301–15.

Lavergne, M., and S. Mullainathan. 2004. Are emily and greg more employable than lakisha and jamal? a field experiment on labor market discrimination. *American Economic Review* 94:991–1013. ISSN 0002-8282. doi:10.1257/0002828042002561.

Lundberg, S., and J. Stearns. 2019. Women in economics: Stalled progress. *Journal of Economic Perspectives* 33:3–22.

Molloy, R., and E. Nielsen. 2018. How can we measure the value of a home? Comparing model-based estimates with owner-occupant estimates. *FEDs Notes* .

Moss-Racusin, C. A., J. F. Dovidio, V. L. Brescoll, M. J. Graham, and J. Handelsman. 2012. Science faculty's subtle gender biases favor male students. *Proceedings of the national academy of sciences* 109:16474–9.

Nakamura, L. I., et al. 2010. How much is that home really worth? appraisal bias and house-price uncertainty. *Business Review* 11–22.

Neng-Guin Chen v. Citibank. 2011. *US Dist Lexis 94738, 2011 WL 3739535 (S.D. Cal. Aug. 24, 2011), Court Opinion* .

Niederle, M., and L. Vesterlund. 2010. Explaining the gender gap in math test scores: The role of competition. *Journal of economic perspectives* 24:129–44.

Nomura Asset Acceptance Corp. Alt. Loan Tr. v. Nomura Credit & Capital, Inc. 2018. *167 A.D.3d 432, 91 N.Y.S.3d 3 (App Div, 1st Dept 2018), Court Opinion* .

Nosek, B. A., F. L. Smyth, J. J. Hansen, T. Devos, N. M. Lindner, K. A. Ranganath, C. T. Smith, K. R. Olson, D. Chugh, A. G. Greenwald, et al. 2007. Pervasiveness and correlates of implicit attitudes and stereotypes. *EUROPEAN REVIEW OF SOCIAL PSYCHOLOGY* 1:53–.

Pinto, E., and T. Peter. 2021. How common is appraiser racial bias? Working report, American Enterprise Institute Housing Center. https://www.aei.org/how-common-is-appraiser-racial-bias/.

Piskorski, T., A. Seru, and J. Witkin. 2015. Asset quality misrepresentation by financial intermediaries: Evidence from the RMBS market. *The Journal of Finance* 70:2635–2678.

Rudman, L. A., and S. A. Goodwin. 2004. Gender differences in automatic in-group bias: Why do women like women more than men like men? *Journal of personality and social psychology* 87:494–.

Sabin, J. A., B. A. Nosek, A. G. Greenwald, and F. P. Rivara. 2009. Physicians' implicit and explicit attitudes about race by md race, ethnicity, and gender. *Journal of health care for the poor and underserved* 20:896–913.

Seagraves, P., and P. Gallimore. 2013. The gender gap in real estate sales: Negotiation skill or agent selection? *Real Estate Economics* 41:600–31.

Shi, L., and Y. J. Zhang. 2015. Appraisal inflation: Evidence from 2009 GSE HVCC intervention. *Journal of Housing Economics* 27:71–90.

Sunden, A. E., and B. J. Surette. 1998. Gender differences in the allocation of assets in retirement savings plans. *The American economic review* 88:207–11.

Williamson, J., and M. Palim. 2022. Appraising the appraisal. *Fannie Mae Working Paper* .

Yap et al, Maureen, e. a. 2022. Identifying bias and barriers, promoting equity: An analysis of the uspap standards and appraiser qualifications criteria. *National Fair Housing Alliance* .

