Better understanding the sources of racial disparities in economic outcomes is a focus of research and policy (Lang and Spitzer 2020; Small and Pager 2020). An emerging literature finds that racial disparities in the labor market may beget disparities in the provision of critical services. For instance, minority students tend to achieve better outcomes when taught by minority teachers (Dee 2004, 2005; Fairlie, Hoffmann, and Oreopoulos 2014) and minority patients achieve better outcomes when treated by minority doctors (Alsan, Garrick, and Graziani 2019), yet minorities are underrepresented among teachers and doctors. Much of the work in this literature studies contexts with significant regulatory and competitive frictions, such as education and health care. A key question is whether the underrepresentation of minorities in the labor force and its adverse effect on minority consumers persist even in settings with fewer frictions and greater competition.

In this paper, we study the relationship between racial disparities in the labor market for loan officers and economic outcomes in the highly competitive market for originating U.S. home mortgages. We find that working with minority loan officers improves credit access for minority mortgage applicants along several dimensions. These results suggest that underrepresentation of minorities among loan officers may have an adverse effect on minority access to credit in the aggregate. Home equity is an important source of household wealth and exhibits large racial disparities (e.g., Bhutta, Chang, Dettling, Hsu, and Hewitt 2020; Gupta, Hansman, and Mabille 2021; Kermani and Wong 2021). Given the importance of access to credit for home purchases, frictions between borrowers and lenders related to race and ethnicity may contribute to these wealth disparities.

Our analysis leverages a novel dataset linking the confidential version of the recently expanded Home Mortgage Disclosure Act (HMDA) data to information on loan officers from the Nationwide Mortgage Licensing System (NMLS). We start our analysis by providing a description of the racial/ethnic composition of mortgage loan officers. As with other white-collar professions, we find that minorities are underrepresented. In 2019, minorities accounted for 39% of the U.S. labor force, but only an estimated 15% of mortgage loan officers.

We next explore whether the race/ethnicity of loan officers and applicants matters for mortgage application completion, approval, and origination. We find that minority applications are about 2 percentage points less likely to be completed than white applications handled by the same white loan officer. For minority loan officers, however, the gap in completion rates between minority and white applicants is 1-2 percentage points smaller. We find similar effects for loan approval conditional on application completion. We focus on "high-discretion" loan applications, those for which automated underwriting systems do not make definitive recommendations. For these applications, we find that minority applicants are about 3 percentage points less likely to be approved than white applicants working with the same white loan officer. For minority officers however, the difference in approval rates between minority and white applicants is 1-2 percentage points smaller.

The effects we find on overall loan origination rates are economically meaningful. Loan applications from minority borrowers are about 5 percentage points less likely to result in an origination than applications from white borrowers handled by the same white loan officer, but this difference is 2-4 percentage points smaller for minority officers. In other words, minority loan officers close much of the gap in credit access between white and minority borrowers.

We then examine whether the expanded credit access that results when minority officers handle minority applications leads to higher default rates using loan-level data from the Federal Housing Administration (FHA). Conditional on standard underwriting risk factors, minority borrowers are 1.7 percentage points more likely to default than white borrowers working with the same white loan officer. Despite the fact that minority applications handled by minority officers are more likely to result in loan originations, the same loans are less likely to default. Indeed, the full difference in default rates between minority and white borrowers (i.e., the full 1.7 percentage points) disappears when the loan officer is a minority. Our evidence on defaults cuts against simple taste-based discrimination explanations. Under taste-based discrimination, we would expect loan applications from minority borrowers handled by white loan officers to have both lower approval rates (as we find) and lower default rates (contrary to what we find).

To further explore the mechanism behind our results, we examine the cross section of borrowers, financial institutions, and loan officers. Along each dimension, we find evidence consistent with the idea that minority loan officers are better able to produce soft information about minority borrowers. In the cross section of borrowers, our baseline results—that minority applicants are more likely to be approved and less likely to default when working with minority loan officers—are amplified when we look at matches between minority borrowers and loan officers of the same race/ethnicity, for which there is most plausibly a soft information advantage. Similarly, we find that our baseline results are strongest for low-income borrowers, for whom traditional hard information is less predictive of defaults and soft information is likely important (Blattner and Nelson 2021; Di Maggio, Ratnadiwakara, and Carmichael 2021; Mayer 2021). In the cross section of financial institutions, our baseline results are strongest for small banks, which may be more likely to exploit soft information in lending decisions (e.g., Stein 2002; Berger, Miller, Petersen, Rajan, and Stein 2005; Liberti and Mian 2009). Finally, in the cross section of loan officers, we find that our baseline results are stronger for minority loan officers who handle many minority loan applications and weaker for experienced white officers. In addition, when minority officers work with minority borrowers, application outcomes are less correlated with hard information on loan applications like credit scores and debt-to-income ratios.

Taken together, these results suggest that certain loan officers may receive and act upon more precise soft information signals about minority borrowers. A soft information mechanism is surprising because mortgage lending in the U.S. is a setting where hard information dominates. Most mortgage applications are evaluated with the aid of automated underwriting systems that use hard information that has been verified with documentation (e.g., credit reports, property appraisals, and tax returns). In light of these institutional features, a natural interpretation of our results is that in some cases loan officers' soft information is a key determinant of the hard information that ends up on loan applications. For instance, minority loan officers may be better informed when deciding whether to exert effort to document alternative sources of borrower income or assemble more compelling documentation for minority applications. Thus, by influencing the quality of hard information on loan applications, loan officers' soft information may influence the loans that get originated and how they ultimately perform.

Throughout our analysis, we take two separate approaches to isolate supply-side effects running from loan officers to mortgage applicants. First, we saturate our regressions with fixed effects. In our most stringent specifications, we include branch-loan officer-year fixed effects, as well as fixed effects controlling for narrow ranges of credit scores (FICO), loan-to-value ratios (LTV), and debt-to-income ratios (DTI). These specifications essentially compare two borrowers, one a minority and one white, with observationally equivalent mortgage applications facing the same loan officer. Our regressions then ask whether differences in outcomes between these borrowers vary with the race/ethnicity of the loan officer.

Despite the tight controls in these OLS specifications, one might still worry that our results are driven in part by endogenous matching on unobservable characteristics between loan officers and borrowers. To address this concern, we instrument for whether an application is handled by a minority loan officer with the share of applications at the same branch handled by minority officers on the same day of the week in previous weeks. So long as application quality is unrelated to loan officer work schedules, this instrument captures exogenous variation in the probability that an application is handled by a minority officer. We find very similar results using this identification approach. If anything, our instrumental variables results are somewhat stronger than our OLS results, consistent with the idea that unobservably riskier minority borrowers endogenously match with minority loan officers.

We contribute to several strands of the vast literature on racial disparities in economics.[1] First, we contribute to recent work showing that racial disparities in labor

[1] Early foundational work includes Becker (1957), Phelps (1972), and Arrow (1972, 1973). A large literature documents racial disparities in a variety of economic outcomes such as wealth, wages, and housing returns

markets can create inequalities in downstream customers' outcomes by using comprehensive and novel data to show that minorities' underrepresentation in skilled labor positions (loan officers) gives rise to racial disparities in the U.S. residential mortgage market. Our findings highlight the importance of minority representation at firms even in a competitive market setting with low search costs, where relationships play a relatively small role and the logic of Becker (1957) suggests disparities should be competed away.

Second, racial disparities in the mortgage market have received considerable attention since the seminal work of Munnell, Tootell, Browne, and McEneaney (1996). Many studies find that minorities face lower approval rates, and if approved, pay higher interest rates. This strand of the literature includes recent work such as Bhutta, Hizmo, and Ringo (2021) and Bartlett, Morse, Stanton, and Wallace (2022), which use detailed data on borrower credit scores, loan-to-value ratios, and debt-to-income ratios that have historically not been available.[2] We contribute to this literature by showing that minority loan officers appear to have an advantage in terms of soft information on minority loan applicants, which allows them to achieve higher approval rates and lower default rates. In this way, our paper relates to studies examining the effects of shared group status between lenders and borrowers. Much of this work, including Fisman, Paravisini, and Vig (2017), Fisman, Sarkar, Skrastins, and Vig (2020), and D'Acunto, Ghosh, Jain, and Rossi (2021), studies the effects of shared religion or caste between loan officers and borrowers in India.[3] In the U.S., Ambrose, Conklin, and Lopez (2021) study brokered loans originated by New Century Financial Corporation from 2003-2007 and show that brokers charge borrowers higher fees when they are from different races/ethnicities. We contribute to this literature

(e.g., Charles and Guryan 2008; Bayer and Charles 2018; Kuhn, Schularick, and Steins 2020; Kermani and Wong 2021).

[2] Additional evidence from correspondence experiments (Hanson, Hawley, Martin, and Liu 2016) and audit studies (Ross, Turner, Godfrey, and Smith 2008) often supports a discrimination explanation for racial disparities in mortgage lending. However, some empirical studies also find that minority borrowers default more (e.g., Berkovec, Canner, Gabriel, and Hannan 1998), which may be inconsistent with taste-based discrimination.

[3] A much larger literature shows that loan officers and brokers affect loan outcomes. See, e.g., Tzioumis and Gee (2013), Drexler and Schoar (2014), Berg (2015), Cole, Kanz, and Klapper (2015), Agarwal and Ben-David (2018), Bushman, Gao, Margin, and Pacelli (2021), and Dobbie, Liberman, Paravisini, and Pathania (2021), among others.

by documenting in-group advantages based on race and ethnicity in the U.S. mortgage market and showing that soft information remains important even in a setting with large amounts of hard information and relatively little scope for relationship building.

Perhaps the most closely related paper to ours is Jiang, Lee, and Liu (2022), which was developed independently and contemporaneously to our paper. They also link confidential HMDA data to the NMLS loan officer data and find that minority loan officers are more likely to approve minority mortgage applications. They focus on the ability of FinTech lenders and machine learning to reduce differences in outcomes across races/ethnicities, while we use differences within the cross sections of white and minority workers to help pin down the economic mechanisms at work.

We argue that the joint patterns of application completion rates, approval rates, and loan default rates, as well as the ways in which loan officers react to hard information on applications, are all consistent with the idea that minority loan officers have a soft information advantage in handling minority applications. Finally, our back-of-the-envelope calculations suggest that improving minority representation among loan officers could close nearly half of the gap in access to mortgage credit between white and minority borowers.

2. Data and Methodology

We leverage three novel datasets to conduct our empirical analysis. First, we build the first nationwide panel of mortgage loan officers based on licensing and registration information from the Nationwide Mortgage Licensing System from 2012 to 2019. Second, we connect loan officers to their mortgage applications handled in 2018 and 2019 using the newly expanded confidential version of the Home Mortgage Disclosure Act data maintained by the Federal Reserve System. Third, we connect loan officers to their FHA-insured mortgage originations from 2012 to 2018 using comprehensive data provided by the Federal Housing Administration. We supplement these datasets with information on ZIP code-level demographic and economic characteristics from the U.S. Census Bureau. Appendix A provides detailed definitions of all the variables used in the analysis.

2.1 Nationwide Mortgage Licensing System Data

The Secure and Fair Enforcement for Mortgage Licensing Act of 2008 (SAFE Act) was designed to enhance consumer protection and reduce fraud in the mortgage market.[4] The SAFE Act requires all residential mortgage loan originators (i.e., loan officers) to be either state licensed or federally registered. Loan officers employed by federally insured depository institutions or their subsidiaries must be federally registered. All other loan officers working at nonbank mortgage companies must be state licensed. Importantly for our study, the SAFE Act requires that all loan officer licenses and registrations must be recorded in the Nationwide Mortgage Licensing System (NMLS).[5] By 2012, all state and federal regulators had integrated their licensing/registration with the NMLS, making it a comprehensive registry of mortgage lenders and their loan officers.

We obtain access to the data from NMLS Consumer Access[SM] through an agreement with the State Regulatory Registry, a wholly-owned subsidiary of the Conference of State Bank Supervisors.[6] The data contain historical snapshots of files with information on licenses, registrations, and other filings for loan officers, as of the end of each calendar year from 2012 to 2019. Importantly, the NMLS assigns each loan officer a unique NMLS ID that stays with them over time and across employment spells, allowing us to accurately track officers throughout their career in the mortgage industry. Thus, the data allow us to construct a nationwide loan officer-year panel which contains their name, NMLS ID, current employer, work address, and employment history in the industry.

2.2 Identifying Loan Officer Race/Ethnicity

We do not directly observe the race and ethnicity of loan officers in the NMLS data. Instead, we infer this information using the Bayesian Improved First Name Surname Geocoding (BIFSG) method developed by Voicu (2018) and adopted by Ambrose,

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[4] See https://www.hud.gov/sites/documents/DOC_19673.PDF.
[5] The NMLS was created in 2008 by the Conference of State Bank Supervisors (CSBS) and the American Association of Residential Mortgage Regulators (AARMR), see https://nationwidelicensingsystem.org.
[6] For additional information on NMLS Consumer Access[SM], see https://nmlsconsumeraccess.org/.

Conklin, and Lopez (2021).[7] The BIFSG method utilizes each individual's first name, last name, and physical location to calculate the probability that they belong to a particular racial/ethnic category (i.e., non-Hispanic white, non-Hispanic black, non-Hispanic American Indian and Alaskan Native, non-Hispanic Asian and Pacific Islander, Hispanic, and non-Hispanic other/multiracial).

The BIFSG method calculates the probability of an individual with surname *s*, first name *f*, and ZIP code *z* belonging to each race group *r* as:

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

where $p(r|s,f,z)$ is the posterior probability of belonging to race group *r*; $p(r|s)$ is the probability of belonging to race group *r* conditional on surname *s*; $p(f|r)$ is the probability of having first name *f* conditional on race *r*; and $p(z|r)$ is the probability of locating in ZIP code *z* conditional on race *r*. In the denominator, we sum over the six race and ethnicity groups.[8]

The NMLS data provide us with the surname, first name, and branch office ZIP code for each loan officer. We first standardize the loan officer first and last names and limit ZIP codes to the first five digits. Then, we match loan officers' last names to the 2010 U.S. Census surname list, which includes surnames found more than 100 times, covers about 90% of the U.S. population, and lists the probability of a given surname belonging to one of the six racial/ethnic groups. We match loan officers' first names to a list created by Tzioumis (2018), which is derived from mortgage application data and covers over 4,000 first names and provides the probability of each name belonging to one of the six groups.[9] Lastly, we match branch ZIP codes to the share of each racial/ethnic group in the ZIP code based on the 2010 U.S. Census.[10]

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[7] The BIFSG methodology is an improvement from the Bayesian Improved Surname Geocoding (BISG) method developed by Elliott et al. (2009), which is used by government agencies such as the Consumer Financial Protection Bureau. For additional details, see U.S. Consumer Financial Protection Bureau (2014).

[8] The BIFSG methodology assumes $p(f|r) = p(f|r,s)$ and $p(z|r) = p(z|r,f,s)$.

[9] See https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/TYJKEZ

[10] Throughout the paper, we refer to loan officers' office addresses as "branches", although in some cases these could be single office lending institutions.

For each loan officer, we calculate the probability that they belong to each of the six race and ethnicity groups according to equation (1). We rank the six probabilities from highest to lowest and assign each loan officer to the specific racial/ethnic group with the highest probability, following Ambrose, Conklin, and Lopez (2021). Voicu (2018) conducts validation exercises in voter registration and mortgage application data to show that this method provides classifications with high accuracy (i.e., low probability of false positives or false negatives) and low bias (i.e., the distribution of imputed classifications is similar to the population distribution). We describe loan officer demographics and characteristics in Section 3 below.

2.3 Confidential HMDA Data

The Home Mortgage Disclosure Act (HMDA) requires nearly all mortgage lenders to report detailed information on the applications they receive, and whether they originate the loan. Only very small or exclusively rural lenders are exempt from HMDA reporting, making it the most comprehensive source of information on mortgage applications with over 95% coverage (Avery et al. 2017).[11] The public version of the HMDA data includes borrower income, race, and ethnicity, as well as loan size, loan purpose (purchase, refinance, home improvement), loan type (conventional, government-insured), loan priority (first or second lien), the existence of any co-applicants, and property location (census tract).

Starting in 2018, the confidential version of the HMDA data maintained by the Federal Reserve System includes a host of new variables, which are not publicly available. Important additions include key underwriting variables like borrower credit score, loan-to-value ratio, and debt-to-income ratio, as well as the automated underwriting system (AUS) used and its recommendation code. Critical to our study, the new confidential HMDA data

[11] As of 2019, any depository institution must report to the HMDA database if it has: (i) at least one branch or office in a metropolitan statistical area (MSA), (ii) at least $46 million in assets, and (iii) originated at least 25 mortgages in each of the previous two years. Non-depository institutions must report data if they have a branch/office in an MSA (or receive at least five applications from MSAs) and originated at least 25 mortgages in each of the previous two years.

include the loan officer identifier (NMLS ID), which allows us to link loan officers in our NMLS panel directly to the applications they handle.