9. Figures

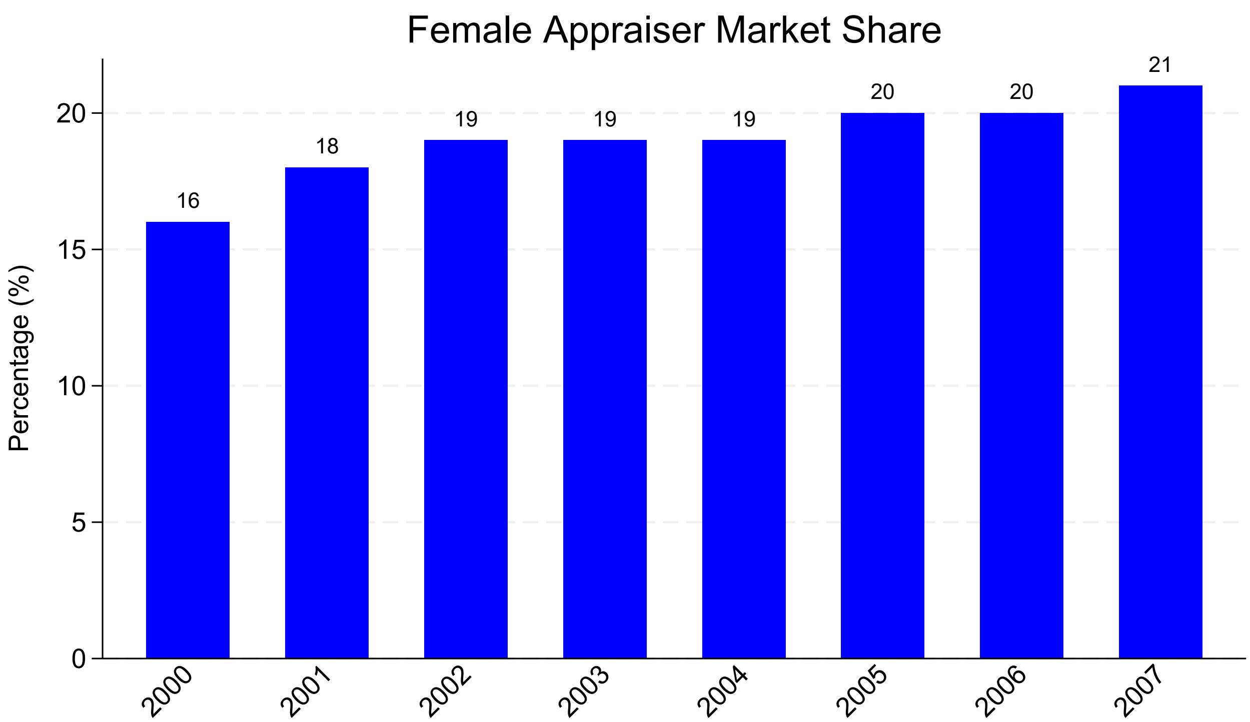


Figure 1. Female Appraiser Market Share in NCEN by Year

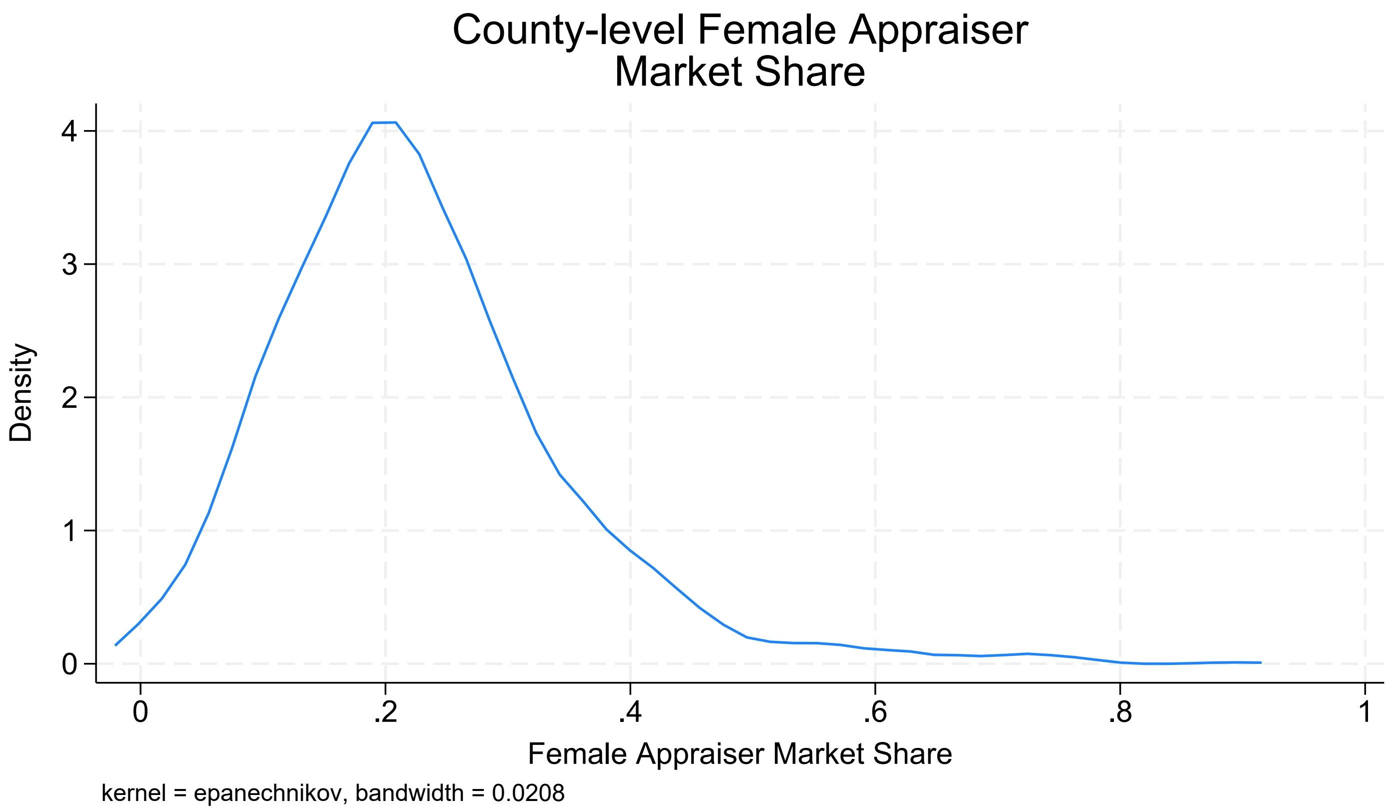


Figure 2. Density of County-level Female Appraiser Market Share in NCEN

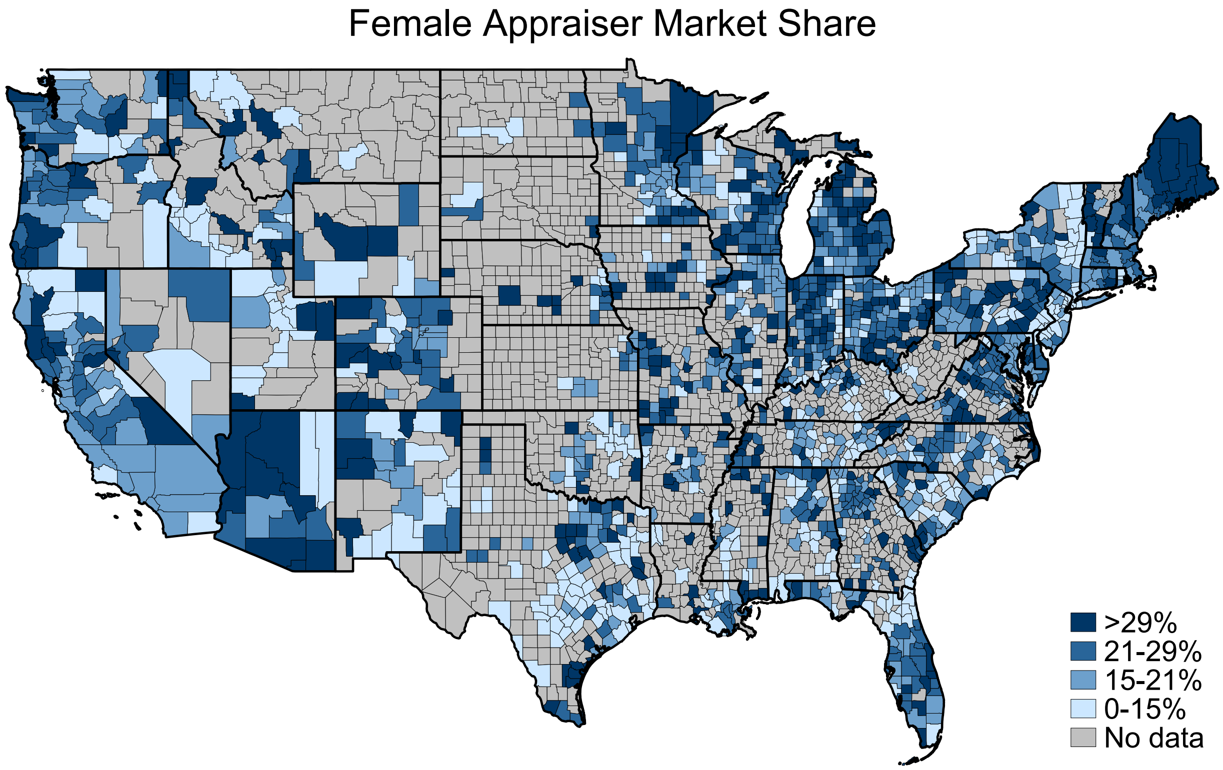


Figure 3. County-level Female Appraiser Market Share in NCEN

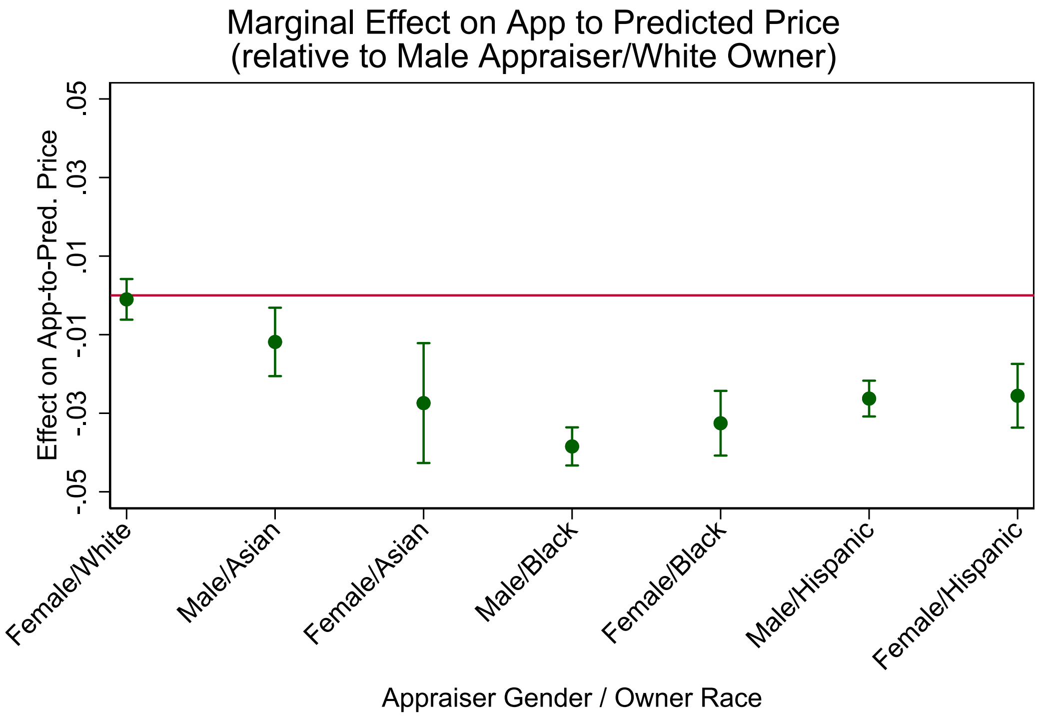


Figure 4. Marginal Effect of Appraiser Gender and Owner Race on App-to-$\hat{V}$
Note: Corresponds to the coefficient estimates in column 7 of Table 6.

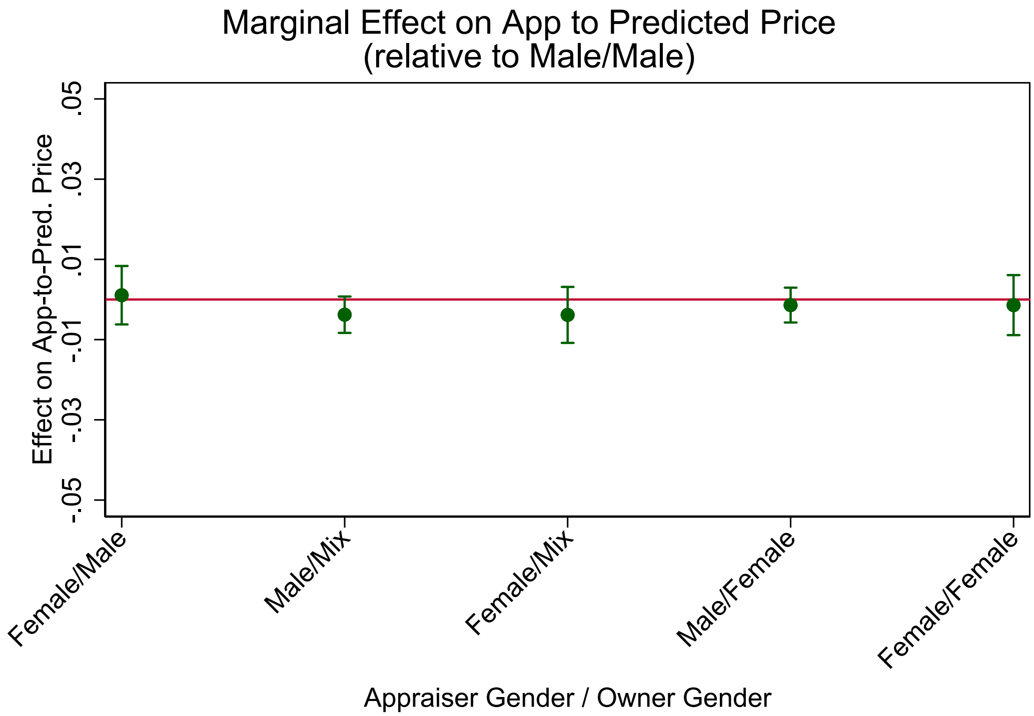


Figure 5. Marginal Effect of Appraiser Gender and Owner Race on App-to-$\hat{V}$
Note: Corresponds to the coefficient estimates in column 7 of Table 9.

10. Tables

Table 1. Appraiser-Level Descriptive Statistics

Panel A: Male Appraisers	Obs	Mean	Std. Dev.	Min	Max
Total Volume	46,886	21	48	1	1,409
# Unique Zips	46,886	12	20	1	369
# Unique Counties	46,886	3	3	1	57
# Unique MLOs	41,112	10	16	1	496
Appraiser's Zip Concentration	46,886	0.36	0.34	0.00	1.00
Appraiser's County Concentration	46,886	0.65	0.30	0.04	1.00
Appraiser's MLO Concentration	41,112	0.38	0.34	0.00	1.00
Panel B: Female Appraisers	**Obs**	**Mean**	**Std. Dev.**	**Min**	**Max**
Total Volume	16,189	15	32	1	1,089
# Unique Zips	16,189	9	14	1	255
# Unique Counties	16,189	3	3	1	38
# Unique MLOs	14,124	8	11	1	189
Appraiser's Zip Concentration	16,189	0.40	0.35	0.01	1.00
Appraiser's County Concentration	16,189	0.69	0.29	0.05	1.00
Appraiser's MLO Concentration	14,124	0.43	0.35	0.01	1.00

Note: Panel A reports appraiser-level descriptive statistics for the 46,886 male appraisers. Panel A reports appraiser-level descriptive statistics for the 46,886 male appraisers. Numbers are based off the full sample consisting of 1,207,013 mortgage applications. Total Volume is the total number of appraisals completed by the appraiser in our sample. # Unique Zips is the number of different zip codes where the appraiser completed appraisals. # Unique Counties is the number of different counties where the appraiser completed appraisals. # unique MLOs is the number of unique mortgage loan officers (MLO) associated with the appraiser's appraisals. Concentration ratios at the zip and county level are HHIs of where the appraiser completes appraisals. The MLO concentration ratio is the HHI of the appraiser's business across mortgage loan officers.

Table 2. 15 Lowest and Highest Female Appraiser Share Counties in NCEN

Panel A: 15 Lowest Female Share Counties		
County	State	Female Share
Carbon County	UT	0%
Franklin County	NY	0%
Autauga County	AL	0%
Gooding County	ID	0%
Brown County	TX	0%
Luna County	NM	0%
Escambia County	AL	0%
Sanpete County	UT	0%
Beaver County	UT	0%
Webster County	IA	0%
Burt County	NE	0%
Gillespie County	TX	0%
Sweetwater County	WY	0%
Maverick County	TX	0%
Hale County	TX	1%
Panel B: 15 Highest Female Share Counties		
County	State	Female Share
Warren County	PA	89%
Decatur County	GA	76%
Platte County	NE	76%
Archuleta County	CO	75%
Silver Bow County	MT	75%
Scotts Bluff County	NE	73%
Lake County	MN	73%
Gunnison County	CO	72%
Halifax County	VA	70%
Cole County	MO	70%
Inyo County	CA	69%
Jasper County	SC	69%
Ogemaw County	MI	65%
Boundary County	ID	65%
Garland County	AR	64%

Note: Panel A reports the 15 counties with the lowest female appraiser market share. Panel B reports the 15 counties with the highest female appraiser market share. The sample includes the 1,596 counties with at least 30 appraisals in our sample.

Table 3. Application-Level Descriptive Statistics

Variable	Mean	
	Male Appraiser	Female Appraiser
Appraisal Outcomes		
Appraisal Value	$259,706	$252,123
App-to-AVM Ratio	1.08	1.09
Below Price	0.02	0.02
Days to Appraisal	-11.42	-11.39
Appraisal Fee	$349	$347
Property Purpose and Type		
Second Home	0.02	0.02
Investment Property	0.08	0.09
Multi-Unit	0.07	0.06
Condo	0.06	0.06
PUD	0.10	0.10
Other		
Married Borrower	0.59	0.59
Ln(Inc)	8.61	8.59
Ln(Assets)	12.30	12.26
Dependents	1.30	1.30
Property Age	33.18	32.73
Years at Residence	6.77	6.68
AVM Confidence	82.64	82.43
CLTV	83.37	83.81

Note: Mean values across mortgage applications by appraiser gender.