2.4 FHA Data

Since the HMDA dataset does not include information on loan performance, we use data from the Federal Housing Administration (FHA). The FHA operates the largest government mortgage insurance program, which facilitates home financing opportunities for first-time and low- and moderate-income homebuyers by guaranteeing loans with small down payments (high LTVs) to borrowers with relatively low credit scores. In 2019, FHA mortgages constituted 18% of all first-lien home purchase mortgage originations.

The FHA has provided the Federal Reserve Banks of Atlanta and Dallas with comprehensive data on the population of their insured single-family mortgage originations between 2000 and 2018. These data include mortgage terms and standard underwriting variables such as credit score, loan-to-value ratio, debt-to-income ratio, etc. The data also contain information on loan performance through September 2019, including an indicator for whether the loan ever became 90 or more days past due, which is a standard definition of mortgage default. Importantly, the data also include the loan officer's NMLS ID, which allows us to link loan officers to their FHA originations from 2012 to 2018.

2.5 Merges and Screens

We first merge all HMDA mortgage applications in 2018 and 2019 to information on the loan officer handling the application from NMLS using their NMLS ID—we find matches for 99.3% of applications. We then drop the 2.9% of applications where the loan officer's branch (i.e., work office) address is missing or is located outside the U.S. Additionally, we drop the 9.4% of applications where the loan officer's race/ethnicity cannot be assigned using the BIFSG algorithm. Therefore, our analysis focuses on the remaining 87% of applications where we have sufficient data on loan officers' location and race/ethnicity.

We use HMDA data on all mortgage applications to compute loan officer-year statistics for 2018-2019, which we tabulate and discuss in the next section. However, for our main application-level tests, we pare down the sample along a few dimensions to make it more homogeneous, consistent with prior studies (e.g., Bhutta, Hizmo, and Ringo 2021; Bartlett, Morse, Stanton, and Wallace 2022). First, we drop any observations where applicant/borrower race is not reported. Second, we drop loans originated through mortgage brokers to ensure that the borrower was dealing directly with the loan officer. Third, we focus only on first-lien, 30-year, fixed-rate, home purchase mortgages financing owner-occupied single-family properties. Focusing on a single mortgage contract helps address selection concerns that would arise if we considered multiple contracts, and 30-year fixed-rate mortgages are the most popular contract in the U.S. Focusing on purchase mortgages also helps address selection concerns, as refinancing borrowers are more likely to use the same loan officer as they had for their first mortgage if they had a good experience with the first mortgage.

We follow a similar matching and filtering process for the FHA data. We find sufficient information on loan officer location and race/ethnicity for 89.9% of FHA home purchase mortgages from 2012 to 2018. We report summary statistics for these main samples in subsequent sections, immediately preceding the related analyses.

3. Minority Loan Officers and Access to Mortgage Credit

This section studies the influence of minority loan officers on borrower access to mortgage credit. We document two main results. First, minorities are underrepresented among the ranks of loan officers. Second, applications by minority borrowers that are handled by minority loan officers are more likely to be completed, approved, and result in an originated mortgage. To deal with the fact that there may be endogenous matching between loan officers and borrowers, we show that similar results obtain using an instrumental variables (IV) approach that aims to approximate random assignment of loan officers to borrowers.

3.1 Minority Representation among Mortgage Loan Officers

Table 1 presents summary statistics for the loan officers in our HMDA/NMLS matched panel. Panel A shows a 2019 snapshot of minority representation among mortgage loan officers. Our sample in 2019 is comprised of around 255,000 active loan officers.[12] Among these individuals, we identify 84.6% as white, 8.9% as Hispanic, 1.8% as Black, and 4.7% as Asian. By contrast, for the U.S. population that year, the shares were white 60.7%, Hispanic 18.0%, Black 13.2%, and Asian 6.2%. If we compare the minority share of U.S. mortgage loan officers to jobs that require similar skills, we find a persistent minority representation gap. For example, according to the Current Population Survey maintained by the Bureau of Labor Statistics (BLS), in 2019 non-whites accounted for 29.3% of financial managers, 28.0% of credit counselors, and 21.8% of personal financial advisors, whereas they represent only 15.4% of the loan officers in our sample.[13]

Panel B of Table 1 provides descriptive statistics on loan officer, lender, and branch ZIP code characteristics overall and by race/ethnicity using the loan officer data for 2018 and 2019. The average level of experience for mortgage loan officers is 9.1 years. For white officers, average experience is 9.3 years, while the figure is 7.7 years for Hispanic officers, 8.0 years for Black officers, and 8.3 years for Asian officers. We see similar patterns for turnover and tenure at current employer. White loan officers average 41 applications per year, while Hispanic, Black, and Asian loan officers all handle around 32 applications per year on average. In dollar terms, the application patterns are somewhat different. Asian loan officers handle loan applications totaling $11 million on average each year, while Black loan officers handle $6 million. The average dollar volume of mortgages handled by a loan officer across all races is around $9 million.

We construct *Lender Minority LO* $\%_{i,f,c,t}$ as the fraction of minority loan officers at the mortgage originator f that officer i works at in year t, excluding the county c where officer i works, to measure minority representation at the institution level. The average

[12] Some lenders also register other (non-loan officer) employees in NMLS. Therefore, we focus on the matched 2018-2019 data, because we can directly confirm that the person is an active loan officer by requiring them to handle at least one mortgage application at a HMDA-reporting institution that year.
[13] For a list of professions, see https://www.bls.gov/cps/aa2019/cpsaat11.pdf.

value of the variable is 15%, matching the overall composition of our loan officer sample. When we focus on minority loan officers, the variable takes on values above 15%, indicating that there is heterogeneity in minority representation across lenders: When a lender has more minority loan officers outside county *c*, it has more minority loan officers in county *c* as well. In other words, Hispanic, Black, and Asian loan officers all tend to work at lenders with more minority loan officers in other locations.

[Insert Table 1 Here]

Figure 1 illustrates our first main result. We plot the share of minority loan officers in a ZIP code against the minority population share in that ZIP code for deciles of the minority population share distribution. If the share of minority loan officers simply reflects local population demographics, we would expect a 45-degree line with a y-intercept at zero (depicted in the plot for reference). However, the figure shows that the intercept of the best-fit line is negative, and the slope is less than one. In other words, mortgage lenders employ fewer minorities than the ZIP code level minority share, and minorities are most underrepresented among loan officers in the ZIP codes with the highest minority share. Taking the far-right bin as an example, for ZIP codes in the top decile of minority share (around 80% minority residents), only around 55% of loan officers are minorities. Internet Appendix Table IA1 provides regression evidence corresponding to Figure 1 and shows that similar patterns persist when we control for region, population density, average income in the ZIP code, and average income among minorities in the ZIP code.

[Insert Figure 1 Here]

3.2 Minority Loan Officers and Mortgage Application Outcomes

This subsection shows our second main result—that mortgage loan applications opened by minorities are more likely to be completed, approved, and ultimately originated if they are handled by a minority loan officer. These tests use the sample of home purchase mortgage applications in HMDA from 2018-2019, as described in Section 2.5. Table 2 reports summary statistics for this sample of approximately 5.65 million applications as well as statistics splitting by both the applicant and loan officer race/ethnicity. About 10% of opened loan applications are handled by minority loan officers, while minority borrowers account for about 30% of all opened applications. The average applicant is 41 years old with an income of $94,000, a credit score of 725, and is requesting a loan for just under $260,000. Minority applicants tend to have slightly lower incomes and credit scores and slightly higher LTVs. The raw statistics also show large minority gaps in mortgage application completions, approvals, and originations under white officers, and smaller gaps under minority officers, which we will now examine more carefully.

[Insert Table 2 Here]

3.2.1 Completion Rates

Table 3 presents application-level linear probability models of the form:

$$Y_i = \beta_1 1\{Minority\}_i + \beta_2 1\{Minority\ Officer\}_i + \beta_3 1\{Minority\}_i \times 1\{Minority\ Officer\}_i + \gamma' \mathbf{X}_i + \varepsilon_i \quad (2)$$

The main independent variables of interest are indicators for the applicant filing application i being a minority (*Minority*$_i$), and for the loan officer being a minority (*Minority Officer*$_i$), as well as their interaction. We two-way cluster standard errors by lender and county.

In the first two columns of Table 3, the dependent variable is a dummy variable indicating that an opened application i was completed (*Completed*$_i$). The control variables ($\mathbf{X}_i$) are loan type indicators, ten-year bins of applicant age, centile bins of the applicant income-to-MSA median income ratio,[14] log(loan amount), an indicator for jumbo loans, and an indicator for joint applications. We choose these controls because they are available

[14] We use the income-to-MSA median income ratio because there are cost of living differences across MSAs and certain government program incentives (e.g., Community Reinvestment Act requirements) are a function of MSA median income.

for all applications, including those that were not completed, and we refer to them in the tables as *Basic App Controls.* Appendix A provides variable definitions.

Table 3 column 1 reports results conditioning on these controls as well as branch-year and property county fixed effects. Thus, the specification exploits comparisons between two borrowers applying at the same branch in the same year, financing properties in the same county, with similar loan application characteristics. The coefficient β_1 on the minority applicant dummy is negative and statistically significant, indicating that minority applications handled by white loan officers are 2.1 percentage points less likely to be completed than white applications handled by white loan officers. (For reference, the baseline application completion rate is 83.7%.) The coefficient β_2 on the minority loan officer dummy is negative but small in magnitude (-0.2 percentage points), indicating that white applications handled by minority officers are slightly less likely to be completed than white applications handled by white officers. The coefficient β_3 on the interaction of minority applicant and minority loan officer is positive and statistically significant, indicating that minority applications handled by minority loan officers are 1.5 percentage points more likely to be completed than minority applications handled by white loan officers.

In column 2, we replace our branch-year fixed effects with branch-year-officer fixed effects. Thus, we can no longer identify the coefficient β_2 on the minority loan officer dummy, but we are now exploiting variation within a loan officer. In other words, we are taking the difference in how the same loan officer handles minority applicants relative to white applicants and asking how that difference varies with the officer's race. The results are similar to those in column 1. The coefficient β_1 on the minority applicant dummy is negative and significant, indicating that averaging across white loan officers, minority applications are 1.9 percentage points less likely to be completed than white applications handled by the same officer. The coefficient β_3 on the interaction of minority applicant and minority loan officer is positive and statistically significant. When the loan officer is a minority, this difference in completion rates between minority and white applicants is 1.1 percentage points smaller.

[Insert Table 3 Here]

3.2.2 Approval Rates

Next, we restrict the sample to completed mortgage applications and examine whether minority applicants are more likely to be approved when working with a minority loan officer. Figure 2 shows the raw data on approval rates based on whether the applicant and loan officer are racial/ethnic minorities. The left panel plots the average approval rate for applications handled by white loan officers by decile of borrower credit score, splitting white and minority applicants. Minority applications handled by white loan officers have lower approval rates across the entire credit score distribution. The right panel plots applications handled by minority loan officers, again splitting by whether applicants are minorities or not. In stark contrast to the left panel, the approval rates for white and minority applicants working with minority loan officers are very similar when the credit score is above 680. At low credit scores, minority applicants have slightly higher approval rates than white applicants.

[Insert Figure 2 Here]

Columns 3-6 of Table 3 present formal regression evidence. Within the set of completed mortgage applications, we run a regression in line with Eq. (2) but now the dependent variable is a dummy indicating that application i was approved ($Approved_i$). The main independent variables of interest are again indicators that the applicant is a minority ($Minority_i$), the loan officer is a minority ($Minority\ Officer_i$), and their interaction. The basic application controls are again: loan type indicators, bins for applicant age and income, log(loan amount), and indicators for jumbo loans and joint applications. Since completed loan applications contain more information in the confidential HMDA file, we expand the set of control variables to include indicators for narrow bins of FICO, LTV, and DTI, all interacted with the loan type indicators. We refer to these as *Extended App Controls*. Again, standard errors are two-way clustered at the lender and county level.

The confidential HMDA data also allow us to observe the automated underwriting system (AUS) used to evaluate the mortgage application, and the output code it produces. We control directly for each AUS output code with fixed effects. To further isolate the importance of loan officers, we split our sample into low versus high-discretion cases based on the AUS output code. We label an application as a "low discretion" case if the average approval rate for the AUS code that the application receives is greater than 90%. Applications receiving AUS codes with less than 90% approval rates are deemed to be "high discretion." We select the 90% threshold because there is a sharp break in the distribution of approval rates (see Internet Appendix Figure IA1), but we obtain similar results with different thresholds. By our definition, approximately 86% of applications are low discretion.

Table 3 columns 3 and 4 examine low-discretion applications. The coefficient on the minority dummy indicates that, even among these applications, completed minority applications are one percentage point less likely to be approved. The small and statistically insignificant interaction between the minority applicant and minority loan officer dummies implies that in low-discretion cases, minority application approvals are unrelated to the race/ethnicity of the loan officer handling the application.

In column 5 of Table 3, we re-estimate the same specification using the high-discretion applications. The coefficient on the minority applicant dummy is now more negative, indicating that high-discretion minority applications handled by white loan officers are 2.9 percentage points less likely to be approved than high-discretion white applications. (For reference, the average approval rate for high-discretion applications is 70.3%.) The coefficient on the minority loan officer dummy is small and statistically insignificant. However, the interaction between the minority applicant and minority loan officer dummies is now positive and significant, indicating that minority applications handled by minority loan officers are 1.2 percentage points more likely to be approved than minority applications handled by white loan officers. In other words, the difference in approval rates between minority and white applications with high discretion is about 40% smaller when the loan officer is a minority.

In column 6, we replace our branch-year fixed effects with branch-year-loan officer fixed effects. Thus, we can no longer identify the coefficient on the minority loan officer dummy, as we are exploiting variation within a loan officer. The results are similar to those in column 5. Averaging across white loan officers, minority applicants are 2.6 percentage points less likely to be approved than white applicants handled by the same loan officer. When the officer in question is a minority, this difference is 1.4 percentage points smaller.

3.2.2 All-in Origination Rates

Columns 7 and 8 of Table 3 combine the two previous results, by studying all-in probabilities that opened mortgage applications result in loan originations. As in columns 1 and 2, the sample is all loan applications, including those never completed, and hence the tests use the basic application controls.

Column 7 shows that minority applications handled by white loan officers are 5.0 percentage points less likely to end in a loan origination than white applications. (For reference, the average origination rate for all applications is 74.9%.) The coefficient on the minority loan officer dummy is negative, indicating that applications handled by minority officers are slightly less likely to result in originations. The interaction between the minority applicant and minority loan officer dummies is positive and significant, indicating that minority applications handled by minority loan officers are 2.5 percentage points more likely to result in originations than minority applications handled by white loan officers. In other words, the difference in origination rates between minority and white applications is about 50% smaller for minority loan officers than white loan officers. Column 8 shows that the results are similar when we replace our branch-year fixed effects with branch-year-loan officer fixed effects.

As we show in Table 7 below, most of the effect of minority applicant-minority loan officer pairings appears to be driven by the roughly 80% of such pairings that are same-race/ethnicity pairings. In our main results, we continue estimate the overall effects of minority applicants matching with minority loan officers because we have limited power to distinguish between all combinations of race/ethnicity pairings between borrowers and loan officers.[15]

3.3 Instrumental Variables

In our previous tests, we rely on tight controls and fixed effects for identification. However, the results still mix endogenous matching between loan officers and borrowers within a branch with the causal effect of loan officer race/ethnicity on loan application outcomes. To better identify the causal effect, we use day-of-the-week as an instrument to capture loan officer work schedules. Specifically, for application *i* opened at branch *b* on day of the week *d* in week *w*, we compute the share of applications opened at the same branch *b* on the same day of the week *d* during the prior 12 weeks (*w*-12 to *w*-1) that were handled by minority loan officers. We use this variable to instrument for $1\{Minority\ Officer\}_i$, the dummy indicating whether application *i* was handled by a minority officer.

Formally, the instrument is defined as:

$$Z_{i,b,d,w} = \frac{\#MinorityOfficerApplications_{b,d,w-12\rightarrow w-1}}{\#Applications_{b,d,w-12\rightarrow w-1}},$$

The first stage for this instrument relies on the idea that loan officer work schedules are persistent. If minority loan officers have handled a larger fraction of the applications on a specific day of the week at a particular branch in previous weeks, then they are more likely to handle applications on that day of the week at the same branch this week. The exclusion restriction here is that the instrument's influence on whether a minority loan officer handles an application is the only channel through which the instrument affects application outcomes. This essentially boils down to the restriction that the quality of applications arriving at a specific branch on a particular day of the week this week is

[15] Internet Appendix Tables IA2, IA3, and IA4 show results disaggregating all pairings.

unrelated to minority loan officer work schedules at the branch over prior weeks. The first stage of the instrumental variables regression is:

$$1\{Minority\ Officer\}_{i,b,d,w} = \alpha_{b,w} + \beta Z_{i,b,d,w} + \boldsymbol{\gamma}'\boldsymbol{X}_{i,b,d,w} + \varepsilon_{i,b,d,w} \tag{3}$$

The dependent variable is a dummy indicating that the loan officer is a minority (*Minority Officer*). The independent variable of interest is our instrument $Z_{i,b,d,w}$. As in our earlier tests, we include our basic and extended application controls, as well as property county fixed effects. We also include branch-week and day-of-the-week fixed effects, so that the instrument isolates within-week variation beyond consistent daily patterns that should capture loan officer work schedules and/or rotation policies. We construct instruments for interactions with the minority officer dummy by interacting the variable of interest with $Z_{i,b,d,w}$. For instance, when we are interested in the interaction of the minority applicant dummy and the minority loan officer dummy, we construct the instrument $Z_{i,b,d,w}1\{MinorityApplicant\}_{i,b,d,w}$.[16]

Table 4 Panel A reports the first stage regression results. Each column corresponds to the sample we use to study different outcome variables. For instance, in column 1 the sample is all opened applications, which we use to study application completion rates. Across the columns, the instrument is strong, with first stage F-statistics in excess of 15. The exclusion restriction would be violated if the instrument is correlated with any unobservable determinants of application outcomes. While the exclusion restriction is untestable, in Internet Appendix Table IA5 we report covariate balance tests that support the notion it holds. We find little-to-no correlation between the instrument and observable borrower characteristics.[17]

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[16] In untabulated results, we find similar results if we simply run separate IV regressions for minority borrowers and white borrowers. These specifications make clearer that the exclusion restriction needed is that the instrument is uncorrelated with loan application outcomes except through its effect on loan officer race/ethnicity, conditional on borrower race/ethnicity.

[17] A particularly sharp test of covariate balance is in columns 4 and 5 of Table IA5, where we examine the output codes from automated underwriting systems. These AUS output codes essentially aggregate information across all observable borrower characteristics, and we use the average approval rate for a given

[Insert Table 4 Here]

In Table 4 Panel B, we revisit the main results from Table 3 using our instrumental variables strategy.[18] The IV results are similar to our OLS results. Indeed, if anything, they are slightly stronger, consistent with the idea that higher risk minority applicants tend to endogenously match with minority loan officers (we provide further evidence of this in Table 10 below). For instance, when we look at approval rates for high-discretion applications, our OLS specifications in Table 3 suggest that minority applicants are 1.2 percentage points more likely to be approved when their loan officer is a minority. In Table 4, our corresponding IV estimate is 3.6 percentage points. Similarly, examining all-in origination rates in Table 3, we find that a minority application is 2.5 percentage points more likely to result in a loan origination when handled by a minority officer than a white officer. In Table 4, our corresponding IV estimate is 3.8 percentage points.

Overall, the results presented in this section provide strong evidence of a causal link between loan officer race/ethnicity and access to credit for minority borrowers. Loan applications from minority borrowers are significantly more likely to be completed, approved, and result in a loan origination when they are handled by minority loan officers.

4. Minority Loan Officers and Loan Performance

One possible explanation for our results on application outcomes is that minority loan officers help riskier minority borrowers access mortgage credit. In this section, we examine the relationship between loan officer race/ethnicity and loan performance and show this is not the case. Minority loans handled by minority loan officers default less than minority loan handled by white officers.

code as a continuous measure of the AUS recommendation. The balance tests show that the instrument is uncorrelated with the AUS recommendation, suggesting that it is unrelated to any hard information about borrower creditworthiness. We thank James Vickery for suggesting this test.

[18] The sample sizes shrink for the IV tests because we drop the first three months of 2018 to construct the instrument, and the branch-week fixed effects create some singletons that are dropped in the estimation.

The HMDA data from our prior tests do not include information on loan performance. Fortunately, we have data on the population of FHA mortgages which we can link to NMLS loan officer information back to 2012. We first confirm in the HMDA application data that our main results from Table 3 showing minority loan officers' impact on credit access hold in the FHA subsample (see Table IA6). We then examine the performance of FHA-insured mortgages made by white and minority officers from 2012 to 2018. The key result of this section is that loans to minority borrowers by white loan officers have higher default rates than either observationally similar loans to minority borrowers by minority officers or observationally similar loans to white borrowers.

Table 5 reports summary statistics for our sample of FHA home purchase mortgages, as described in Section 2.5. We report statistics for the full sample of approximately 3.39 million loans as well as splitting by both the borrower and loan officer race/ethnicity. Compared to the average home purchase mortgage applicant (see Table 2), FHA borrowers have lower incomes and credit scores, and request smaller loans with higher LTVs, as the FHA program intends. As is standard in the literature, we define mortgage default as the loan ever going 90 days delinquent, which occurs for 9.1% of the loans in our sample. The sample splits show that white loan officers have particularly high default rates with minority borrowers (11.7%) compared to their white borrowers (8.0%), or to minority loan officers' white or minority borrowers (8.4% and 9.2%, respectively).

[Insert Table 5 Here]

Before turning to formal regression evidence, Figure 3 presents the raw data. The left panel plots average default rates for FHA mortgages handled by white loan officers by decile of borrower credit score, splitting white and minority borrowers. White officers' loans to minority borrowers have higher default rates, particularly for borrowers with low credit scores. In other words, despite our results in Section 3—that minority applications handled by white loan officers have lower completion and approval rates—here we see that the minority loans that white officers do approve have higher default rates. At the lowest credit scores, the difference is economically large, with approximately 19% of minority borrowers defaulting, compared to 15% of white borrowers.

[Insert Figure 3 Here]

The right panel of Figure 3 shows the analogous plot for mortgages handled by minority loan officers. Here there is little discrepancy between default rates for minority and white borrowers. Furthermore, the default rates for both minority and white borrowers handled by minority loan officers are similar to those for white borrowers handled by white loan officers. Of the four sets of loans, loans to minorities handled by white loan officers stand out as having higher default rates.

Table 6 provides regression evidence. We run linear probability models similar to our prior tests, except the dependent variable is a dummy indicating that the loan defaulted. The *FHA Controls* include log(loan amount), centile bins of the borrower income-to-MSA median income ratio, indicators for narrow bins of FICO, LTV, and DTI, the interest rate on the loan, and an indicator for whether the borrower is a first-time home buyer. In addition, we include fixed effects for branch-year, property county, and month-of-origination.[19]

Columns 1 and 2 report OLS results. Column 1 shows that minority borrowers whose applications are handled by white loan officers have a default rate that is 1.8 percentage points higher than white borrowers whose applications are handled by white loan officers. However, the coefficient on the interaction of minority borrower and minority loan officer is -2.2 percentage points, indicating that minority borrowers handled by minority officers do not default more than white borrowers. In column 2, we add loan officer-year fixed effects and find similar results.

We next turn to IV results, using the day-of-the-week instrument defined in Section 3.3 above. The instrument is the same as in Table 4, except it is calculated within our FHA

[19] These month-of-origination fixed effects run from January 2012 to December 2018 and absorb any variation in default rates due to the length of time over which we measure default. We also find similar results if we measure default over certain time horizons, e.g., within one or two years after origination.

sample. Because FHA loans comprise only about 20% of the mortgage market, this instrument is somewhat noisier in this analysis than in the full sample of loans in Table 4. Therefore, we run the IV regression including branch-month fixed effects rather than branch-week fixed effects. In other words, we exploit variation in the loan officer assigned to a borrower driven by work schedules within the same month rather than the same week.

Column 3 of Table 6 replicates our OLS results from column 1 using the IV sample, and column 4 shows the corresponding IV results.[20] If anything, the IV results are stronger than the OLS results. Minority borrowers whose applications are handled by white loan officers have a default rate that is 1.7 percentage points higher than other borrowers whose applications are handled by white loan officers. However, the coefficient on the interaction of minority borrower and minority loan officer is -5.2 percentage points, indicating that minority borrowers handled by minority officers are not more likely to default than white borrowers handled by white officers.

[Insert Table 6 Here]

These loan performance results are not consistent with simple explanations centered on taste-based discrimination, which posit that white loan officers would apply stricter standards to minority loan applications. Taste-based discrimination would predict that loan applications from minority borrowers handled by white loan officers should have lower completion, approval, and origination rates, as we see in the data. However, it also predicts that loans to minority borrowers handled by white loan officers should have lower default rates. That is not what we see in Table 6.

5. Exploring the Mechanism

[20] The IV sample is smaller because we drop the first three months of 2012 and require FHA lending to occur at the branch on the same day of the week during the prior 12 weeks in order to construct the instrument. The branch-month fixed effects also create some singletons which are dropped in the estimation. Internet Appendix Table IA7 reports the IV first stage regression and balance tests.

In this section, we further explore the economic mechanism driving our results. We present three main results. First, the impact of working with a minority loan officer on minority application and loan outcomes is larger for same race/ethnicity pairings, for low-income borrowers, and at small banks, whereas it is weaker at FinTech lenders. Second, we find particularly strong effects for two subgroups of loan officers: minority loan officers who appear to specialize in loans to minority borrowers and white loan officers with high industry experience. Third, these two subgroups of loan officers respond similarly to hard information: applications with low credit scores and high DTIs handled by these officers are more likely to be approved and less likely to default, even though low credit scores and high DTIs are associated with higher default risk in the data. Taken together, these results suggest that certain loan officers are better able to produce soft information about minority applicants, allowing them to simultaneously achieve higher approval rates and lower default rates.

In interpreting our results, some institutional context is helpful, as mortgage lending is somewhat different from other types of lending like small business lending. At many financial institutions, particularly the largest ones, the role of the loan officer is to help the borrower complete the application and provide all relevant documentation, such as bank statements and pay stubs. At these institutions, loan officers do not make credit approval decisions, which are made by a separate group of underwriters using application information and property appraisals. In other words, in most cases application decisions are largely driven by the hard information captured by a completed application.

This institutional background suggests the following interpretation of our results. Loan officers can expend effort to help borrowers complete their applications with more compelling documentation, and minority loan officers are particularly helpful for minority borrowers. In deciding which applications to exert effort on, loan officers use their own personal assessments of the borrowers' creditworthiness. These assessments then show up in default rates if the loan is originated. In other words, even when loan officers are not directly making mortgage approval decisions, their soft information is still important in driving the hard information that ends up on loan applications and in turn the loans that get originated and how they ultimately perform.[21]

5.1 Heterogeneity Across Borrowers and Lenders

We start by examining how the impact of loan officer and borrower race/ethnicity on mortgage approval and default rates varies in the cross section.[22]

Table 7 studies the cross section of borrowers and lenders. In columns 1-3, we study the probability that completed FHA home purchase mortgage applications in our 2018-2019 HMDA sample are approved. In column 1, we split the interaction of minority loan officers and minority applicants by whether the pair share the same race/ethnicity.[23] We find that such matching is associated with a positive effect on loan approval, while the effect is statistically insignificant when a minority borrower matches with a minority loan officer of a different race/ethnicity. The importance of same race/ethnicity matches is consistent with the soft information channel described above. Loan officers may be particularly adept at helping mortgage borrowers of the same race/ethnicity complete applications in a compelling manner. These results also suggest that the effect of loan officer-borrower matches is driven more by homophily (i.e., preferences for shared backgrounds or demographics) than a taste for diversity (i.e., preference for any underrepresented group), an important distinction highlighted by D'Acunto, Fuster, and Weber (2021).

In column 2, we focus on low-income borrowers, defined as those in the bottom third of the ratio of applicant income to MSA median income. (Note that the controls

[21] Bartos et al. (2016) use correspondence studies to examine the idea that disparities can arise when decision makers must exert effort to acquire information. Our results can be interpreted as showing that minority officers either have a pre-existing informational advantage when working with minority borrowers or face lower costs of acquiring information.

[22] Ideally, we would study approval decisions and subsequent defaults for the exact same set of loans. This is not possible due to the data limitations that (i) HMDA only began tracking loan officer identifiers and detailed borrower information (e.g., credit scores) starting in 2018, and (ii) it takes several years after loan origination to accurately measure default rates. Therefore, we focus on FHA loans from 2012 to 2018, and FHA applications in HMDA in 2018-2019. In Internet Appendix Table IA8, we verify that the patterns we document for FHA loan approval hold in our broader HMDA sample as well (i.e., across all loan types).

[23] Structuring the regression this way allows us to separate same race/ethnicity effects within minorities from such effects between white borrowers and white loan officers.

include centile bins of the applicant income to MSA median income ratio, so this coefficient captures the comparison between how white loan officers treat low-income minorities relative to other low-income borrowers.) The interaction of the indicators for minority applicant and low income shows that low-income minority applicants are 0.5 percentage points less likely to be approved than other minority applicants when handled by white loan officers. The triple interaction of the indicators for minority applicant, minority loan officer, and low income, however, shows that low-income minority applicants are 1.7 percentage points more likely to be approved for an FHA mortgage when handled by minority loan officers.

In column 3, we compare small commercial banks (i.e., less than $10 billion in total assets) and FinTech lenders (as defined by Buchak, Matvos, Piskorski, and Seru, 2018) to all other mortgage originators. The triple interaction of the indicators for minority applicant, minority loan officer, and small bank implies that minority applications handled by minority loan officers are more likely to be approved at small banks than at other financial institutions. In contrast, the triple interaction with the FinTech lender indicator implies that minority loan applications handled by minority loan officers are less likely to be approved at FinTech lenders than at other financial institutions, consistent with the contemporaneous findings of Jiang, Lee, and Liu (2022). Note that the double interactions of either minority borrower or minority loan officer with finance institution type are insignificant, suggesting that the effect of institution type is operating through the loan officer-borrower match.

Columns 4-6 provide the corresponding results for defaults in our sample of FHA loans originated between 2012 and 2018. While in column 1 we saw that minority applications handled by minority loan officers are more likely to be approved when the borrower and loan officers are of the same race/ethnicity, in column 4 we see that the lower default rate for minority borrowers when working with minority loan officers (Table 6) is driven by same-race pairings (2.7 percentage points). Similarly, while in column 2 we saw that low-income minority applications handled by minority loan officers are more likely to be approved, in column 5 we see that they are also less likely to default. Finally, while column 3 showed larger effects of minority loan officers on increasing minority approvals at small banks (and smaller effects at FinTech lenders), column 6 shows similar patterns in the institutions where minority officers reduce minority default rates.

In other words, our baseline results from Tables 3 and 6—that minority applicants are more likely to be approved and less likely to default when working with minority loan officers—are amplified when we look at matches between borrowers and loan officers of the same race/ethnicity, are amplified for low-income borrowers and at small banks, and are dampened at FinTech lenders. These patterns are consistent with minority officers having more precise soft information about minority applicants, and in particular loan officers having more precise soft information about applicants of the same race/ethnicity. This soft information is particularly important for low-income borrowers for whom hard information may be noisier and at small banks where loan officers may be afforded more discretion. As discussed above, any soft information possessed by minority loan officers may not directly enter application approval decisions. It may instead be that loan officers use their soft information in deciding which applicants they should exert effort to help in the application completion process.[24]

[Insert Table 7 Here]

5.2 Heterogeneity Across Loan Officers

In Table 8, we examine how our baseline results vary with loan officer characteristics. The structure is similar to Table 7, with the dependent variables being mortgage approvals (columns 1-2) and defaults (columns 3-4).

In column 1, we examine variation across loan officers in the share of minority applications they handle. The triple interaction of the officer's share of minority

[24] Differences in soft information most naturally explain the differences in approval and default rates we see between white and minority loan officers. The fact that the level of defaults is higher for white loan officers handling minority loans suggests that the marginal costs and benefits of loan origination may differ across loan officers. If the marginal costs and benefits were the same, in many soft information based explanations, white officers application approval rates would fall to equalize default rates.

applications with the minority officer and minority borrower indicators is positive and statistically significant. In other words, minority loan officers who handle a lot of applications from minority borrowers are better able to facilitate minority application approvals. The interaction of the minority borrower indicator with the officer's share of minority applications is statistically insignificant, suggesting that increased exposure to minority applications has no effect on white loan officers.

In column 2, we study the effects of loan officer years of experience. Experienced loan officers have higher approval rates, particularly for minority applications. The triple interaction of loan officer experience, minority loan officer, and minority borrower is statistically insignificant, suggesting that experience affects white and minority loan officers similarly. There are two possible explanations for experience effects: learning on the part of loan officers or survivorship. Internet Appendix Table IA9 provides evidence of survivorship. Loan officers who approve more minority loans in a given year are more likely to be in our sample the following year. However, the effect exists for both white and minority loan officers, suggesting that survivorship is not driving the importance of experience for white loan officers handling minority applications we see in column 2.

Columns 3-4 show the corresponding results for defaults. Column 3 shows that, in general, loan officers handling larger fractions of minority loan applications experience higher default rates. However, minority loan officers who handle many minority applications have significantly lower default rates among their minority borrowers. The results in column 4 show that loan officer experience is associated with lower minority default rates, especially for white loan officers.

Overall, the tests in Table 8 show that our baseline results from Tables 3 and 6—that minority applicants are more likely to be approved and less likely to default when working with minority loan officers—are amplified when we look at minority officers who specialize in handling minority applications. In addition, experienced loan officers also achieve higher approvals and lower defaults with minority borrowers compared to their less experienced peers.