Table 4. Differences in Appraisal Outcomes

	(1) App-to-AVM	(2) Below Contract	(3) Fees
Female Appraiser	0.002	0.000	-0.903***
	(0.002)	(0.001)	(0.330)
Observations	207,822	366,625	444,427
Adjusted R-squared	0.159	0.003	0.193
Zip FE	Y	Y	Y
Year FE	Y	Y	Y
$\overline{Y}$	1.09	0.02	349
Sample	Refi-ABS	Purch	Fees

Note: This table presents estimates from regression models where the dependent variable is listed in the column header. The sample in column 1 includes the NCEN-ABSNet matched refinance sample. The sample in column 2 consists of purchase mortgage applications. The sample in column 3 includes refinance and purchase mortgage applications with non-missing appraisal fees. Robust standard errors are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.10

Table 5. Appraiser Gender and Owner Race

	Owner Race				
	Asian	Black	Hispanic	White	Total
Male Appraiser	4%	16%	18%	43%	81%
Female Appraiser	1%	4%	4%	11%	19%
Total	4%	20%	22%	54%	100%

Note: Share of appraisals in each appraiser-owner race combination, rounded to whole percentages.

Table 6. Differences in App-to-AVM Ratios Across Appraiser Gender and Owner Race

	(1) App-to-AVM	(2) App-to-AVM	(3) App-to-AVM	(4) App-to-AVM	(5) App-to-AVM	(6) App-to-AVM	(7) App-to-$\hat{V}$
Female Appraiser / White Owner	-0.000	-0.000	-0.000	-0.000	-0.000	-0.002	-0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.004)	(0.003)
Male Appraiser / Asian Owner	-0.005*	-0.006*	-0.011***	-0.011***	-0.008**	-0.008	-0.012***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.006)	(0.004)
Female Appraiser / Asian Owner	-0.007	-0.008	-0.013**	-0.013**	-0.010*	-0.015	-0.027***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.010)	(0.008)
Male Appraiser / Black Owner	-0.010***	-0.010***	-0.006***	-0.006***	-0.005**	-0.004	-0.038***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)
Female Appraiser / Black Owner	-0.003	-0.003	0.000	0.000	0.002	0.003	-0.033***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.006)	(0.004)
Male Appraiser / Hispanic Owner	-0.005***	-0.007***	-0.002	-0.002	-0.001	-0.001	-0.026***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)
Female Appraiser / Hispanic Owner	-0.003	-0.004	0.000	-0.000	0.001	-0.004	-0.026***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.006)	(0.004)
Second Home		0.006	-0.035***	-0.034***	-0.038***	-0.016	0.016
		(0.009)	(0.009)	(0.009)	(0.009)	(0.015)	(0.012)
Investment Property		0.007**	-0.027***	-0.026***	-0.031***	-0.038***	0.065***
		(0.003)	(0.003)	(0.003)	(0.003)	(0.005)	(0.004)
Multi-unit		0.035***	0.031***	0.029***	0.028***	0.026***	0.004
		(0.004)	(0.004)	(0.004)	(0.004)	(0.006)	(0.004)
Condo		-0.028***	-0.012***	-0.013***	-0.009***	-0.007*	-0.012***
		(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.003)
PUD		-0.004*	-0.010***	-0.010***	-0.009***	-0.007**	-0.011***
		(0.002)	(0.002)	(0.002)	(0.002)	(0.004)	(0.003)
Borrower Married			0.000	-0.000	0.000	0.002	0.009***
			(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
Ln(Income)			0.067***	0.067***	0.075***	0.065***	-0.033***
			(0.002)	(0.002)	(0.002)	(0.003)	(0.002)
Ln(Total Assets)			0.017***	0.016***	0.015***	0.020***	0.036***
			(0.003)	(0.003)	(0.003)	(0.004)	(0.003)
Dependents			-0.002**	-0.002**	-0.002**	-0.001	-0.004***
			(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
Property Age			-0.000**	-0.000**	-0.000***	-0.000***	0.000
			(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Years at Residence			-0.000*	-0.000**	-0.001***	-0.000***	-0.002***
			(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
AVM Confidence				-0.001***	-0.001***	-0.001***	-0.000***
				(0.000)	(0.000)	(0.000)	(0.000)
CLTV					-0.001***	-0.001***	-0.001***
					(0.000)	(0.000)	(0.000)
Observations	190,907	190,803	190,803	190,803	190,803	109,545	108,790
Adjusted R-squared	0.160	0.162	0.173	0.174	0.176	0.188	0.228
Zip FE	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y
Missing Char. Dummies	N	N	Y	Y	Y	Y	Y
Originator FE	N	N	N	N	N	Y	Y
$\overline{Y}$	1.09	1.09	1.09	1.09	1.09	1.09	1.04
Sample	Refi-ABS	Refi-ABS	Refi-ABS	Refi-ABS	Refi-ABS	Refi-ABS	Refi-ABS

Note: This table presents estimates from regression models where the dependent variable is the appraisal-to-AVM ratio in columns 1-6 and app-to-$\hat{V}$ in column 7. The omitted appraiser gender / owner race category is male appraiser / white owner. The sample includes the NCEN-ABSNet refinance sample. Robust standard errors are reported in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.10$

Table 7. Differences in Appraisal Outcomes Across Appraiser Gender and Owner Race

	(1) Below Contract	(2) Fees
Female Appraiser / White Owner	-0.000	-1.393*
	(0.002)	(0.785)
Male Appraiser / Asian Owner	0.002	3.043**
	(0.003)	(1.455)
Female Appraiser / Asian Owner	0.002	-2.497
	(0.006)	(2.652)
Male Appraiser / Black Owner	-0.000	1.596**
	(0.002)	(0.723)
Female Appraiser / Black Owner	0.001	1.425
	(0.003)	(1.167)
Male Appraiser / Hispanic Owner	0.002	0.461
	(0.002)	(0.718)
Female Appraiser / Hispanic Owner	0.003	0.154
	(0.002)	(1.194)
Second Home	0.000	0.766
	(0.003)	(1.620)
Investment Property	-0.005***	15.723***
	(0.002)	(0.921)
Multi-unit	0.007***	126.111***
	(0.002)	(1.381)
Condo	0.012***	-7.235***
	(0.002)	(0.941)
PUD	0.003	-1.789**
	(0.002)	(0.778)
Borrower Married	0.001	-0.769*
	(0.001)	(0.407)
Ln(Income)	0.001	7.236***
	(0.001)	(0.485)
Ln(Total Assets)	0.005***	5.021***
	(0.002)	(1.075)
Dependents	-0.001	-0.363
	(0.001)	(0.337)
Property Age	-0.000***	0.024*
	(0.000)	(0.013)
Years at Residence	0.000**	-0.026
	(0.000)	(0.030)
AVM Confidence	-0.000	-0.141***
	(0.000)	(0.045)
CLTV	-0.001***	-0.050***
	(0.000)	(0.016)
Observations	180,324	230,155
Adjusted R-squared	0.022	0.399
Zip FE	Y	Y
Year FE	Y	Y
Missing Char. Dummies	Y	Y
Originator FE	Y	Y
$\overline{Y}$	.02	352
Sample	Purch	Fees

Note: This table presents estimates from regression models where the dependent variable is listed in the column header. The omitted appraiser gender / owner race category is male appraiser / white owner. The sample in column 1 consists of purchase mortgage applications. The sample in column 2 includes refinance and purchase mortgage applications with non-missing appraisal fees. Robust standard errors are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.10

Table 8. Appraiser and Owner Gender

	Owner			
	Male	Mixed	Female	Total
Male Appraiser	30%	26%	24%	81%
Female Appraiser	7%	6%	6%	19%
Total	37%	33%	30%	100%

Note: Share of appraisals in each appraiser-owner gender combination.

Table 9. Differences in App-to-AVM Ratios Across Appraiser and Owner Gender

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	(7) App-to-$\hat{V}$
Female Appraiser / Male Owner	0.008***	0.008***	0.008***	0.008***	0.008***	0.007	0.000
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.003)
Male Appraiser / Mixed Owners	0.006***	0.006***	-0.005***	-0.005***	-0.006***	-0.003	-0.003
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)
Female Appraiser / Mixed Owners	0.006**	0.006**	-0.006**	-0.006**	-0.006**	-0.006	-0.003
	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.003)
Male Appraiser / Female Owner	-0.013***	-0.012***	-0.001	-0.000	-0.001	-0.000	-0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)
Female Appraiser / Female Owner	-0.014***	-0.013***	-0.002	-0.002	-0.002	-0.004	-0.001
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.003)
Second Home		0.003	-0.037***	-0.037***	-0.041***	-0.015	0.015
		(0.009)	(0.009)	(0.009)	(0.009)	(0.014)	(0.012)
Investment Property		0.006*	-0.027***	-0.027***	-0.031***	-0.037***	0.064***
		(0.003)	(0.003)	(0.003)	(0.003)	(0.005)	(0.004)
Multi-unit		0.034***	0.029***	0.028***	0.026***	0.024***	0.003
		(0.003)	(0.003)	(0.003)	(0.003)	(0.005)	(0.004)
Condo		-0.025***	-0.012***	-0.013***	-0.009***	-0.007*	-0.012***
		(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.003)
PUD		-0.003	-0.010***	-0.009***	-0.008***	-0.008**	-0.012***
		(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)
Borrower Married			0.004**	0.003**	0.004**	0.004*	0.010***
			(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Ln(Income)			0.066***	0.066***	0.074***	0.064***	-0.031***
			(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Ln(Total Assets)			0.017***	0.017***	0.015***	0.020***	0.037***
			(0.002)	(0.002)	(0.002)	(0.004)	(0.003)
Dependents			-0.002**	-0.002**	-0.002***	-0.002	-0.005***
			(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Property Age			-0.000**	-0.000**	-0.000**	-0.000***	0.000
			(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Years at Residence			-0.000	-0.000	-0.000***	-0.000***	-0.002***
			(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
AVM Confidence				-0.001***	-0.001***	-0.001***	-0.000***
				(0.000)	(0.000)	(0.000)	(0.000)
CLTV					-0.001***	-0.001***	-0.001***
					(0.000)	(0.000)	(0.000)
Observations	204,839	204,728	204,728	204,728	204,728	118,648	108,790
Adjusted R-squared	0.160	0.161	0.172	0.173	0.174	0.185	0.225
Zip FE	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y
Missing Char. Dummies	N	N	Y	Y	Y	Y	Y
Originator FE	N	N	N	N	N	Y	Y
$\overline{Y}$	1.09	1.09	1.09	1.09	1.09	1.09	1.04
Sample	Refi-ABS	Refi-ABS	Refi-ABS	Refi-ABS	Refi-ABS	Refi-ABS	Refi-ABS

Note: This table presents estimates from regression models where the dependent variable is the appraisal-to-AVM ratio. The omitted gender category is male appraiser / male owner. The sample includes the NCEN-ABSNet refinance sample. Robust standard errors are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.10

Table 10. Differences in Appraisal Outcomes Across Appraiser and Owner Gender

	(1) Below Contract	(2) Fees
Female Appraiser / Male Owner	-0.000	-1.030
	(0.002)	(0.816)
Male Appraiser / Mixed Owners	0.001	-1.577***
	(0.001)	(0.551)
Female Appraiser / Mixed Owners	0.002	-1.812*
	(0.002)	(0.938)
Male Appraiser / Female Owner	0.001	0.118
	(0.001)	(0.497)
Female Appraiser / Female Owner	0.003	-0.759
	(0.002)	(0.885)
Second Home	0.000	1.916
	(0.003)	(1.566)
Investment Property	-0.005***	15.673***
	(0.002)	(0.886)
Multi-unit	0.006***	124.499***
	(0.002)	(1.319)
Condo	0.012***	-7.736***
	(0.002)	(0.898)
PUD	0.002	-1.637**
	(0.002)	(0.749)
Borrower Married	0.001	-0.054
	(0.001)	(0.450)
Ln(Income)	0.002*	7.551***
	(0.001)	(0.472)
Ln(Total Assets)	0.006***	4.176***
	(0.002)	(1.009)
Dependents	-0.001	-0.327
	(0.001)	(0.323)
Property Age	-0.000***	0.022*
	(0.000)	(0.012)
Years at Residence	0.000**	-0.007
	(0.000)	(0.028)
AVM Confidence	-0.000	-0.137***
	(0.000)	(0.044)
CLTV	-0.001***	-0.045***
	(0.000)	(0.016)
Observations	193,603	249,558
Adjusted R-squared	0.022	0.396
Zip FE	Y	Y
Year FE	Y	Y
Missing Char. Dummies	Y	Y
Originator FE	Y	Y
$\overline{Y}$	.02	352
Sample	Purch	Fees

Note: This table presents estimates from regression models where the dependent variable is listed in the column header. The omitted gender category is male appraiser / male owner. The sample in column 1 consists of purchase mortgage applications. The sample in column 2 includes refinance and purchase mortgage applications with non-missing appraisal fees. Robust standard errors are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.10

Table 11. Likelihood of a Female Appraiser

VARIABLES	(1) Female Appraiser	(2) Female Appraiser	(3) Female Appraiser
2001	0.017***	0.015***	0.051***
	(0.004)	(0.004)	(0.014)
2002	0.025***	0.024***	0.085***
	(0.003)	(0.003)	(0.014)
2003	0.026***	0.026***	0.077***
	(0.003)	(0.003)	(0.014)
2004	0.027***	0.029***	0.066***
	(0.003)	(0.003)	(0.014)
2005	0.032***	0.035***	0.072***
	(0.003)	(0.003)	(0.014)
2006	0.037***	0.041***	0.077***
	(0.003)	(0.003)	(0.014)
2007	0.045***	0.049***	0.080***
	(0.004)	(0.004)	(0.014)
Zip White (%)	0.000***		
	(0.000)		
Zip HS or above (%)	0.000		
	(0.000)		
Zip Foreign Born (%)	-0.002***		
	(0.000)		
Zip Employed (%)	0.000		
	(0.000)		
Zip Ln(Median HH Income)	0.237***		
	(0.052)		
Zip Ln(Median HH Income)^2	-0.012***		
	(0.002)		
Zip Ln(Median OwnOcc Property Value)	0.003***		
	(0.001)		
Asian Owner			-0.004
			(0.003)
Black Owner			-0.002
			(0.002)
Hispanic Owner			-0.001
			(0.002)
Mixed Owners			0.003**
			(0.001)
Female Owner			0.002*
			(0.001)