[Insert Table 8 Here]

Figures 4 and 5 summarize these results. Figure 4 plots the unexplained minority gaps in approvals and defaults against the handling officer's minority application share, for white loan officers (left panel) and minority loan officers (right panel). The unexplained minority gap estimates come from OLS regressions with the full set of controls from Table 8, where the minority borrower indicator is interacted with indicators for each combination of white/minority officer and the group the officer falls into in terms of minority application share (<25%, 25-50%, 50-75%, >75%). The left panel does not show a strong relationship between minority gaps in approvals/defaults and minority application shares for white officers. In contrast, the right panel shows that minority gaps shrink—approvals rise and defaults fall—when minority borrowers work with minority officers who appear to specialize in minority applications.

Figure 5 similarly plots unexplained minority gaps against the handling officer's industry experience, split into four groups (1-4 years, 5-8 years, 9-12 years, >12 years). The left panel shows a clear pattern: mortgage approvals rise, and defaults fall when minority borrowers work with more experienced white loan officers. In the right panel, we see a similar, although quantitatively weaker, pattern for minority borrowers working with minority loan officers.

[Insert Figures 4 and 5 Here]

5.3 Differential Reactions to Hard Information

If not driven by taste-based discrimination, the differences between white and minority loan officers we document in approval rates and default rates for minority borrowers could stem either from different reactions to hard information or different soft information. In Table 9, we examine the possibility of differential reactions to hard information. For FHA loan applications by minority borrowers, we study the probability of approval as a function of all available hard information characteristics, including income, credit scores, and DTIs.[25] For compactness and interpretability, the table imposes a linear functional form on the relationship between approval and these variables, as opposed to the fine-grained indicator variables we used as nonparametric controls in earlier tables. However, in Internet Appendix Table IA10 we show that similar conclusions obtain if we take a nonparametric approach.

Columns 1 and 2 of Table 9 report the results for applications handled by white officers and minority officers, respectively. Column 3 reports that there are statistically significant differences between the way white and minority loan officers treat credit scores and DTIs for minority loan applications. Minority officers penalize low credit scores and high DTIs less than white officers. The magnitudes are economically meaningful. A 100-point reduction in credit score reduces the likelihood that an application handled by a white officer is approved by 4.6 percentage points, while the reduction for minority officers is only 3.7 percentage points.[26] The remaining columns show that we see similar differences in reactions to hard information when we compare inexperienced white loan officers to experienced white officers, and when we compare minority officers who handle relatively few minority applications to specialists that handle many.[27] Internet Appendix Table IA11 shows that similar results obtain when we directly analyze the reasons for rejecting a loan application reported in HMDA. Holding fixed a borrower's credit score and DTI, minority borrowers with applications handled by white loan officers are more likely to be rejected with the reported reason being "credit history" or "debt-to-income." When minority borrowers' applications are handled by minority loan officers, this difference shrinks.

These different responses to hard information can explain our results on approval rates. The fact that minority officers penalize low credit scores less means that they are more likely to approve low credit score applicants. However, the different responses to

[25] We exclude the jumbo loan indicator and loan-to-value ratios, both of which exhibit very little variation in the FHA sample.

[26] These results are consistent with Blattner and Nelson (2021), who find that credit scores are less informative for minority borrowers. Our results suggest that minority loan officers have soft information that can help improve access to credit for minority borrowers when hard information is noisy.

[27] We classify loan officers as "experienced" if they have worked in the industry for at least 10 years. We classify minority loan officers as "specialists" if the share of minority applications in their portfolio is over 80% (which is the median share within minority officers).

hard information we see cannot explain our results on default rates. If minority officers were only relying on hard information and penalized low credit scores less, we would expect the loans they approve to have higher default rates. This is not what we see in the data. Instead, the data suggest that minority loan officers are using soft information and therefore relying less on hard information.

[Insert Table 9 Here]

5.4 Other Results

In the Internet Appendix, we provide several additional analyses. First, in Table IA12 we show that our results are not stronger at financial institutions where a larger fraction of loan officers are minorities. This suggests that our results are driven by information available to the loan officers, rather than policy decisions made at the institution level. Second, Table IA12 also shows that our results do not vary depending on how competitive the local mortgage market is, as measured by the county-level HHI. In other words, we find no evidence that competition disciplines the way white loan officers handle applications from minority borrowers. Third, in Table IA13, we show that interactions between minority loan officers and minority borrowers do not affect mortgage interest rates.

6. Matching Minority Borrowers and Loan Officers

The previous sections document that matching minority loan officers with minority mortgage applicants can significantly increase loan originations and decrease default rates. In this section, we first assess the extent to which these gains are captured by endogenous matching in the existing market equilibrium with the existing pool of loan officers. We show that there is already a significant amount of matching. We then conduct a back-of-the-envelope calculation to provide a rough estimate of the potential benefits of increasing minority representation among loan officers.

To assess the degree of matching between minority applicants and loan officers, we estimate application-level linear probability models of the form:

$$1\{Minority\ Officer\}_i = \beta 1\{Minority\}_i + \gamma'\mathbf{X}_i + \varepsilon_i. \qquad (4)$$

Table 10 presents the results. Column 1 reports the raw regression without any controls. The constant of 4.8% indicates that white applicants have a 4.8% probability of working with a minority loan officer and thus a 95.2% probability of working with a white loan officer. The coefficient on the minority applicant indicator is 16.7%, indicating that minority applicants have a 4.8%+16.7% = 21.5% probability of working with a minority loan officer. In other words, there is significant matching between minority loan officers and minority borrowers. Column 2 adds the loan type, branch-year, and county-of-property fixed effects and shows that much of this matching is driven by the geographic colocation of minority borrowers and loan officers. Yet, even within a given branch office, minority applications are 4.6 percentage points more likely to be handled by minority officers. This correlation is large relative to the baseline probability of working with a minority loan officer of 9.7%.

The remaining columns of Table 10 examine heterogeneity in matching. Column 3 shows that low-income minority applications are particularly likely to be handled by minority loan officers, suggesting that lenders may recognize minority officers' information advantage with certain applicants.[28] Column 4 shows less matching at FinTech lenders where loan officers are less likely to have personalized interactions with applicants, reducing the likelihood of collecting soft information.

[Insert Table 10 Here]

[28] By themselves, our matching results could also be consistent with taste-based discrimination. It is possible that certain loan officers choose to avoid certain borrowers. However, given that many of our other results are inconsistent with taste-based discrimination, an information-based explanation seems more likely. We also note that the tendency of minority loan officers to work with the lowest income minority applicants should work against our main OLS results in Table 3 showing better application outcomes, making them conservative. Our slightly larger IV estimates in Table 4 also support this notion.

While Table 10 shows a meaningful amount of matching from the perspective of mortgage applicants, there is a much larger amount of matching from the perspective of loan officers because minorities are underrepresented among their ranks. In Table 10, the probability a minority application is handled by a minority officer is 21.5%. The summary statistics in Table 2 show that 65.3% of applications handled by minority officers are from minority borrowers. By Bayes Rule, the difference between these two numbers stems from the fact that the fraction of applications handled by minority loan officers (9.7%) is significantly smaller than the fraction of minority loan applications (29.5%).[29] This implies that increasing the proportion of minority applications handled by minority loan officers would likely require increasing the representation of minorities among loan officers, rather than simply reshuffling applications within the existing pool of loan officers.

How much might increasing minority representation among loan officers increase minority access to credit? To give a rough sense of the magnitudes, suppose minority representation among loan officers increased enough that minority applicants were as likely to work with a minority loan officer as white applicants are to work with a white officer.[30] That is, suppose the percentage of minority applications handled by minority loan officers increased 73.7 percentage points, from 21.5% to 95.2%. For this additional 73.7% of minority applications, our IV results in Table 4—which (approximately) randomly assign minority loan officers to applications—suggest a meaningful increase in the probability that each application ultimately results in a loan origination. Table 4 column 4 shows that the gap in origination rates for minority applications handled by white loan officers is 5.0 percentage points conditional on our basic controls, while minority loan officers increase origination rates for minority applicants by 3.1 percentage points (0.038-0.007=0.031 in Table 4 column 4). In other words, minority loan officers close about 62% of the gap relative to white applicants under white officers. Applying this 62% minority loan officer

[29] Formally, Pr(MinorityOfficer|Minority Applicant) = 21.5% = Pr(Minority Applicant| MinorityOfficer) x Pr(MinorityOfficer)/Pr(Minority Applicant) = 65.3% x 9.73%/29.5%.

[30] The exact increase in the fraction of minority loan officers required to attain this benchmark depends on the patterns in geographic colocation and matching within lenders.

"treatment effect" to 73.7% of minority applicants would then reduce the overall minority gap in mortgage origination rates by roughly 46%.[31]

Equilibrium levels of minority representation among mortgage loan officers are determined by many labor market factors outside the scope of our study. Yet, two points are clear from our analysis. First, minority representation matters. It is difficult to substitute for an adequate supply of informed minority loan officers with either skilled white officers or through matching minority applicants to minority officers. And second, the economic importance of minority representation is significant.

7. Conclusion

This paper studies the effect of minority loan officers on minority access to mortgage credit using novel data linking loan applications to the loan officers who handle them. We first show that minorities are significantly underrepresented among the ranks of loan officers. We then document the consequences of this underrepresentation for minority access to mortgage credit. Minority applications handled by minority loan officers are more likely to be completed, approved, and result in loan originations than those handled by white loan officers. Moreover, minority loans handled by minority loan officers are less likely to default than those handled by white loan officers.

Our results suggest that minority loan officers have an informational advantage in handling loan applications from minority borrowers. An implication of these findings is that improving the representation of minorities among loan officers could improve credit access and credit outcomes for minority borrowers. It is worth noting that the setting we study, home mortgage lending, is one where hard information predominates. The underrepresentation of minorities among loan officers could have even larger consequences for minority borrowers in other contexts like small business lending, where soft information is more crucial.

[31] This calculation (0.62 x .737 = 0.46) is conservative for two reasons. First, it assumes that the full 5% gap is available to be reduced to begin with (i.e., no minority applicants are already working with minority officers). Second, it assumes matching of minority borrowers with minority loan officers, rather than matching with an officer of the same race/ethnicity.

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Appendix A: Variable Definitions

This table provides the definitions and data sources for all variables. Panels A, B, and C contain the variables used in the analyses of minority representation levels, mortgage lending, and loan performance, respectively.

Panel A: Variables used to analyze minority representation among mortgage loan officers

Variable	Source	Definition
Officer		
I(Minority Officer)	NMLS	Indicator equal to one if the loan officer is a racial/ethnic minority
Officer Experience	NMLS	Number of years the loan officer has worked in the industry
Tenure	NMLS	Number of years the loan officer has worked for the lender
Turnover (2018)	NMLS	Indicator equal to one if the loan officer leaves the lender next year - only defined for 2018
Apps Handled (N)	HMDA	Number of mortgage applications handled by the officer this year - inclusive of all loan types
Apps Handled ($M)	HMDA	Total dollar value (in millions) of the mortgage applications handled by the officer this year
Originations (N)	HMDA	Number of mortgages originated by the officer this year – inclusive of all loan types
Originations ($M)	HMDA	Total dollar value (in millions) of the mortgages originated by the officer this year
HP App Share	HMDA	Percentage of the applications handled by the officer this year that are for home purchases
Lender		
Lender Minority LO %	NMLS	Percentage of the lender's loan officers that are racial/ethnic minorities, excluding all officers working at branches in the same county as the focal officer
Lender Mortgage Orig (#)	HMDA	Number of mortgages originated by the lender this year
Credit Union	HMDA	Indicator equal to one if the lender is a credit union
Mortgage Company	HMDA	Indicator equal to one if the lender is a not a depository institution
Branch ZIP Code		
Minority Population Share	Census	Percentage of the population that are racial/ethnic minorities in the branch's ZIP code
Minority to White PIPC	Census	Ratio of minorities' personal income per capita to that of whites in the branch's ZIP code
PIPC	Census	Personal income per capita in the branch's ZIP code
Population Density	Census	Population per square mile in the branch's ZIP code
Census Regions		
Northeastern U.S.	Census	Indicator equal to one if the officer's branch is in the Northeastern U.S. Census Region
Southern U.S.	Census	Indicator equal to one if the officer's branch is in the Southern U.S. Census Region
Midwestern U.S.	Census	Indicator equal to one if the officer's branch is in the Midwestern U.S. Census Region

Panel B: Variables used in the mortgage lending analyses

Variable	Source	Definition
Application Outcomes		
I(Completed)	HMDA	Indicator equal to one if the application is completed and submitted for a decision
I(Approved)	HMDA	Indicator equal to one if the application is approved
I(Origination)	HMDA	Indicator equal to one if the application leads to a loan origination
Loan Pricing (for originated loans)		
Interest Rate	HMDA	The interest rate on the loan (in percentage point units)
Net Discount Points	HMDA	The dollar value paid for any rate discount minus the dollar value of any lender credits, expressed as a percentage of the loan amount (in percentage point units)
Key Independent Vars		
Minority	HMDA	Indicator equal to one if the applicant is a racial/ethnic minority
Minority Officer	NMLS	Indicator equal to one if the loan officer is a racial/ethnic minority
Low Income	HMDA	Indicator equal to one if the ratio of applicant income to MSA median income is in the bottom third of all applicants
Small Bank	Call Report	Indicator equal to one if the lender is a bank with less than $10 Billion in total assets
FinTech	See Def:	Indicator equal to one if the lender is a FinTech firm according to Buchak et al. (2018)
Officer Minority Share	HMDA	Fraction of applications handled by the officer that are from minorities (ranges 0 to 1)
Officer Experience	NMLS	Number of years the loan officer has worked in the industry
Basic App Controls		
Age	HMDA	Applicant age, controlled for with 10-year bins from age 20/younger to 90/older
Income	HMDA	Applicant income, controlled for with centile bins for the ratio of income to MSA median income (or the median income in the state's non-MSA areas if not in MSA)
Loan Amount	HMDA	Requested loan amount in dollars, controlled for with Log(Loan Amount)
Jumbo	HMDA	Indicator equal to one if the loan amount is over the conforming loan limit in the county
Joint Application	HMDA	Indicator equal to one if there are multiple people on the application
Loan Type - Conventional	HMDA	Indicator equal to one if the application is not associated with any government program
Loan Type - FHA	HMDA	Indicator equal to one if the application is for a FHA loan
Loan Type - VA	HMDA	Indicator equal to one if the application is for a VA loan
Loan Type - FSA/RHS	HMDA	Indicator equal to one if the application is for a FSA or RHS loan
Extended App Controls (for completed apps)		
Credit Score	HMDA	FICO Score, controlled for with 10-point bins ranging from 500 to 850
Loan-to-Value	HMDA	LTV ratio, controlled for with bins for each percentage point from 10% to 110%
Debt-to-Income	HMDA	DTI ratio, controlled for with bins for each percentage point from 10% to 80%
Underwriting Sys. Rec.	HMDA	Each combination of underwriting system X output code is given a number, used for FE

Panel C: Variables used in the FHA loan performance analysis		
Variable	Source	Definition
Loan Performance		
I(Default)	FHA	Indicator equal to one if the borrower ever becomes 90 or more days delinquent
Key Independent Vars		
Minority	FHA	Indicator equal to one if the borrower is a racial/ethnic minority
Minority Officer	NMLS	Indicator equal to one if the loan officer is a racial/ethnic minority
Low Income	FHA	Indicator equal to one if the ratio of borrower income to MSA median income is in the bottom third of all borrowers
Small Bank	Call Report	Indicator equal to one if the lender is a bank with less than $10 Billion in total assets
FinTech	See Def:	Indicator equal to one if the lender is a FinTech firm according to Buchak et al. (2018)
Officer Minority Share	FHA	Fraction of loans made by the officer that are to minorities (ranges 0 to 1)
Officer Experience	NMLS	Number of years the loan officer has worked in the industry
FHA Controls		
Interest Rate	FHA	The interest rate on the loan (in percentage point units)
Loan Amount	FHA	The loan amount in dollars, controlled for with Log(Loan Amount)
Income	FHA	Borrower income, controlled for with centile bins for the ratio of income to MSA median income (or the median income in the state's non-MSA areas if not in MSA)
Credit Score	FHA	FICO Score, controlled for with 10-point bins ranging from 500 to 850
Loan-to-Value	FHA	LTV ratio, controlled for with bins for each percentage point from 60% to 97%
Debt-to-Income	FHA	DTI ratio, controlled for with bins for each percentage point from 10% to 57%
FT Buyer	FHA	Indicator equal to one if the borrower is a first-time home buyer

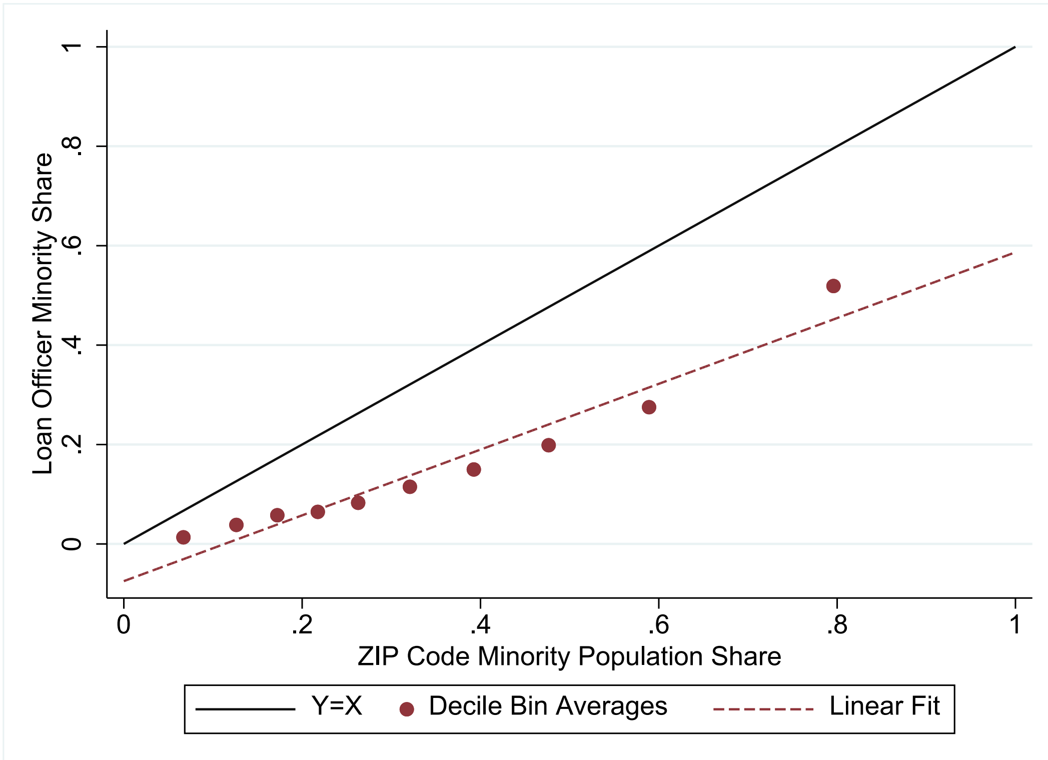

Figure 1: Minority Loan Officers Relative to Population Share

This figure shows a binned scatter plot of the percentage of loan officers that are minorities against the ZIP code minority population share. The sample includes all loan officer-years in the HMDA/NMLS matched panel, which covers 2018 to 2019. The bin averages are computed for decile bins formed based on the ZIP code minority population share. The plot also includes the best fit line and the 45-degree line for reference.

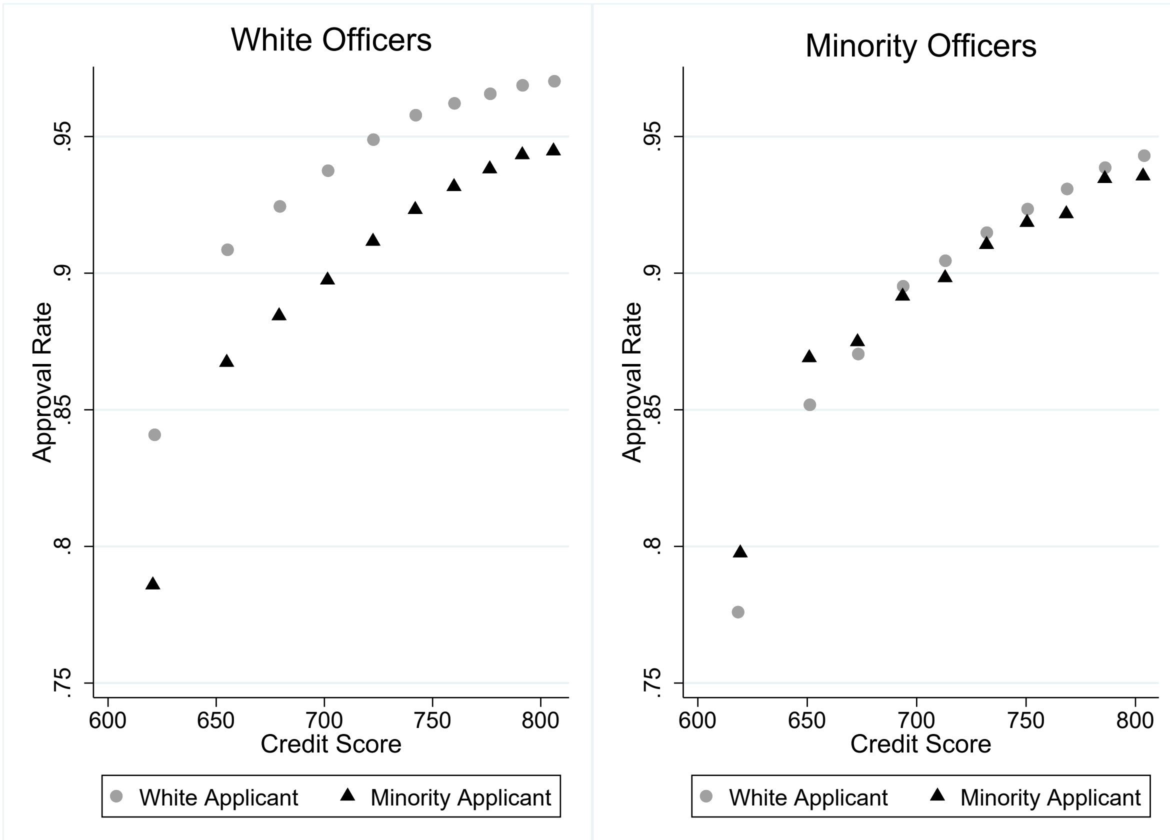

Figure 2: Loan Officer Race and Mortgage Approval

This figure plots mortgage approval rates for white and minority applicants against credit scores (in decile bins). The left panel shows applications handled by white loan officers, and the right panel shows those handled by minority officers. The sample includes all completed home purchase mortgage applications in the HMDA database in 2018 and 2019, subject to the standard data filters described in Section 2.5.

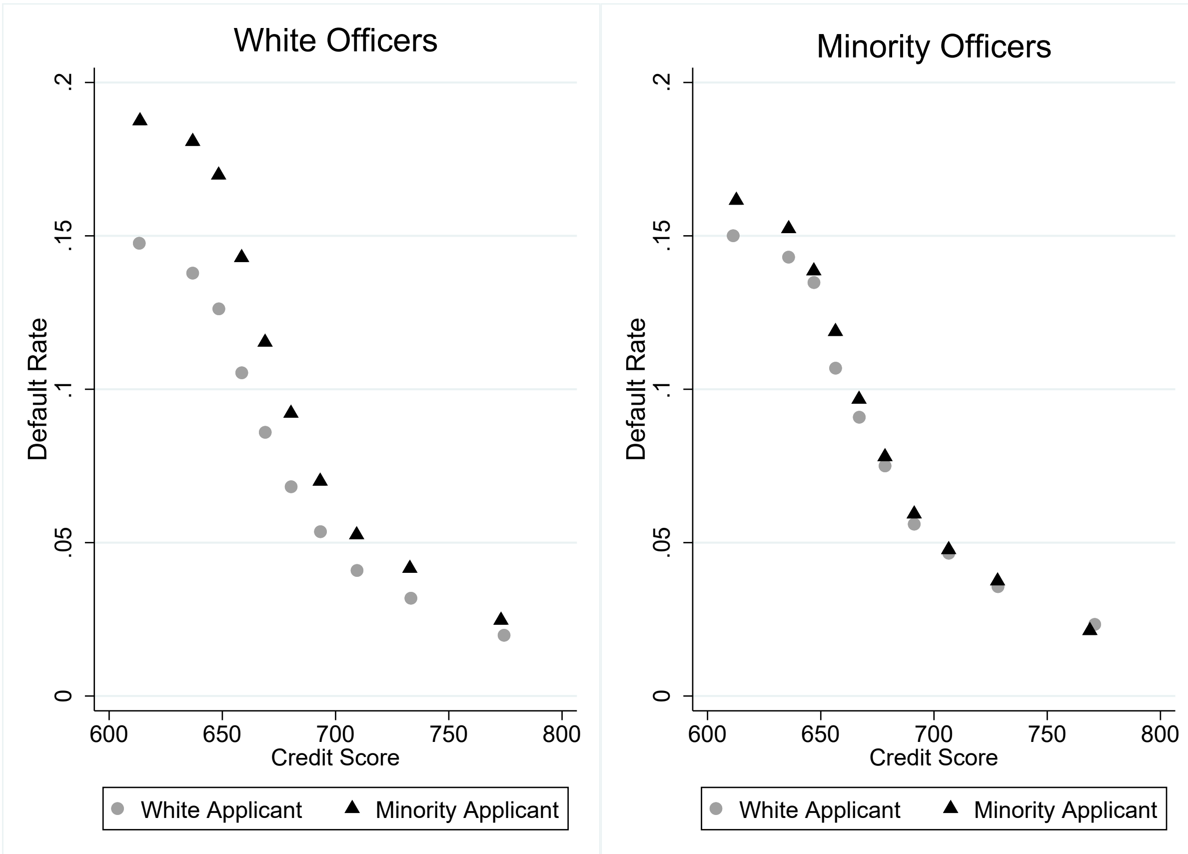

Figure 3: Loan Officer Race and Mortgage Default Rates

This figure plots mortgage default rates for white and minority borrowers against credit scores (in decile bins). Default is defined as the loan ever becoming 90 or more days delinquent. The left panel shows loans handled by white loan officers, while the right panel shows loans handled by minority loan officers. The sample includes FHA home purchase mortgages originated between 2012 and 2018, subject to the standard data filters described in Section 2.5.

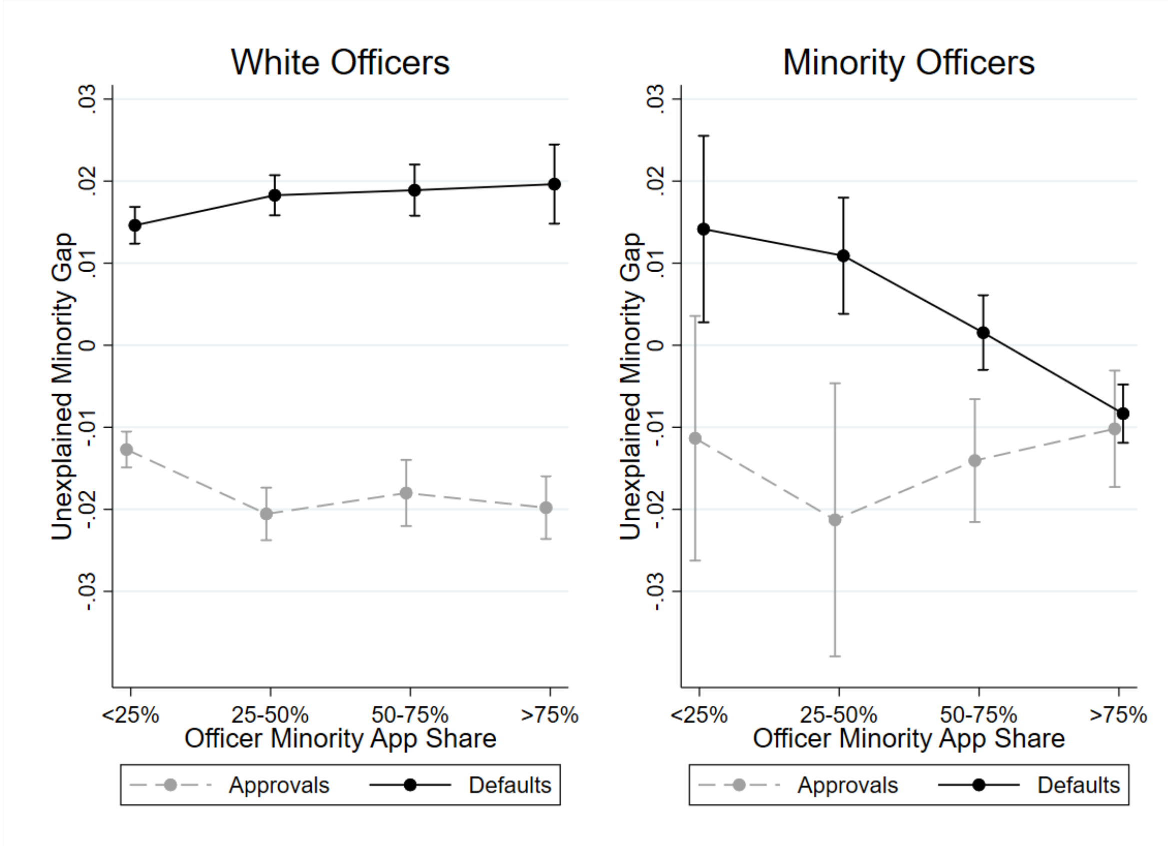

Figure 4: Loan Officer Race and Minority Gaps – Specialization

This figure plots unexplained minority gaps in mortgage approvals and defaults against the handling loan officer's minority application share. The unexplained minority gap estimates come from OLS regressions with the full set of controls in Table 8, where the minority borrower indicator is interacted with indicators for each combination of white/minority officer and the group the officer falls into in terms of minority application share. The left panel shows the estimated minority gaps for white officers (with 95% confidence intervals), and the right panel shows the results for minority officers. The samples match those in Table 8. For approvals, the sample is all completed FHA home purchase mortgage applications in the HMDA database in 2018 and 2019. For defaults, the sample is all FHA home purchase mortgages originated from 2012 to 2018. Both samples implement the standard data filters described in Section 2.5.

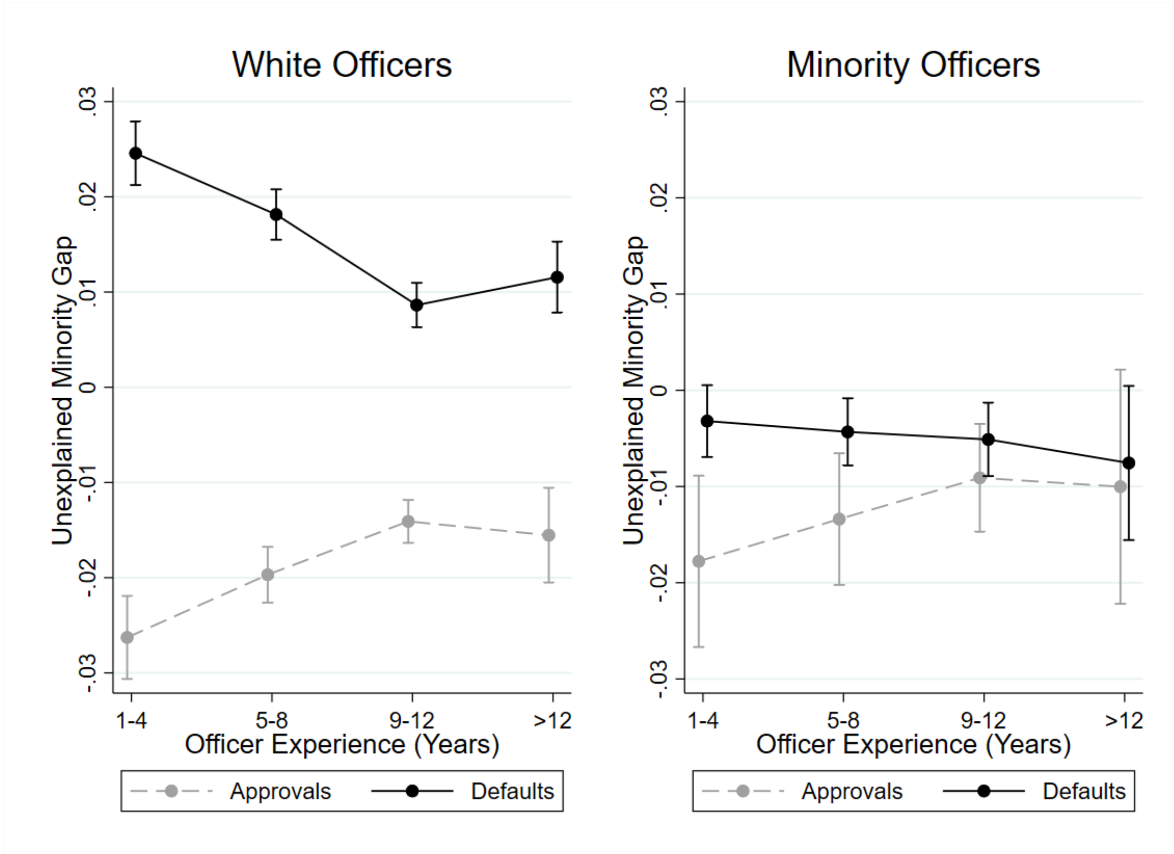

Figure 5: Loan Officer Race and Minority Gaps – Experience

This figure plots unexplained minority gaps in mortgage approvals and defaults against the handling loan officer's years of experience. The unexplained minority gap estimates come from OLS regressions with the full set of controls in Table 8, where the minority borrower indicator is interacted with indicators for each combination of white/minority officer and the group the officer falls into in terms of experience. The left panel shows the estimated minority gaps for white officers (with 95% confidence intervals), and the right panel shows the results for minority officers. The samples match those in Table 8. For approvals, the sample is all completed FHA home purchase mortgage applications in the HMDA database in 2018 and 2019. For defaults, the sample is all FHA home purchase mortgages originated from 2012 to 2018. Both samples implement the standard data filters described in Section 2.5.