Table 11. (cont.) Likelihood of a Female Appraiser

Second Home			0.004
			(0.004)
Investment Property			0.001
			(0.002)
Multi-unit			-0.001
			(0.002)
Condo			0.004
			(0.002)
PUD			0.002
			(0.002)
Borrower Married			-0.001
			(0.001)
Ln(Income)			-0.000
			(0.001)
Ln(Total Assets)			0.003
			(0.002)
Dependants			0.001
			(0.001)
Property Age			-0.000
			(0.000)
Years at Residence			0.000
			(0.000)
Ln(Income) Missing			-0.002
			(0.012)
Total Assets Missing			0.033
			(0.021)
Dependents Missing			0.001
			(0.002)
Missing Property Age			-0.002
			(0.002)
Missing Years at Residence			0.014***
			(0.005)
AVM Confidence Missing			-0.013
			(0.010)
AVM Confidence			-0.000
			(0.000)
CLTV			0.000**
			(0.000)
Observations	1,192,416	1,206,607	646,093
Adjusted R-squared	0.004	0.035	0.263
Zip FE	N	Y	Y
Missing Char. Dummies	N	N	Y
Originator FE	N	N	Y
$\overline{Y}$	.19	.19	.2
Sample	Full	Full	Full

Note: This table presents estimates from regression models where the dependent variable is is a binary variable indicating whether the appraiser is female. The omitted owner gender category is male owner. The full sample (Refi-ABS, Purch, Dates, and Fees) is included in all columns. Robust standard errors are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.10

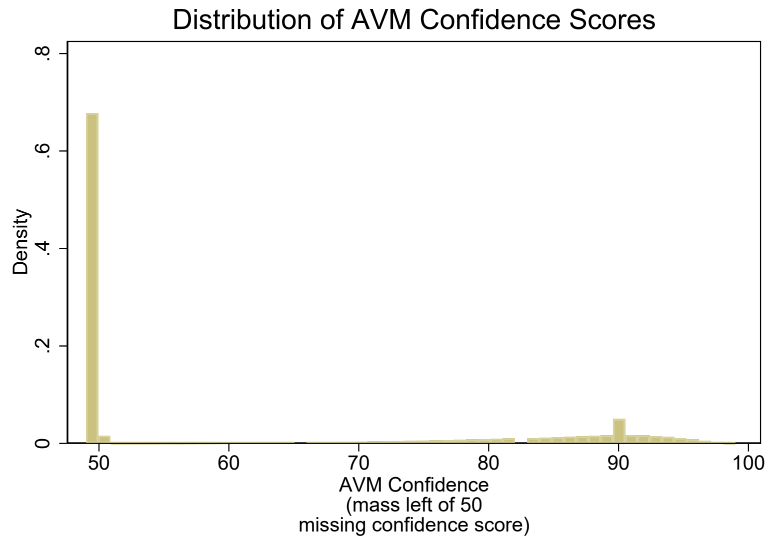
Table 12. Differences in Appraisal Outcomes for Applications with Only One Borrower that is Unmarried or Separated

	(1) App-to-AVM	(2) Below Contract	(3) Fees
Female Appraiser / Male Owner	0.021**	-0.001	1.096
	(0.009)	(0.003)	(1.448)
Male Appraiser / Female Owner	0.001	0.003	-0.523
	(0.005)	(0.002)	(0.797)
Female Appraiser / Female Owner	0.004	0.005*	-0.074
	(0.008)	(0.003)	(1.381)
Second Home	0.013	0.003	4.158
	(0.029)	(0.004)	(2.876)
Investment Property	-0.047***	-0.005*	15.335***
	(0.010)	(0.003)	(1.604)
Multi-unit	0.033***	0.007**	125.740***
	(0.011)	(0.003)	(2.076)
Condo	-0.011	0.009***	-6.122***
	(0.007)	(0.003)	(1.503)
PUD	-0.010	0.002	-1.515
	(0.008)	(0.003)	(1.448)
Borrower Married	-	-	-
Ln(Income)	0.054***	-0.000	8.257***
	(0.005)	(0.002)	(0.913)
Ln(Total Assets)	0.018**	0.007**	0.872
	(0.008)	(0.003)	(1.928)
Dependents	-0.003	-0.000	-0.275
	(0.004)	(0.002)	(0.820)
Property Age	-0.000	-0.000***	0.026
	(0.000)	(0.000)	(0.023)
Years at Residence	-0.001**	0.000	0.029
	(0.000)	(0.000)	(0.052)
AVM Confidence	-0.001***	-0.000	-0.041
	(0.000)	(0.000)	(0.080)
CLTV	-0.001***	-0.001***	-0.033
	(0.000)	(0.000)	(0.029)
Observations	32,763	77,223	83,998
Adjusted R-squared	0.174	0.029	0.411
Zip FE	Y	Y	Y
Year FE	Y	Y	Y
Missing Characteristics Dummies	Y	Y	Y
Originator FE	Y	Y	Y
$\overline{Y}$	1.09	.02	354
Sample	Refi-ABS	Purch	Fees

Note: This table presents estimates from regression models where the dependent variable is listed in the column header. The omitted gender category is male appraiser / male owner. The samples in all columns include properties where there was only one borrower on the mortgage application, and that borrower marital status is either unmarried or separated. The sample in column 1 consists of purchase mortgage applications. The sample in column 3 includes refinance and purchase mortgage applications with non-missing appraisal fees. Robust standard errors are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.10

INTERNET APPENDIX

Panel A



Panel B

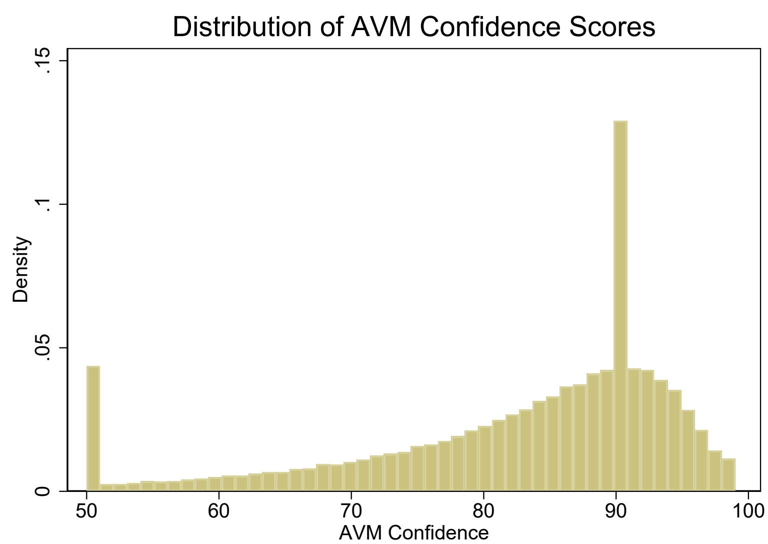
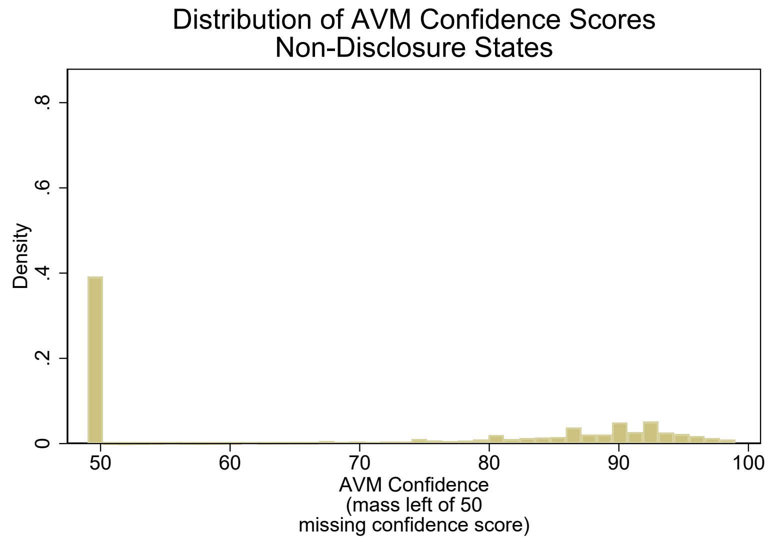