Table 1: Summary Statistics for Mortgage Loan Officers

This table presents summary statistics for the mortgage loan officers in our HMDA/NMLS matched panel. Panel A provides a 2019 snapshot of racial/ethnic groups' share of the U.S. population (column 1), and of the loan officers in our data (column 2). Columns 3-5 show similar statistics for loan officers working at banks, credit unions, and mortgage companies, respectively. Panel B provides summary statistics for loan officer, lender, and ZIP code characteristics for the full 2018-2019 loan officer-year panel (columns 1-3), as well as sample means by race/ethnicity (columns 4-7). Appendix A provides variable definitions.

Panel A: Loan Officer Race (2019 Snapshot)

	U.S. Population	Loan Officers (N=255,277)	Bank LO (N=134,257)	Credit Union LO (N=23,073)	Mort. Co. LO (N=97,947)
White	60.70%	84.59%	84.16%	86.65%	84.70%
Hispanic	18.00%	8.88%	8.80%	9.31%	8.89%
Black	13.24%	1.76%	2.21%	1.64%	1.17%
Asian	6.22%	4.74%	4.80%	2.36%	5.22%
Other	1.84%	0.03%	0.04%	0.03%	0.02%

Panel B: Summary Statistics (All Loan Officer-Years 2018-2019)

	Full Sample			White LO	Hispanic LO	Black LO	Asian LO
	Mean	Median	Std Dev	Mean	Mean	Mean	Mean
Officer							
Officer Experience	9.11	9.00	6.38	9.32	7.73	8.02	8.26
Tenure	5.71	3.00	6.21	5.83	4.72	5.58	5.40
Turnover (2018)	0.21	0.00	0.41	0.21	0.23	0.23	0.19
Apps Handled (N)	39.91	14.00	63.07	41.32	31.53	31.62	32.94
Apps Handled ($M)	9.39	2.18	16.28	9.60	7.06	5.97	11.12
Originations (N)	25.13	8.00	38.64	26.29	18.04	16.56	20.48
Originations ($M)	6.06	1.32	10.52	6.24	4.22	3.30	7.17
HP App Share	0.37	0.27	0.37	0.38	0.33	0.24	0.34
Lender							
Lender Minority LO %	0.15	0.14	0.11	0.14	0.22	0.17	0.26
Lender Mortgage Orig (#)	61,317	15,900	101,321	58,089	72,955	80,938	91,139
Branch ZIP Code							
Minority Population Share	0.34	0.29	0.22	0.31	0.54	0.57	0.55
Minority to White PIPC	0.77	0.78	0.15	0.76	0.85	0.74	0.79
PIPC	40,758	37,106	16,912	40,807	37,785	35,080	47,553
Population Density	3,217	2,066	4,415	2,808	5,112	4,529	6,644

Table 2: Summary Statistics for Home Purchase Mortgage Applications

This table presents summary statistics for our sample of mortgage applications, which includes all home purchase applications in the HMDA database in 2018-2019 (including those never completed), subject to the standard data filters described in Section 2.5. Columns 1-3 present summary statistics for application outcomes, key independent variables, as well as the basic and extended application controls. Columns 4-7 present sample means for each combination of white/minority loan officer and white/minority applicant. Appendix A provides variable definitions.

	Full Sample N=5.65M			White Officers		Minority Officers	
				Whites N=3.79M	Minorities N=1.31M	Whites N=191K	Minorities N=359K
	Mean	Median	Std Dev	Mean	Mean	Mean	Mean
Application Outcomes							
Completed	83.7%	1	0.369	84.8%	81.3%	80.6%	82.8%
Approved, given completed	92.1%	1	0.270	93.7%	88.3%	90.1%	88.6%
Taken-up, given approved	97.2%	1	0.164	97.4%	96.8%	97.1%	96.8%
All-in Origination %	74.9%	1	0.433	77.4%	69.5%	70.5%	71.0%
Key Independent Vars							
Minority Officer	0.097	0	0.296	0	0	1	1
Minority	0.295	0	0.456	0	1	0	1
Low Income	0.330	0	0.470	0.314	0.375	0.250	0.379
Small Bank	0.104	0	0.305	0.121	0.076	0.045	0.056
FinTech	0.127	0	0.332	0.123	0.141	0.142	0.105
Basic App Controls							
Age	40.8	38.0	13.2	41.0	40.2	42.1	40.0
Income	94,209	77,000	63,796	96,483	88,151	106,500	85,658
Loan Amount	255,897	223,250	147,453	251,226	258,932	288,973	276,594
Jumbo	0.037	0	0.188	0.037	0.031	0.062	0.038
Joint Application	0.426	0	0.495	0.449	0.363	0.464	0.397
Loan Type - Conventional	0.614	1	0.487	0.653	0.508	0.642	0.569
Loan Type - FHA	0.228	0	0.420	0.185	0.331	0.155	0.351
Loan Type - VA	0.126	0	0.332	0.123	0.142	0.191	0.071
Loan Type - FSA/RHS	0.031	0	0.174	0.039	0.018	0.011	0.009
Extended App Controls (for completed apps)							
Credit Score	725	731	58	731	707	732	711
Loan-to-Value	0.892	0.950	0.129	0.882	0.920	0.877	0.905
Debt-to-Income	0.389	0.397	0.103	0.378	0.415	0.387	0.425

Table 3: Do Minority Loan Officers Improve Minorities' Access to Credit?

This table presents regressions examining the effect of loan officer and applicant race/ethnicity on whether mortgage applications are completed, approved, and ultimately originated. The dependent variable in columns 1 and 2 is an indicator for the application being completed. In columns 3-6, the dependent variable is an indicator for the application being approved. We split mortgage approval decisions into two cases: applications where the Automated Underwriting System (AUS) gives a clear decision (columns 3-4), and applications where the AUS does not give a definitive decision, allowing for discretion (columns 5-6). In columns 7-8, the dependent variable is an indicator for a started application ultimately resulting in an origination. The key independent variables across all specifications are indicators for the applicant being a minority, the loan officer being a minority, and their interaction. The sample in columns 1-2 and 7-8 includes all home purchase mortgage applications in the HMDA database in 2018-2019 (including those never completed), subject to the standard data filters described in Section 2.5. The sample in columns 3-6 is restricted to completed applications. Appendix A lists the controls and provides variable definitions. The standard errors are two-way clustered at the lender and county level, and the symbols *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Dependent Variable:	I(Completed)		I(Approved)				I(Origination)	
			Low Discretion		High Discretion			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Minority	-0.021***	-0.019***	-0.010***	-0.010***	-0.029***	-0.026***	-0.050***	-0.046***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)	(0.002)
Minority X Minority Officer	0.015***	0.011***	0.002	-0.000	0.012***	0.014***	0.025***	0.017***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.004)	(0.004)	(0.003)	(0.003)
Minority Officer	-0.002*		-0.003		-0.002		-0.005**	
	(0.001)		(0.002)		(0.003)		(0.002)	
Basic App Controls	Y	Y	Y	Y	Y	Y	Y	Y
Extended App Controls	-	-	Y	Y	Y	Y	-	-
Underwriting Sys. Rec. FE	-	-	Y	Y	Y	Y	-	-
Branch-Year-Officer FE	-	Y	-	Y	-	Y	-	Y
Branch-Year FE	Y	-	Y	-	Y	-	Y	-
Property County FE	Y	Y	Y	Y	Y	Y	Y	Y
R-Squared	0.057	0.090	0.167	0.202	0.562	0.618	0.080	0.114
Observations	5,643,662	5,625,635	3,628,307	3,609,947	544,380	514,953	5,643,662	5,625,635

Table 4: IV Estimates of Minority Officers' Effect on Completions, Approvals, and Originations

This table presents instrumental variables tests examining the effect of minority loan officers on application completions, approvals, and originations. We instrument for the application being handled by a minority officer with the share of applications at the branch that were handled by minority officers on the same day of the week as the current application during the prior 12 weeks (*P12 DOW Min. Off. Share*). Given the branch-week fixed effects, the intra-week variation in this instrument captures loan officer work schedules and/or rotation policies. We also instrument for *Minority X Minority Officer* with the interaction of *Minority* and our instrument. Panel A reports the first-stage regression results and Panel B reports the second-stage results. In columns 1 and 4, we study application completion and all-in origination effects using all home purchase mortgage applications in the HMDA database in 2018-2019 (including those never completed), subject to the standard data filters described in Section 2.5, and the requirement that the application is opened after the 12th week of 2018. In columns 2 and 3, we restrict the sample to completed applications in order to study credit approval. The reported controls and fixed effects apply to both panels—see Appendix A for variable definitions. The standard errors are two-way clustered at the lender and county level, and the symbols *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Sample:	All Apps	Completed Apps		All Apps
		Low Discretion	High Discretion	
	(1)	(2)	(3)	(4)
Panel A: First-stage				
Dependent Variable:	I(Minority Officer)			
P12 DOW Min. Off. Share	0.067***	0.080***	0.101***	0.067***
	(0.007)	(0.009)	(0.022)	(0.007)
R-Squared	0.550	0.557	0.597	0.550
First-stage F-stat	67.3	55.2	18.3	67.3
Panel B: Second-stage				
Dependent Variable:	I(Completed)	I(Approved)		I(Origination)
Minority	-0.021***	-0.010***	-0.031***	-0.050***
	(0.002)	(0.001)	(0.003)	(0.002)
Minority X Minority Officer	0.018**	0.008	0.036**	0.038***
	(0.008)	(0.006)	(0.016)	(0.011)
Minority Officer	-0.001	-0.005	-0.009	-0.007
	(0.033)	(0.021)	(0.065)	(0.043)
Basic App Controls	Y	Y	Y	Y
Extended App Controls	-	Y	Y	-
Underwriting Sys. Rec. FE	-	Y	Y	-
Branch-Week FE	Y	Y	Y	Y
Day-of-Week FE	Y	Y	Y	Y
Property County FE	Y	Y	Y	Y
Observations	3,958,927	2,408,755	225,785	3,958,927

Table 5: Summary Statistics for FHA Loans

This table presents summary statistics for the sample of FHA home purchase mortgages originated between 2012 and 2018, subject to the standard data filters described in Section 2.5. Columns 1-3 present summary statistics for default (the loan ever becoming 90 or more days delinquent), key independent variables, as well as the control variables. Columns 4-7 present the sample means for each combination of white/minority loan officer and white/minority borrower. Appendix A provides variable definitions.

				White Officers		Minority Officers	
	Full Sample N=3.39M			Whites N=2.12M	Minorities N=910K	Whites N=80K	Minorities N=282K
	Mean	Median	Std Dev	Mean	Mean	Mean	Mean
Loan Outcome							
I(Default)	0.091	0	0.287	0.080	0.117	0.084	0.092
Key Independent Vars							
Minority Officer	0.107	0	0.308	0	0	1	1
Minority	0.351	0	0.477	0	1	0	1
Low Income	0.330	0	0.470	0.316	0.354	0.264	0.380
Small Bank	0.125	0	0.331	0.143	0.104	0.077	0.069
FinTech	0.122	0	0.327	0.119	0.127	0.181	0.111
FHA Controls							
Interest Rate	4.117	4.000	0.559	4.075	4.177	4.143	4.237
Loan Amount	185,871	166,920	90,895	179,706	192,286	206,168	205,844
Income	66,772	59,256	33,688	68,253	64,398	72,950	61,541
Credit Score	681	673	46	684	674	682	678
Loan-to-Value	0.954	0.965	0.040	0.954	0.955	0.951	0.954
Debt-to-Income	0.412	0.420	0.090	0.402	0.425	0.414	0.437
FT Buyer	0.813	1	0.390	0.779	0.867	0.810	0.895

Table 6: Loan Officer Race and Default Rates

This table presents regressions examining default rates based on borrower and loan officer race/ethnicity. The dependent variable is an indicator for the loan ever becoming 90 or more days delinquent. The key independent variables are indicators for the borrower being a minority, the loan officer being a minority, and their interaction. Columns 1 and 2 present the OLS results for the full sample of FHA home purchase mortgages originated between 2012 and 2018, subject to the standard data filters described in Section 2.5. The remaining columns implement an instrumental variables test that uses the share of FHA loans at the branch that were handled by minority officers on the same day of the week during the prior 12 weeks to instrument for a minority officer handling the loan. The sample is similar to the first two columns, with the additional requirement that the application date is after the 12th week of 2012 and the instrument can be computed. Columns 3 and 4 present the OLS and IV results in this sample, respectively. Appendix A lists the controls and provides variable definitions. The standard errors are two-way clustered at the lender and county level, and the symbols *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Dependent Variable:	I(Default)			
	Full Sample		IV Sample	
	OLS	OLS	OLS	IV
	(1)	(2)	(3)	(4)
Minority	0.018***	0.017***	0.018***	0.017***
	(0.001)	(0.001)	(0.001)	(0.002)
Minority X Minority Officer	-0.022***	-0.017***	-0.023***	-0.052**
	(0.002)	(0.002)	(0.002)	(0.025)
Minority Officer	0.002**		0.002	0.028
	(0.001)		(0.002)	(0.075)
FHA Controls	Y	Y	Y	Y
Origination Month FE	Y	Y	-	-
Branch-Year-Officer FE	-	Y	-	-
Branch-Year FE	Y	-	-	-
Branch-Month FE	-	-	Y	Y
Day-of-Week FE	-	-	Y	Y
Property County FE	Y	Y	Y	Y
R-Squared	0.103	0.158	0.229	-
Observations	3,370,855	3,297,801	2,239,026	2,239,026
First-stage F-stat	-	-	-	59.1

Table 7: Heterogeneity Across Borrowers and Lenders

This table presents regressions that explore the heterogeneity across borrowers and lenders in the impact of loan officer and borrower race on mortgage approval and default. The analysis of mortgage approval (columns 1-3) is based on completed FHA home purchase mortgage applications in the HMDA database in 2018-2019. The analysis of mortgage default (columns 4-6) uses FHA home purchase mortgages originated from 2012 to 2018. Both samples implement the standard data filters described in Section 2.5. The key independent variables are an indicator for the borrower being a minority, an indicator for the loan officer being a minority, their interaction, and further triple interactions with indicators for the borrower and officer being of the same/different race, or for the borrower having a low income, or for the application occurring at a small bank or FinTech lender, respectively. All base terms for the interactions are included unless they are subsumed by the binned controls or fixed effects. Appendix A lists the controls and provides variable definitions. The standard errors are two-way clustered at the lender and county level, and the symbols *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Dependent Variable:	I(Approved)			I(Default)		
	(1)	(2)	(3)	(4)	(5)	(6)
Minority	-0.017***	-0.015***	-0.016***	0.018***	0.021***	0.018***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Minority Officer	-0.002	-0.001	-0.003	0.003**	0.004***	0.002*
	(0.002)	(0.003)	(0.003)	(0.001)	(0.001)	(0.001)
Minority X Minority Officer		0.004	0.007***		-0.017***	-0.023***
		(0.004)	(0.003)		(0.002)	(0.002)
Minority X Min. Off. X Other Race	0.004			-0.003		
	(0.003)			(0.003)		
Minority X Min. Off. X Same Race	0.008***			-0.027***		
	(0.003)			(0.002)		
Minority X Min. Off. X Low Inc.		0.017**			-0.012***	
		(0.007)			(0.003)	
Minority X Low Inc.		-0.005***			-0.010***	
		(0.001)			(0.001)	
Min. Off. X Low Inc.		-0.003			-0.004	
		(0.006)			(0.003)	
Minority X Min. Off. X Small Bank			0.013*			-0.002
			(0.007)			(0.006)
Minority X Small Bank			-0.002			-0.003
			(0.003)			(0.002)
Min. Off. X Small Bank			0.001			0.004
			(0.007)			(0.006)
Minority X Min. Off. X FinTech			-0.012**			0.008**
			(0.005)			(0.003)
Minority X FinTech			-0.005			0.002
			(0.005)			(0.002)
Min. Off. X FinTech			-0.000			-0.001
			(0.007)			(0.003)
Basic App Controls	Y	Y	Y	-	-	-
Extended App Controls	Y	Y	Y	-	-	-
Underwriting Sys. Rec. FE	Y	Y	Y	-	-	-
Branch-Year FE	Y	Y	Y	Y	Y	Y
Property County FE	Y	Y	Y	Y	Y	Y
FHA Controls	-	-	-	Y	Y	Y
Origination Month FE	-	-	-	Y	Y	Y
R-Squared	0.403	0.403	0.403	0.103	0.103	0.103
Observations	956,543	956,543	956,543	3,370,855	3,370,855	3,370,855

Table 8: Heterogeneity Across Loan Officers

This table presents regressions that explore the heterogeneity across loan officers in the impact of race/ethnicity on mortgage approval and default. The analysis of mortgage approval (columns 1 and 2) is based on completed FHA home purchase mortgage applications in the HMDA database in 2018-2019. The analysis of mortgage default (columns 3 and 4) uses FHA home purchase mortgages originated from 2012 to 2018. Both samples implement the standard data filters described in Section 2.5. The key independent variables are an indicator for the borrower being a minority, an indicator for the loan officer being a minority, their interaction, and further triple interactions with the officer's minority share in their application/loan portfolio, and the officer's years of industry experience, respectively. Appendix A lists the controls and provides variable definitions. The standard errors are two-way clustered at the lender and county level, and the symbols *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Dependent Variable:	I(Approved)		I(Default)	
	(1)	(2)	(3)	(4)
Minority	-0.0153***	-0.0213***	0.0165***	0.0260***
	(0.0016)	(0.0022)	(0.0014)	(0.0019)
Minority Officer	-0.0034	-0.0030	0.0039*	0.0020
	(0.0037)	(0.0048)	(0.0021)	(0.0025)
Minority X Minority Officer	-0.0032	0.0104**	0.0051	-0.0278***
	(0.0078)	(0.0051)	(0.0049)	(0.0028)
Off. Minority Share	-0.0074*		0.0078***	
	(0.0039)		(0.0018)	
Minority X Off. Minority Share	-0.0031		0.0002	
	(0.0043)		(0.0036)	
Min. Off. X Off. Minority Share	0.0057		-0.0031	
	(0.0070)		(0.0037)	
Minority X Min. Off. X Off. Minority Share	0.0191**		-0.0340***	
	(0.0090)		(0.0073)	
Off. Experience		0.0008***		0.0001
		(0.0002)		(0.0001)
Minority X Off. Experience		0.0005**		-0.0012***
		(0.0002)		(0.0002)
Min. Off. X Off. Experience		0.0002		0.0001
		(0.0005)		(0.0003)
Minority X Min. Off. X Off. Experience		-0.0006		0.0008**
		(0.0005)		(0.0004)
Basic App Controls	Y	Y	-	-
Extended App Controls	Y	Y	-	-
Underwriting Sys. Rec. FE	Y	Y	-	-
Branch-Year FE	Y	Y	Y	Y
Property County FE	Y	Y	Y	Y
FHA Controls	-	-	Y	Y
Origination Month FE	-	-	Y	Y
R-Squared	0.403	0.403	0.103	0.103
Observations	956,543	956,543	3,370,855	3,370,855

Table 9: Differential Reaction to Hard Information

This table presents regressions that explore loan officers' differential reaction to hard information in mortgage approval. The dependent variable is an indicator for the application being approved. The sample is all completed FHA home purchase mortgage applications by minority borrowers in the HMDA database in 2018-2019, subject to the standard data filters described in Section 2.5. Columns 1 and 2 utilize the subsample of applications handled by white and minority officers, respectively. Columns 4 and 5 use applications handled by inexperienced and experienced white officers, respectively. Columns 7 and 8 use applications handled by non-specialist and specialist minority loan officers, respectively. Columns 3, 6, and 9 test the differences in the coefficients for the preceding two columns. The key independent variables are an indicator for joint applications, log(loan amount), log(income), credit score (scaled by 100), debt-to-income ratio, and age (scaled by 10). Appendix A provides variable definitions. The standard errors are two-way clustered at the lender and county level, and the symbols *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Dependent Variable:	I(Approved)								
	White Officers (1)	Minority Officers (2)	Diff. (3)	Inexp. White Officers (4)	Exp. White Officers (5)	Diff. (6)	Non-Spec. Minority Officers (7)	Specialist Minority Officers (8)	Diff. (9)
Joint Application	-0.007***	-0.005**		-0.006***	-0.007***		-0.008**	-0.005	
	(0.002)	(0.002)		(0.002)	(0.002)		(0.004)	(0.003)	
Log(Loan Amount)	0.031***	0.036***		0.035***	0.027***		0.029*	0.036***	
	(0.006)	(0.007)		(0.009)	(0.005)		(0.017)	(0.006)	
Log(Income)	0.017***	0.012**		0.020***	0.012**	*	0.027***	0.007	**
	(0.004)	(0.005)		(0.005)	(0.005)		(0.009)	(0.005)	
Credit Score / 100	0.046***	0.037***	**	0.049***	0.042***	**	0.045***	0.033***	***
	(0.003)	(0.005)		(0.004)	(0.003)		(0.006)	(0.005)	
Debt-to-Income	-0.552***	-0.506***	**	-0.581***	-0.509***	***	-0.522***	-0.496***	
	(0.019)	(0.022)		(0.020)	(0.020)		(0.035)	(0.022)	
Age / 10	-0.007***	-0.006***		-0.008***	-0.006***		-0.007***	-0.006***	
	(0.001)	(0.001)		(0.001)	(0.001)		(0.001)	(0.001)	
Underwriting Sys. Rec. FE	Y	Y		Y	Y		Y	Y	
Branch-Year FE	Y	Y		Y	Y		Y	Y	
Property County FE	Y	Y		Y	Y		Y	Y	
R-Squared	0.395	0.379		0.406	0.413		0.462	0.349	
Observations	310,304	89,720		178,448	128,724		25,082	64,060	

Table 10: Does Race Influence Applicant-to-Loan Officer Matching?

This table presents regressions examining which mortgage applicants are most likely to be matched with a minority loan officer. The dependent variable is an indicator for the application being handled by a minority officer. The key independent variables are an indicator for the applicant being a minority, and its interaction with indicators for the applicant having a low income, or for the application occurring at a small bank or FinTech lender, respectively. All base terms for the interactions are included unless they are subsumed by the fixed effects. The sample includes all home purchase mortgage applications in the HMDA database in 2018-2019 (including those never completed), subject to the standard data filters described in Section 2.5. Appendix A provides variable definitions. The standard errors are two-way clustered at the lender and county level, and the symbols *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Dependent Variable:	I(Minority Officer)			
	(1)	(2)	(3)	(4)
Constant	0.048***			
	(0.006)			
Minority	0.167***	0.046***	0.038***	0.048***
	(0.014)	(0.003)	(0.003)	(0.004)
Minority X Low Inc.			0.022***	
			(0.002)	
Low Income			0.003***	
			(0.001)	
Minority X Small Bank				-0.004
				(0.006)
Minority X FinTech				-0.012**
				(0.005)
Officer Experience		-0.001***	-0.001***	-0.001***
		(0.000)	(0.000)	(0.000)
Loan Type FE	-	Y	Y	Y
Branch-Year FE	-	Y	Y	Y
Property County FE	-	Y	Y	Y
R-Squared	0.066	0.540	0.541	0.540
Observations	5,649,234	5,643,662	5,643,662	5,643,662

Internet Appendix

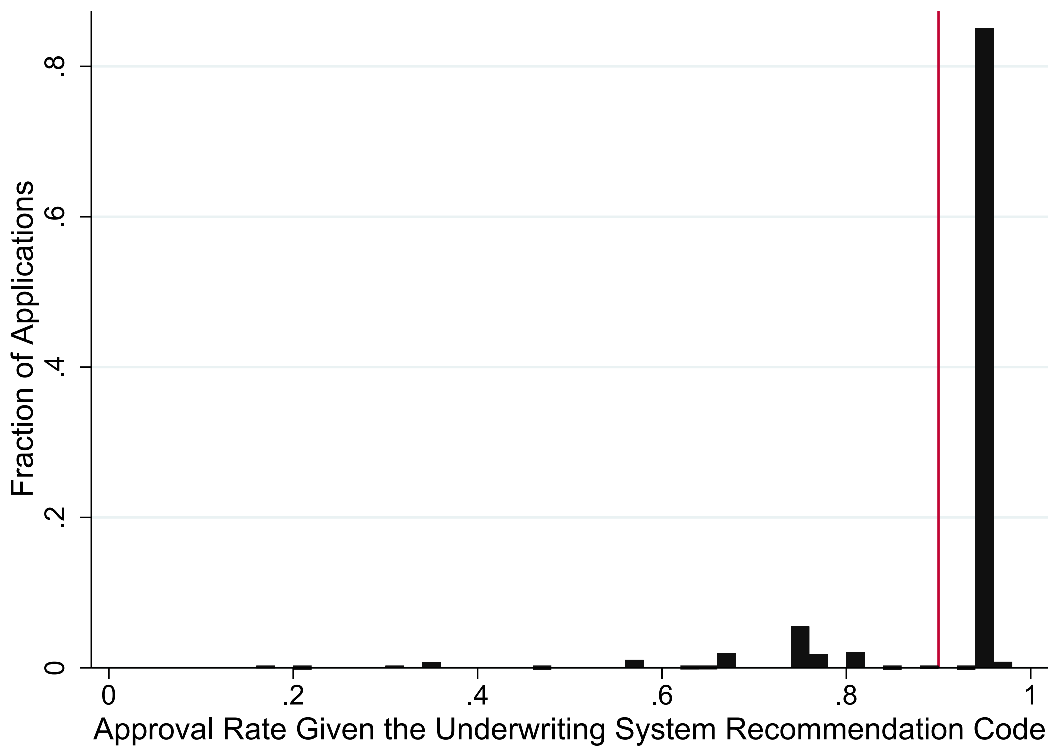

Figure IA1: Classifying Applications as High versus Low Discretion Cases

This figure shows a histogram of the mortgage applications in our sample based on the average approval rate given the output code of the automated underwriting system (AUS). Our sample includes all completed home purchase mortgage applications in the HMDA database in 2018-2019, subject to the standard data filters described in Section 2.5. We classify an application as a "low discretion" case if the average approval rate for the AUS code that the application receives is greater than 90% (see the red line in the plot). Applications receiving AUS codes with less than 90% approval rates are classified as "high discretion."

Table IA1: Minority Representation among Loan Officers—Stylized Facts

This table presents regressions that examine the role of economic, geographic, and institutional factors in determining minority representation levels among mortgage loan officers. The dependent variable is an indicator for the loan officer being a racial/ethnic minority. The key independent variables are ZIP code demographic and economic characteristics, indicators for census regions of the U.S., and lender characteristics. In columns 1-4, the sample includes all loan officer-years in our HMDA/NMLS matched panel. The tests in columns 5-7 focus on loan officers working for banks, credit unions, and mortgage companies, respectively. Appendix A provides variable definitions. The standard errors are two-way clustered at the lender and county level, and the symbols *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Dependent Variable:	I(Minority Officer)						
	Full Sample				Banks	C.U.	Mort. Co.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Minority Population Share	0.662***	0.655***	0.592***				
	(0.052)	(0.049)	(0.042)				
Minority to White PIPC		0.183***	0.162***				
		(0.031)	(0.026)				
Log(PIPC)		0.049***	0.051***				
		(0.013)	(0.008)				
Log(Population Density)		0.004	0.004*				
		(0.003)	(0.002)				
Northeastern U.S.		0.003	-0.022*				
		(0.017)	(0.012)				
Southern U.S.		-0.055***	-0.041***				
		(0.019)	(0.015)				
Midwestern U.S.		-0.037**	-0.060***				
		(0.019)	(0.016)				
Credit Union				-0.014**			
				(0.006)			
Mortgage Company				-0.057***			
				(0.007)			
Lender Minority LO %					0.277***	0.118***	0.352***
					(0.037)	(0.031)	(0.031)
Log(Lender Mortgage Orig #)					0.002	0.006**	0.000
					(0.002)	(0.003)	(0.001)
Constant	-0.075***						
	(0.011)						
Year FE	-	Y	Y	Y	Y	Y	Y
Lender FE	-	-	Y	-	-	-	-
Branch ZIP Code FE	-	-	-	Y	Y	Y	Y
R-Squared	0.161	0.178	0.293	0.294	0.338	0.326	0.315
Observations	514,892	514,892	511,983	513,809	273,823	41,094	190,274

Table IA2: The Effect of Own-Race Officers on Application Completion Rates

This table presents regressions that examine the role of loan officers in whether or not mortgage applicants complete an application they started. The dependent variable is an indicator for the application being completed. The key independent variables are an indicator for the officer and applicant being of the same race, and indicators for each applicant race (white is the omitted group). Column 1 presents the results for the full sample. Columns 2-5 present results for the applications handled by white, Hispanic, Black, and Asian loan officers, respectively. The sample includes all home purchase mortgage applications in the HMDA database in 2018-2019 (including those never completed), subject to the standard data filters described in Section 2.5. Appendix A lists the controls and provides variable definitions. The standard errors are two-way clustered at the lender and county level, and the symbols *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Dependent Variable:	I(Application Completed)				
	Full Sample	White Officers	Hispanic Officers	Black Officers	Asian Officers
	(1)	(2)	(3)	(4)	(5)
Own-Race Officer	0.006^{***}				
	(0.001)				
Hispanic	-0.004^{***}	-0.010^{***}	0.000	0.002	-0.006
	(0.001)	(0.001)	(0.002)	(0.007)	(0.005)
Black	-0.012^{***}	-0.018^{***}	-0.014^{***}	-0.001	-0.017^{***}
	(0.001)	(0.001)	(0.003)	(0.005)	(0.005)
Asian	-0.028^{***}	-0.035^{***}	-0.022^{***}	-0.029^{***}	-0.019^{***}
	(0.002)	(0.002)	(0.004)	(0.007)	(0.005)
Basic App Controls	Y	Y	Y	Y	Y
Branch-Year-Officer FE	Y	Y	Y	Y	Y
Property County FE	Y	Y	Y	Y	Y
R-Squared	0.090	0.089	0.103	0.123	0.133
Observations	5,625,635	5,079,008	380,178	51,045	113,950

Table IA3: The Effect of Own-Race Officers on Credit Approval

This table presents regressions that examine the role of loan officers in mortgage approval. The dependent variable is an indicator for the application being approved. The key independent variables are an indicator for the officer and applicant being of the same race, and indicators for each applicant race (white is the omitted group). Column 1 presents the results for the full sample. Columns 2-5 present results for the applications handled by white, Hispanic, Black, and Asian loan officers, respectively. The sample includes completed home purchase mortgage applications in the HMDA database in 2018-2019 that we classify as "high discretion" and that satisfy the standard data filters described in Section 2.5. Appendix A lists the controls and provides variable definitions. The standard errors are two-way clustered at the lender and county level, and the symbols *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Dependent Variable:	I(Approved)				
	Full Sample	White Officers	Hispanic Officers	Black Officers	Asian Officers
	(1)	(2)	(3)	(4)	(5)
Own-Race Officer	0.008***				
	(0.002)				
Hispanic	-0.013***	-0.021***	-0.005	-0.010	-0.018
	(0.003)	(0.002)	(0.006)	(0.026)	(0.012)
Black	-0.017***	-0.024***	-0.023***	-0.010	-0.012
	(0.003)	(0.002)	(0.008)	(0.011)	(0.011)
Asian	-0.024***	-0.032***	-0.015*	-0.023	-0.011**
	(0.004)	(0.003)	(0.009)	(0.023)	(0.005)
Basic App Controls	Y	Y	Y	Y	Y
Extended App Controls	Y	Y	Y	Y	Y
Underwriting Sys. Rec. FE	Y	Y	Y	Y	Y
Branch-Year-Officer FE	Y	Y	Y	Y	Y
Property County FE	Y	Y	Y	Y	Y
R-Squared	0.619	0.618	0.649	0.670	0.653
Observations	514,953	454,693	35,964	6,493	16,031

Table IA4: All-in Estimate of Own-Race Officers' Effect on Lending to Minorities

This table presents regressions that examine the all-in effect of loan officers on whether a started application ultimately ends in an origination. The dependent variable is an indicator for the application resulting in an origination. The key independent variables are an indicator for the officer and applicant being of the same race, and indicators for each applicant race (white is the omitted group). Column 1 presents the results for the full sample. Columns 2-5 present results for the applications handled by white, Hispanic, Black, and Asian loan officers, respectively. The sample includes all home purchase mortgage applications in the HMDA database in 2018-2019 (including those never completed), subject to the standard data filters described in Section 2.5. Appendix A lists the controls and provides variable definitions. The standard errors are two-way clustered at the lender and county level, and the symbols *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Dependent Variable:	I(Origination)				
	Full Sample	White Officers	Hispanic Officers	Black Officers	Asian Officers
	(1)	(2)	(3)	(4)	(5)
Own-Race Officer	0.009***				
	(0.001)				
Hispanic	-0.021***	-0.029***	-0.012***	-0.026***	-0.027***
	(0.002)	(0.001)	(0.003)	(0.008)	(0.005)
Black	-0.052***	-0.060***	-0.057***	-0.042***	-0.066***
	(0.002)	(0.001)	(0.004)	(0.006)	(0.007)
Asian	-0.044***	-0.054***	-0.038***	-0.053***	-0.029***
	(0.003)	(0.003)	(0.005)	(0.009)	(0.005)
Basic App Controls	Y	Y	Y	Y	Y
Branch-Year-Officer FE	Y	Y	Y	Y	Y
Property County FE	Y	Y	Y	Y	Y
R-Squared	0.114	0.113	0.119	0.147	0.147
Observations	5,625,635	5,079,008	380,178	51,045	113,950

Table IA5: IV Balance Tests for the Analyses of Completions, Approvals, and Originations