Figure A.1 . Distribution of AVM Confidence Scores in the Refi-ABSNet Sample. Panel A includes observations where the confidence score is missing, while Panel B only includes observatations where a confidence score is observed.

Panel A



Panel B

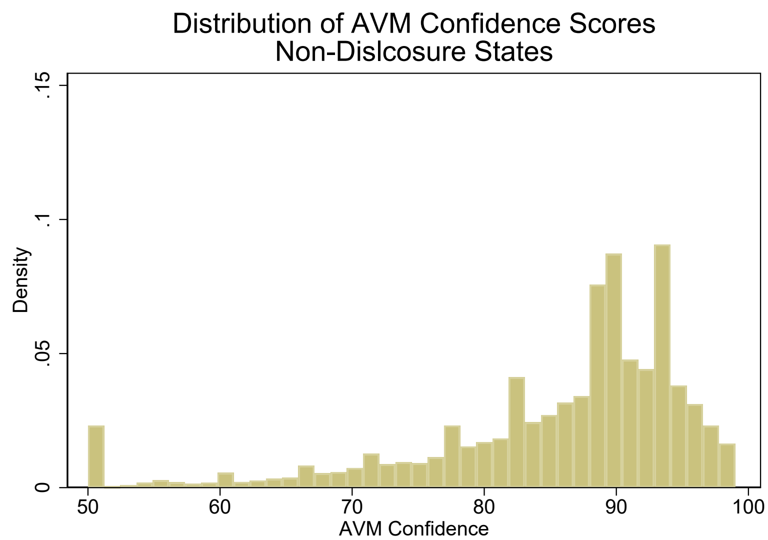


Figure A.2 . Distribution of AVM Confidence Scores in the Refi-ABSNet Sample from states where transaction prices are not fully disclosed (AK, ID, KS, MT, MS, NM, WY, TX, and UT). Panel A includes observations where the confidence score is missing, while Panel B only includes observations where a confidence score is observed.

Table A.1. Variable Names and Descriptions

Variable Name	Description
Appraisal Value	Appraised value of the property
App-to-AVM Ratio	Appraised value of the property divided by an AVM value estimate
Below Price	Binary variable set to one if the appraised value is below the contract sales price on a purchase mortgage application
Days to Appraisal	Number of days between appraisal completion and original application received by NCEN (negative indicates appraisal completed before application)
Appraisal Fee	Appraisal fee(s) charged to the borrower
Second Home	Binary variable set to one if the property is a second home
Investment Property	Binary variable set to one if the property is an investment property
Multi-Unit	Binary variable set to one for a multi-unit property
Condo	Binary variable set to one if the property is a condominium
PUD	Binary variable set to one if the property is part of a planned unit development
Married Borrower	Binary variable set to one if the borrower is married
Ln(Inc)	Natural logarithm of the combined monthly income of mortgage applicants
Ln(Assets)	Natural logarithm of the applicant's assets
Dependents	Applicant's number of dependents
Property Age	Property age
Years at Residence	Years applicant has lived at the property
AVM Confidence	AVM estimate confidence score
CLTV	Combined loan to value ratio (%)

Note: Variable names and descriptions.

Table A.2. Application-Level Counts with Non-Missing Information

Variable	Obs Male Appraiser	Female Appraiser
Appraisal Value	976,581	235,552
App-to-AVM Ratio	268,367	64,425
Below Price	297,817	73,528
Days to Appraisal	974,851	235,167
Appraisal Fee	360,220	88,984
Second Home	976,581	235,552
Investment Property	976,581	235,552
Multi-Unit	973,840	234,706
Condo	973,840	234,706
PUD	973,840	234,706
Married Borrower	976,581	235,552
Ln(Inc)	963,032	232,213
Ln(Assets)	367,042	83,968
Dependents	292,771	70,515
Property Age	306,714	75,596
Years at Residence	947,610	229,141
AVM Confidence	96,034	22,853
CLTV	976,581	235,552

Note: The number of observations for which the variable is populated by appraiser gender.

Table A.3. Comparison of Matched and Unmatched Samples of Funded Refinance Loans

	Unmatched Mean	Matched Mean	Mean Difference
Appraisal Value	$240,447	$260,590	-$20,143
Days to Appraisal	-8.759	-7.412	-1.347
Appraisal Fee	$343	$344	-$1
Second Home	0.005	0.007	-0.002
Investment Property	0.067	0.064	0.003
Multi-Unit	0.057	0.053	0.004
Condo	0.047	0.047	0.000
PUD	0.089	0.097	-0.008
Married Borrower	0.637	0.638	-0.001
Ln(Inc)	8.519	8.546	-0.027
Ln(Assets)	12.247	12.220	0.027
Dependents	1.096	1.344	-0.248
Property Age	34.704	34.570	0.135
Years at Residence	8.240	7.766	0.473
CLTV	77.940	79.340	1.400

Note: This table reports mean values in the sample of funded refinance mortgages that does not match to the ABSNet/HomeVal data and the sample of funded refinance mortgages that matches to ABSNet/HomeVal. Mean differences are tested using two-sample t-tests allowing for unequal variances. All differences are significant at the 1% level of confidence with the following exceptions: Appraisal fee (10% level of confidence); Condo (not significant); Married (not significant); Property Age (not significant).

Table A.4. Mean differences across ABSNet matched that do and do not have AVM confidence scores

	No AVM Confidence	AVM Confidence	Mean Difference
Appraisal Value	$276,161	$280,318	-$4,156
Days to Appraisal	-8.037	-6.484	-1.553
Appraisal Fee	$344	$345	$0
Second Home	0.006	0.006	0.000
Investment Property	0.062	0.065	-0.003
Multi-Unit	0.056	0.058	-0.002
Condo	0.053	0.049	0.005
PUD	0.100	0.122	-0.022
Married Borrower	0.622	0.644	-0.022
Ln(Inc)	8.568	8.584	-0.016
Ln(Assets)	12.356	12.156	0.200
Dependents	1.344	1.491	-0.147
Property Age	34.555	33.787	0.768
Years at Residence	7.463	8.001	-0.538
CLTV	78.802	79.087	-0.286

Note: This table compares average listing characteristics for properties with and without AVM confidence scores. Mean differences are tested using two-sample t-tests allowing for unequal variances. All differences are significant at the 1% of confidence with the following exceptions: Appraisal Fee (not significant); Second Home (not significant); Investment Property (5% level of confidence); Multi-Unit (5% level of confidence).

Table A.5. Differences in Appraisal Outcomes

Panel A: Disclosure States	(1) App-to-AVM	(2) Below Contract	(3) Fees
Female Appraiser	0.003**	0.000	-0.539
	(0.002)	(0.001)	(0.353)
Observations	187,092	327,580	390,982
Adjusted R-squared	0.139	0.002	0.193
Zip FE	Y	Y	Y
Year FE	Y	Y	Y
$\overline{Y}$	1.08	.02	348
Sample	Refi-ABS	Purch	Fees

Panel B: Non-disclosure States	(1) App-to-AVM	(2) Below Contract	(3) Fees
Female Appraiser	0.007	-0.001	-4.693***
	(0.007)	(0.002)	(1.001)
Observations	18,901	35,202	47,239
Adjusted R-squared	0.237	0.009	0.199
Zip FE	Y	Y	Y
Year FE	Y	Y	Y
$\overline{Y}$	1.19	.01	353
Sample	Refi-ABS	Purch	Fees

Note: This table presents estimates from regression models where the dependent variable is listed in the column header. Panel A includes observations in states where sales transaction prices are fully disclosed. Panel B includes observations in states where sales transaction prices are not fully disclosed (AK, ID, KS, MT, MS, NM, WY, TX, and UT). MO is excluded from both samples as the price disclosure status varies across counties. The sample in column 1 includes the NCEN-ABSNet matched refinance sample. The sample in column 2 consists of purchase mortgage applications. The sample in column 3 includes refinance and purchase mortgage applications with non-missing appraisal fees. Robust standard errors are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.10

Table A.6. Zip Code Demographics

Variable	Obs	Mean	Std. dev.	Min	Max
White (%)	31,949	87.07	19.36	0	100
HS or Above (%)	31,816	78.75	12.32	0	100
Foreign Born (%)	31,826	4.78	8.33	0	100
Employed (%)	31,951	61.88	10.77	0	100
Ln(Median HH Income)	31,889	10.51	0.38	7.82	12.21
Ln(Median HH Income)^2	31,889	110.69	7.91	61.21	148.99
Ln(Median OwnOcc Property Value)	31,586	11.35	0.63	9.21	13.82

Note: Zip code level demographic information.

A.1. AVM Background

As in Ambrose et al. (2025); Griffin and Maturana (2016); Kruger and Maturana (2021), we use Collateral Analytics' Automated Valuation Model (CA AVM) for benchmark property valuation estimates. In the aftermath of the Great Financial Crisis (GFC) of 2007-2009, Lewtan Technologies, a key data provider for issuers of, and investors in, residential mortgage-backed securities, introduced the ABSnet Loan HomeVal product, which incorporated the CA AVM.[1] This product connected securitized loans within mortgage-backed securities pools to specific properties, giving investors independent valuations of the underlying collateral via the CA AVM. Prior to this innovation, investors lacked access to such independent property value estimates.

The Automated Valuation Model (AVM) generates property valuations using hedonic methods that rely on publicly available property characteristics typically found in assessor records, augmented by data from local multiple listing service providers. The specific model employed by the AVM is proprietary and not publicly disclosed, but research by Jensen and Reifler (2010) demonstrates that the AVM surpasses other valuation metrics, such as repeat sales and transaction-based home price indices. The AVM estimates used in our analysis were generated retroactively but rely exclusively on information available at the original loan closing date, providing an objective estimate of market value at the time of loan origination.

U.S. courts have validated the use of AVMs by lenders for property valuation purposes (Neng-Guin Chen v. Citibank, 2011), and AVM estimates have been accepted as evidence in court cases addressing fraudulent appraisals related to mortgage-backed securities (MBS) (see FHFA v. UBS Ams., Inc., 2012; Nomura Asset Acceptance Corp. Alt. Loan Tr. v. Nomura Credit & Capital, Inc., 2018). Notably, research by Griffin and Maturana (2016) and Kruger and Maturana (2021) employs the CA AVM to identify fraudulent activities in subprime MBS markets. In 2020, Black Knight, Inc., a

[1] For more information, visit https://asreport.americanbanker.com/news/lewtan-technologies-to-launch-absnet-loan-homeval-153-product.

prominent data provider in the real estate sector, acquired Collateral Analytics, thereby obtaining the CA AVM product.[2]

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

A.2. Days to Appraisal Analysis

Table A.7 reports OLS estimates using days to appraisal, our proxy for appraiser efficiency, as the dependent variable. Columns 1-3 are analogous to the results using our other appraisal outcomes in Tables 4, 7, and 10, respectively.

The coefficient of -0.108 in column 1 is extremely modest (one-tenth of a day) and does not provide any visible evidence that female appraisers are less efficient or are back-ups to males. The fragility of this estimate is evident when we examine the differential across racial groups in column 2. For Whites and Hispanics, female appraisers are trivially more delayed in completion, while the opposite is true for Asian and Black borrowers. But, to repeat, all the differentials are trivially small. Column 3 shows that turnaround times are approximately 1.3 days longer for mixed-owner properties relative to male owned properties, but again, this varies little with appraiser gender (1.2 and 1.4 for male and female appraisers, respectively). For female owned properties, the male appraiser coefficient (0.227 days) is relatively small, and it is not statistically distinguishable from the female appraiser coefficient (0.024).

Taken together, the results in Table A.7 suggest that appraiser gender does not play a large role in appraiser efficiency.

Table A.7. Differences in App-to-AVM Ratios Across Appraiser Gender and Owner Race

	(1) Days to Appraisal	(2) Days to Appraisal	(3) Days to Appraisal
Female Appraiser	-0.108*		
	(0.060)		
Female Appraiser / White Owner		0.126	
		(0.113)	
Male Appraiser / Asian Owner		-0.226	
		(0.211)	
Female Appraiser / Asian Owner		-0.397	
		(0.389)	
Male Appraiser / Black Owner		0.175	
		(0.116)	
Female Appraiser / Black Owner		-0.026	
		(0.200)	
Male Appraiser / Hispanic Owner		-0.145	
		(0.112)	
Female Appraiser / Hispanic Owner		0.052	
		(0.187)	
Female Appraiser / Male Owner			0.232*
			(0.136)
Male Appraiser / Mixed Owners			1.232***
			(0.088)
Female Appraiser / Mixed Owners			1.368***
			(0.134)
Male Appraiser / Female Owner			0.227***
			(0.084)
Female Appraiser / Female Owner			0.024
			(0.143)
Observations	1,204,494	648,485	718,684
Adjusted R-squared	0.037	0.218	0.216
Additional Controls	N	Y	Y
Zip FE	Y	Y	Y
Year FE	Y	Y	Y
Missing Char. Dummies	N	Y	Y
Originator FE	N	Y	Y
$\overline{Y}$	-11	-9	-9
Sample	Dates	Dates	Dates

Note: This table presents estimates from regression models where the dependent variable is Days to Appraisal. The sample includes observations where the appraisal completion date and NCEN application date are available. In column 2, The omitted appraiser gender / owner race category is male appraiser / white owner. In column 3, the omitted category is male appraiser / male owner. Additional Controls in columns 2 and 3 are identical to those in Table 7 (Second Home, Investment Property, etc.). Robust standard errors are reported in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.10$