This table presents the balance tests for our instrumental variables analyses. The dependent variable is our instrument—the share of applications at the branch that were handled by minority officers on the same day of the week as the current application during the prior 12 weeks (in percentage point units). The key independent variables are the controls from our IV analyses, including continuous versions of our binned controls. We also include the average approval rate for the AUS code the application received in columns 4-5 (a continuous measure of the AUS recommendation). In column 1, the sample includes all home purchase mortgage applications in the HMDA database in 2018-2019 (including those never completed), subject to the standard data filters described in Section 2.5, and the requirement that the application is opened after the 12th week of 2018. This sample corresponds to the IV analyses of application completions and originations. Columns 2-5 restrict the sample to completed applications, and split the data into cases that are deemed low versus high discretion. These samples correspond to the IV analysis of credit approval. The p-value reported at the bottom of the columns is for an F-test of the joint significance of the control variables. Appendix A provides variable definitions. The standard errors are two-way clustered at the lender and county level, and the symbols *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Dependent Variable:	P12 DOW Min. Off. Share				
	All Apps	Completed Apps			
		Low Discretion	High Discretion	Low Discretion	High Discretion
	(1)	(2)	(3)	(4)	(5)
Age	-0.001**	-0.000	-0.001		
	(0.000)	(0.000)	(0.001)		
Log(Income)	-0.009	-0.014	-0.018		
	(0.009)	(0.012)	(0.039)		
Log(Loan Amount)	0.005	0.006	-0.016		
	(0.010)	(0.015)	(0.037)		
Jumbo	0.001	0.065	-0.004		
	(0.026)	(0.045)	(0.047)		
Joint Application	-0.001	0.007	0.026		
	(0.007)	(0.009)	(0.035)		
Credit Score		0.000	0.000		
		(0.000)	(0.000)		
Loan-to-Value		-0.003	-0.108		
		(0.035)	(0.132)		
Debt-to-Income		-0.038	-0.197*		
		(0.043)	(0.107)		
AUS Code Approval Rate				-0.009	-0.000
				(0.016)	(0.001)
Loan Type FE	Y	Y	Y	Y	Y
Underwriting Sys. Rec. FE	-	Y	Y	-	-
Branch-Week FE	Y	Y	Y	Y	Y
Day-of-Week FE	Y	Y	Y	Y	Y
Property County FE	Y	Y	Y	Y	Y
Observations	3,958,927	2,408,755	225,785	2,408,755	225,785
p-value on Joint F-test	0.305	0.641	0.350	0.575	0.819

Table IA6: Replication of our Main Results in the FHA Subsample

This table presents regressions that replicate our main results using the FHA subsample of the home purchase mortgage applications in the HMDA database in 2018-2019, subject to the standard data filters described in Section 2.5. The tests in columns 1, 2, and 3 correspond to our main results on application completion, approval, and origination in Table 3. Appendix A lists the controls and provides variable definitions. The standard errors are two-way clustered at the lender and county level, and the symbols *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Dependent Variable:	I(Completed)	I(Approved)	I(Origination)
	(1)	(2)	(3)
Minority	-0.016***	-0.017***	-0.045***
	(0.001)	(0.001)	(0.001)
Minority X Minority Officer	0.015***	0.008***	0.031***
	(0.003)	(0.002)	(0.004)
Minority Officer	-0.005*	-0.002	-0.008**
	(0.003)	(0.002)	(0.004)
Basic App Controls	Y	Y	Y
Extended App Controls	-	Y	-
Underwriting Sys. Rec. FE	-	Y	-
Branch-Year FE	Y	Y	Y
Property County FE	Y	Y	Y
R-Squared	0.077	0.403	0.113
Observations	1,281,735	956,543	1,281,735

Table IA7: First Stage and IV Balance Test for the Default Analysis

This table presents the first stage regression and instrument balance test for our IV analysis of defaults. Column 1 presents the first stage, where the dependent variable is an indicator for the loan being handled by a minority loan officer, and the key independent variable is our instrument—the share of FHA loans at the branch that were handled by minority officers on the same day of the week during the prior 12 weeks. This first stage regression also includes the *FHA Controls* and fixed effects used in the IV analysis. Column 2 presents the balance test, where the dependent variable is our instrument, and the key independent variables are the controls from our IV analysis, including continuous versions of our binned controls. The p-value reported at the bottom of column 2 is for an F-test of the joint significance of the control variables. The sample includes all FHA home purchase mortgages originated between 2012 and 2018, subject to the standard data filters described in Section 2.5, and the requirement that the application date is after the 12th week of 2012 and the instrument can be computed. Appendix A lists the controls and provides variable definitions. The standard errors are two-way clustered at the lender and county level, and the symbols *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Dependent Variable:	Minority Officer (1)	P12 DOW Min. Off. Share (2)
P12 DOW Min. Off. Share	0.035***	
	(0.003)	
Interest Rate		0.035
		(0.028)
Log(Loan Amount)		0.003
		(0.035)
FT Buyer		-0.006
		(0.023)
Log(Income)		0.021
		(0.029)
Credit Score		0.000
		(0.000)
Loan-to-Value		-0.043
		(0.220)
Debt-to-Income		-0.083
		(0.097)
FHA Controls	Y	-
Branch-Month FE	Y	Y
Day-of-Week FE	Y	Y
Property County FE	Y	Y
Observations	2,239,026	2,239,026
First-stage F-stat	59.1	-
p-value on Joint F-test	-	0.783

Table IA8: Heterogeneity Across Borrowers, Lenders, and Loan Officers – All Loan Types

This table repeats the regressions from Tables 7 and 8 that examine the cross-sectional variation in the effect of race/ethnicity on mortgage approval, except here we use the broader HMDA sample, rather than only FHA applications. Here the sample includes all completed home purchase mortgage applications in the 2018-2019 HMDA database (subject to the standard data filters described in Section 2.5) that are deemed "high discretion" cases based on the automated underwriting system output. The dependent variable is an indicator for the application being approved. The regression specifications are the same as those in Tables 7 and 8. However, to improve readability, we report here the coefficients for only the key independent variables (i.e., the triple interactions, and the *Minority X Off. Experience* term in column 5). We note that the remaining interaction terms are included in the specifications, and look similar to those reported in Tables 7 and 8. Appendix A lists the controls and provides variable definitions. The standard errors are two-way clustered at the lender and county level, and the symbols *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Dependent Variable:	I(Approved)				
	(1)	(2)	(3)	(4)	(5)
Minority	-0.031***	-0.029***	-0.029***	-0.025***	-0.034***
	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)
Minority X Minority Officer	0.008**	0.013***		-0.003	0.018**
	(0.004)	(0.004)		(0.008)	(0.009)
Minority X Min. Off. X Low Inc.	0.014*				
	(0.008)				
Minority X Min. Off. X Small Bank		0.018*			
		(0.010)			
Minority X Min. Off. X FinTech		-0.026**			
		(0.010)			
Minority X Min. Off. X Other Race			0.005		
			(0.005)		
Minority X Min. Off. X Same Race			0.015***		
			(0.004)		
Minority X Min. Off. X Off. Minority Share				0.024*	
				(0.015)	
Minority X Min. Off. X Off. Experience					-0.001
					(0.001)
Minority X Off. Experience					0.001**
					(0.000)
Remaining Interaction Terms	Y	Y	Y	Y	Y
Basic App Controls	Y	Y	Y	Y	Y
Extended App Controls	Y	Y	Y	Y	Y
Underwriting Sys. Rec. FE	Y	Y	Y	Y	Y
Branch-Year FE	Y	Y	Y	Y	Y
Property County FE	Y	Y	Y	Y	Y
R-Squared	0.562	0.562	0.562	0.562	0.562
Observations	544,380	544,380	544,380	544,380	544,380

Table IA9: Loan Officers' Minority Lending and Survival in the Sample

This table presents regressions that examine the effect of loan officers' minority lending on their likelihood of remaining in the FHA sample. The sample includes all loan officer-years in the FHA data from 2012 to 2017 (we collapse the FHA loan-level data to the officer-year level and compute statistics on minority lending outcomes). The dependent variable is an indicator for the loan officer remaining in the sample the following year. The key independent variables are an indicator for the officer being a minority, and its interaction with the officer's share of loans made to minority borrowers (*Off. Minority Share*) and the difference between the officer's default rates on loans to minority versus white borrowers (*Off. Minority Default Gap*). Appendix A provides variable definitions. The standard errors are clustered by lender, and the symbols *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Dependent Variable:	I(Remain in Sample Next Year)			
	(1)	(2)	(3)	(4)
Minority Officer	-0.007	-0.052***	-0.002	-0.002
	(0.005)	(0.008)	(0.004)	(0.004)
Off. Minority Share	0.018***	0.011***		
	(0.003)	(0.004)		
Min Off. X Off. Minority Share		0.068***		
		(0.009)		
Off. Minority Default Gap			0.002	0.001
			(0.003)	(0.003)
Min Off. X Off. Minority Default Gap				0.009
				(0.014)
Officer Experience	0.005***	0.005***	0.005***	0.005***
	(0.000)	(0.000)	(0.000)	(0.000)
Lender-Year FE	Y	Y	Y	Y
R-Squared	0.153	0.154	0.145	0.145
Observations	357,660	357,660	177,745	177,745

Table IA10: Differential Reaction to Hard Information – Binned Controls

This table presents results from regressions similar to those in Table 9 exploring loan officers' differential reaction to hard information in mortgage approval. As in Table 9, the dependent variable is an indicator for the application being approved, and we examine differences in approval patterns between minority versus white officers (column 1), experienced versus inexperienced white officers (column 2), and specialist versus non-specialist minority officers (column 3). The difference from Table 9 is that here, the control variables are binned following the descriptions in Appendix A. Therefore, instead of coefficients, this table reports the p-values from Wald tests of the joint significance of the interaction terms between each set of control bin indicators and the indicator for the relevant loan officer group. The sample in column 1 is completed FHA home purchase mortgage applications by minority borrowers in the HMDA database in 2018-2019, subject to the standard data filters described in Section 2.5. Columns 2 and 3 limit the sample to applications handled by white and minority officers, respectively.

Dependent Variable:	I(Approved)		
	Minority Officers vs. White Officers	Exp. White Offs. vs. Inexp. White Offs.	Specialist Min. Offs. vs. Non-Spec. Min. Offs.
	(1)	(2)	(3)
Joint Application X INT	0.892	0.350	0.901
Log(Loan Amount) X INT	0.507	0.276	0.482
Income Ratio Bins X INT	0.000	0.000	0.000
Credit Score Bins X INT	0.000	0.004	0.034
Debt-to-Income Bins X INT	0.000	0.000	0.000
Age Bins X INT	0.207	0.485	0.448
Binned Controls	Y	Y	Y
Underwriting Sys. Rec. FE	Y	Y	Y
Branch-Year FE	Y	Y	Y
Property County FE	Y	Y	Y
R-Squared	0.445	0.457	0.439
Observations	401,582	310,304	89,720

Table IA11: Reasons for Denial

This table examines the reported reasons for denying a mortgage application. The sample includes all completed home purchase mortgage applications in the HMDA database in 2018-2019, subject to the standard data filters described in Section 2.5. Panel A tabulates the frequency of the nine potential denial reasons available to HMDA-reporting lenders. The columns report frequencies within the set of all denied applicants, and for denied white and minority applicants, separately. The regressions in Panel B examine racial differences in denial reason usage. The dependent variable is an indicator for the application being denied due to "debt-to-income" or "credit history" in columns 1 and 2, respectively. The key independent variables are an indicator for the borrower being a minority, an indicator for the loan officer being a minority, and their interaction. The specifications include fixed effects for each combination of lender, year, loan type, and narrow bins of debt-to-income ratio (column 1) and credit score (column 2). Appendix A provides variable and bin definitions. The standard errors are two-way clustered at the lender and county level, and the symbols *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Denial Reason Frequencies

Denial Reason	All Denials (%)	White Denials (%)	Minority Denials (%)
Debt-to-Income	31.78	29.45	34.92
Credit History	17.99	17.73	18.34
Collateral	16.09	18.48	12.88
Incomplete Application	9.70	10.61	8.46
Other	8.16	8.12	8.22
Insufficient Cash	6.55	6.59	6.50
Unverifiable Info	5.84	5.10	6.83
Employment History	3.74	3.74	3.73
Mortgage Insurance Denied	0.15	0.17	0.12

Panel B: Racial Differences in Denial Reason Usage

Dependent Variable:	I(Denied for DTI)	I(Denied for Credit History)
	(1)	(2)
Minority	0.0057***	0.0035***
	(0.0004)	(0.0003)
Minority X Minority Officer	-0.0018***	-0.0026***
	(0.0006)	(0.0005)
Minority Officer	0.0011***	0.0011***
	(0.0004)	(0.0004)
Lender-Year-Loan Type-DTI Bin FE	Y	-
Lender-Year-Loan Type-FICO Bin FE	-	Y
R-Squared	0.496	0.235
Observations	4,054,501	4,114,910

Table IA12: Additional Heterogeneity in the Minority Officer Effect?

This table presents regressions that examine potential heterogeneity in the impact of loan officer and borrower race on lending outcomes across different types of lenders and competitive environments. The analysis of mortgage approval (columns 1 and 2) is based on completed FHA home purchase mortgage applications in the HMDA database in 2018-2019. The analysis of mortgage default (columns 3 and 4) uses FHA home purchase mortgages originated from 2012 to 2018. Both samples implement the standard data filters described in Section 2.5. The key independent variables are an indicator for the borrower being a minority, an indicator for the loan officer being a minority, their interaction, and further triple interactions with indicators for the lender ranking in the top third in terms of their minority loan officer share (*Min. Employer*), or for the application occurring in a county in the top tercile of mortgage market HHI (*Low Comp.*), respectively. Appendix A lists the controls and provides variable definitions. The standard errors are two-way clustered at the lender and county level, and the symbols *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Dependent Variable:	I(Approved)		I(Default)	
	(1)	(2)	(3)	(4)
Minority	-0.016***	-0.018***	0.020***	0.019***
	(0.002)	(0.001)	(0.001)	(0.002)
Minority Officer	-0.002	-0.003	0.003	0.003**
	(0.004)	(0.003)	(0.002)	(0.002)
Minority X Minority Officer	0.007*	0.007**	-0.021***	-0.023***
	(0.004)	(0.003)	(0.002)	(0.002)
Minority X Min. Off. X Min. Employer	0.002		0.001	
	(0.004)		(0.003)	
Minority X Min. Employer	-0.002		-0.004*	
	(0.002)		(0.002)	
Min. Off. X Min. Employer	-0.001		-0.002	
	(0.004)		(0.003)	
Minority X Min. Off. X Low Comp.		-0.000		0.008*
		(0.005)		(0.004)
Minority X Low Comp.		0.002		-0.004**
		(0.002)		(0.002)
Min. Off. X Low Comp.		-0.000		-0.003
		(0.004)		(0.003)
Basic App Controls	Y	Y	-	-
Extended App Controls	Y	Y	-	-
Underwriting Sys. Rec. FE	Y	Y	-	-
Branch-Year FE	Y	Y	Y	Y
Property County FE	Y	Y	Y	Y
FHA Controls	-	-	Y	Y
Origination Month FE	-	-	Y	Y
R-Squared	0.403	0.403	0.103	0.103
Observations	956,543	956,543	3,370,855	3,370,855

Table IA13: Loan Officer Race and Loan Pricing

This table presents regressions that examine the effect of loan officers on mortgage loan pricing. The dependent variable is the interest rate (in percentage point units), and we control directly for non-rate components of pricing with *Net Discount Points.* The key independent variables are an indicator for the borrower being a minority, an indicator for the loan officer being a minority, and their interaction. Columns 1 and 2 present the OLS results for the low- and high-discretion samples (based on the underwriting system output), respectively. Columns 3 and 4 present the instrumental variables tests that use the share of applications at the branch that were handled by minority officers on the same day of the week during the prior 12 weeks to instrument for a minority officer handling the loan. The sample includes all originated home purchase mortgages in the HMDA database in 2018-2019, subject to the standard data filters described in Section 2.5, and for the IV tests the requirement that the application is opened after the 12th week of 2018. Appendix A lists the controls and provides variable definitions. The standard errors are two-way clustered at the lender and county level, and the symbols *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Dependent Variable:	Interest Rate			
	OLS		IV	
	Low Discretion	High Discretion	Low Discretion	High Discretion
	(1)	(2)	(3)	(4)
Minority	-0.000	-0.001	-0.002	-0.003
	(0.001)	(0.004)	(0.002)	(0.006)
Minority X Minority Officer	0.007**	-0.010	0.011	0.010
	(0.003)	(0.008)	(0.021)	(0.060)
Minority Officer	0.008***	0.017***	0.008	-0.044
	(0.003)	(0.005)	(0.078)	(0.277)
Net Discount Points	-0.156***	-0.120***	-0.157***	-0.120***
	(0.005)	(0.008)	(0.006)	(0.009)
Basic App Controls	Y	Y	Y	Y
Extended App Controls	Y	Y	Y	Y
Underwriting Sys. Rec. FE	Y	Y	Y	Y
Branch-Week FE	Y	Y	Y	Y
Day-of-Week FE	Y	Y	Y	Y
Property County FE	Y	Y	Y	Y
R-Squared	0.805	0.871	-	-
Observations	2,614,823	162,732	2,233,434	138,123
First-stage F-stat	-	-	35.7	5.3